# METHODOLOGY FOR INTEROPERABILITY-ENABLED ADAPTABLE STRATEGIC FLEET MIX PLANNING

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# METHODOLOGY FOR INTEROPERABILITY-ENABLED ADAPTABLE STRATEGIC FLEET MIX PLANNING

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*To my parents and grandparents for believing in me*

*and to Justine, Joshua, Michael, and Matt for supporting me*

*and keeping me in high spirits through this long process.*

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# TABLE OF CONTENTS

**DEDICATION** . . . **iii**

**ACKNOWLEDGEMENTS** . . . **iv**

**LIST OF TABLES** . . . **ix**

**LIST OF FIGURES** . . . **xi**

**SUMMARY** . . . **xv**

**I INTRODUCTION** . . . **1**

1.1 Motivation . . . 1

1.2 Terminology . . . 8

1.2.1 Interoperability . . . 8

1.2.2 System of Systems . . . 10

1.2.3 Fleet Mixes and Force Mixes . . . 12

1.2.4 Fleet Purchasing (or Mix) Plan . . . 13

1.2.5 Threat Environments, Scenarios, and Missions . . . 14

1.3 Military Strategic Decision Making . . . 15

1.4 Interoperability as a Complicating Factor . . . 16

1.5 Defense Acquisition . . . 18

1.6 Observations, Problem Formulation, and Primary Research Objective . . . 21

1.6.1 Summarizing Observations . . . 21

1.6.2 Goal Capability . . . 23

1.6.3 Problem Formulation and Primary Research Objective . . . 29

**II BACKGROUND** . . . **32**

2.1 Research Question Development . . . 32

2.2 Defense Acquisition . . . 35

2.2.1 The Current Approach . . . 35

2.2.2 JCIDS Overview . . . 39

2.2.3 Problems with the Acquisition Process . . . 41

2.3 Fleet Planning Problems . . . . . . . . . . . . . . . . . . . . . . . . . 44
2.3.1 Fleet Sizing and Mix . . . . . . . . . . . . . . . . . . . . . . . . 44
2.3.2 Fleet Mix Scheduling . . . . . . . . . . . . . . . . . . . . . . . . 46
2.3.3 Fleet Grouping and Scaling . . . . . . . . . . . . . . . . . . . . . 52
2.3.4 Discussion of Fleet Mix Problems . . . . . . . . . . . . . . . . . . 55
2.4 Robustness, Adaptability, and Flexibility . . . . . . . . . . . . . . . . . 56
2.4.1 Fleet Sizing and Mix Adaptability . . . . . . . . . . . . . . . . . . 59
2.4.2 Graph and Network Adaptability . . . . . . . . . . . . . . . . . . 60
2.4.3 Decision-Theoretic Approaches to Flexibility in Industrial Decision Making Applications . . . . . . . . . . . . . . . . . . . . . . 63
2.5 Interoperability . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 65
2.5.1 Interoperability Criteria . . . . . . . . . . . . . . . . . . . . . . . 65
2.5.2 Interoperability Types . . . . . . . . . . . . . . . . . . . . . . . . 66
2.5.3 Qualitative Interoperability Methods . . . . . . . . . . . . . . . . 70
2.5.4 Similarity-Based Interoperability Method . . . . . . . . . . . . . 72
2.5.5 A Reliability-Based Interoperability Methodology . . . . . . . . . 74
2.5.6 Discussion of Interoperability Methods . . . . . . . . . . . . . . . 76
2.6 System of Systems . . . . . . . . . . . . . . . . . . . . . . . . . . . . 77
2.6.1 System of Systems Design . . . . . . . . . . . . . . . . . . . . . 77
2.6.2 System of Systems Performance . . . . . . . . . . . . . . . . . . 80
2.6.3 Net Centric Warfare, and the Future of Warfare . . . . . . . . . . 81
2.6.4 Networked Effectiveness . . . . . . . . . . . . . . . . . . . . . . 82
2.7 Mission Modeling . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 83
2.7.1 System Dynamics and Lanchester's Laws . . . . . . . . . . . . . 84
2.7.2 Agent-Based Models . . . . . . . . . . . . . . . . . . . . . . . . 85
2.7.3 Other Approaches . . . . . . . . . . . . . . . . . . . . . . . . . . 86
**III DEVELOPMENT . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 90**
3.1 Summary of Research Question Findings . . . . . . . . . . . . . . . . . 90
3.2 Success Criteria . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 93

3.3 Broad Framework . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 94
3.4 Evaluating Capability Constraints . . . . . . . . . . . . . . . . . . . . . . . 95
3.4.1 Mission Modeling . . . . . . . . . . . . . . . . . . . . . . . 95
3.4.2 Interoperability . . . . . . . . . . . . . . . . . . . . . . . . 97
3.4.3 Fleet Scaling . . . . . . . . . . . . . . . . . . . . . . . . . 104
3.5 Evaluating Costs and Limitations . . . . . . . . . . . . . . . . . . . . . . 111
3.6 Fleet Mix Planning (Scheduling) . . . . . . . . . . . . . . . . . . . . . . 113
3.6.1 Fleet Plan Generation . . . . . . . . . . . . . . . . . . . . . 113
3.6.2 Quantifying Flexibility . . . . . . . . . . . . . . . . . . . . 114
**IV METHODOLOGY DESCRIPTION . . . . . . . . . . . . . . . . . . . . . 118**
4.1 Phase One: Problem Definition . . . . . . . . . . . . . . . . . . . . . . . 120
4.2 Phase Two: Alternative Generation . . . . . . . . . . . . . . . . . . . . . 123
4.2.1 Fleet Design Space Exploration . . . . . . . . . . . . . . . . . 125
4.2.2 Combat and Mission Models . . . . . . . . . . . . . . . . . . 126
4.3 Phase Three: Fleet Scaling . . . . . . . . . . . . . . . . . . . . . . . . . 127
4.4 Phase Four: Fleet Mix Scheduling . . . . . . . . . . . . . . . . . . . . . 130
4.4.1 Generating Fleet Plans . . . . . . . . . . . . . . . . . . . . . 132
4.5 Phase Five: Calculating Fleet Plan Adaptability . . . . . . . . . . . . . . 133
4.5.1 Decision Support . . . . . . . . . . . . . . . . . . . . . . . . 134
**V EXPERIMENTS AND RESULTS . . . . . . . . . . . . . . . . . . . . . . 135**
5.1 Step 1: Testing Constituent Models . . . . . . . . . . . . . . . . . . . . . 135
5.1.1 Experiment 1: Mission Model Interoperability Testing . . . . . . . 135
5.1.2 Experiment 2: Fleet Scaling . . . . . . . . . . . . . . . . . . . 143
5.1.3 Experiment 3: Flexibility Criterion . . . . . . . . . . . . . . . . 147
5.2 Step 2: Testing the Thesis . . . . . . . . . . . . . . . . . . . . . . . . . 156
5.2.1 Experiment 4: Demonstration of the Methodology With and Without Interoperability . . . . . . . . . . . . . . . . . . . . . . . . . 156
5.2.2 Comparing the Effects of Interoperability and Other Variables on Adaptability . . . . . . . . . . . . . . . . . . . . . . . . . . . . 180

5.2.3 Effects of Increasing Asset Overlap in the Force Scaling Step . . . 189

**VI CONCLUDING REMARKS . . . 191**

6.1 Summary of Findings . . . 191

6.2 Contributions . . . 203

6.3 Areas for Future Research . . . 206

**APPENDIX A — OMAHA BEACH MODEL INPUTS . . . 212**

**APPENDIX B — OPERATION COBRA MODEL INPUTS . . . 246**

**APPENDIX C — HAND-CRAFTED FLEET PLAN DATA . . . 259**

**REFERENCES . . . 262**

# LIST OF TABLES


1 Ghanmi Multi-Role Vehicle Tasking, Mission-to-Role Mapping . . . . . . 53
2 Ghanmi Multi-Role Vehicle Tasking, Role-to-Requirements Mapping . . . 54
3 Ghanmi Multi-Role Vehicle Tasking, Vehicle-to-Requirements Mapping . . 54
4 Comparison of Qualitative Interoperability Methods . . . . . . . . . . . . 71
5 Research Questions . . . . . . . . . . . . . . . . . . . . . . . . . . . 92
6 Example cost and penalty methods . . . . . . . . . . . . . . . . . . . . . . 121
7 Notional capability value functions . . . . . . . . . . . . . . . . . . . . . 122
8 Comparison of simulated Omaha beach results to historical results . . . . . 138
9 Notional asset costs . . . . . . . . . . . . . . . . . . . . . . . . . . . 159
10 New asset notional functional characteristic costing . . . . . . . . . . . . 159
11 Most Adaptable Fleet Plan - New Asset Evolution . . . . . . . . . . . . . . 170
12 Second Most Adaptable Fleet Plan - New Asset Evolution . . . . . . . . . 170
13 Least Adaptable Fleet Plan - New Asset Evolution . . . . . . . . . . . . . 170
14 OMAHA Friendly Waves 1-4 . . . . . . . . . . . . . . . . . . . . . . . 214
15 OMAHA Friendly Waves 1-4, Continued . . . . . . . . . . . . . . . . . . 215
16 OMAHA Friendly Waves 5-9 . . . . . . . . . . . . . . . . . . . . . . . 216
17 OMAHA Friendly Waves 5-9, Continued . . . . . . . . . . . . . . . . . . 217
18 OMAHA Friendly Waves 10-13 . . . . . . . . . . . . . . . . . . . . . . 218
19 OMAHA Friendly Waves 10-13, Continued . . . . . . . . . . . . . . . . . 219
20 OMAHA Friendly Waves 14-19 . . . . . . . . . . . . . . . . . . . . . . 220
21 OMAHA Friendly Waves 14-19, Continued . . . . . . . . . . . . . . . . . 221
22 OMAHA Enemy Defenders . . . . . . . . . . . . . . . . . . . . . . . . 223
23 OMAHA Enemy Defenders, Continued . . . . . . . . . . . . . . . . . . . 224
24 OMAHA Offensive Lethality Matrix, Part 1 of 9 . . . . . . . . . . . . . . 226
25 OMAHA Offensive Lethality Matrix, Part 2 of 9 . . . . . . . . . . . . . . 227
26 OMAHA Offensive Lethality Matrix, Part 3 of 9 . . . . . . . . . . . . . . 228
27 OMAHA Offensive Lethality Matrix, Part 4 of 9 . . . . . . . . . . . . . . 229

28 OMAHA Offensive Lethality Matrix, Part 5 of 9 . . . . . . . . . . . . . . . . 230
29 OMAHA Offensive Lethality Matrix, Part 6 of 9 . . . . . . . . . . . . . . . . 231
30 OMAHA Offensive Lethality Matrix, Part 7 of 9 . . . . . . . . . . . . . . . . 232
31 OMAHA Offensive Lethality Matrix, Part 8 of 9 . . . . . . . . . . . . . . . . 233
32 OMAHA Offensive Lethality Matrix, Part 9 of 9 . . . . . . . . . . . . . . . . 234
33 OMAHA Defensive Lethality Matrix, Part 1 of 10 . . . . . . . . . . . . . . . 236
34 OMAHA Defensive Lethality Matrix, Part 2 of 10 . . . . . . . . . . . . . . . 237
35 OMAHA Defensive Lethality Matrix, Part 3 of 10 . . . . . . . . . . . . . . . 238
36 OMAHA Defensive Lethality Matrix, Part 4 of 10 . . . . . . . . . . . . . . . 239
37 OMAHA Defensive Lethality Matrix, Part 5 of 10 . . . . . . . . . . . . . . . 240
38 OMAHA Defensive Lethality Matrix, Part 6 of 10 . . . . . . . . . . . . . . . 241
39 OMAHA Defensive Lethality Matrix, Part 7 of 10 . . . . . . . . . . . . . . . 242
40 OMAHA Defensive Lethality Matrix, Part 8 of 10 . . . . . . . . . . . . . . . 243
41 OMAHA Defensive Lethality Matrix, Part 9 of 10 . . . . . . . . . . . . . . . 244
42 OMAHA Defensive Lethality Matrix, Part 10 of 10 . . . . . . . . . . . . . . 245
43 Operation Cobra Friendly Assets, Part 1 of 3 . . . . . . . . . . . . . . . . . . 247
44 Operation Cobra Friendly Assets, Part 2 of 3 . . . . . . . . . . . . . . . . . . 248
45 Operation Cobra Friendly Assets, Part 3 of 3 . . . . . . . . . . . . . . . . . . 248
46 Operation Cobra Enemy Assets . . . . . . . . . . . . . . . . . . . . . . . . . 250
47 Operation Cobra Offensive Lethality Matrix, Part 1 of 2 . . . . . . . . . . . 252
48 Operation Cobra Offensive Lethality Matrix, Part 2 of 2 . . . . . . . . . . . 253
49 Operation Cobra Defensive Lethality Matrix, Part 1 of 4 . . . . . . . . . . 255
50 Operation Cobra Defensive Lethality Matrix, Part 2 of 4 . . . . . . . . . . 256
51 Operation Cobra Defensive Lethality Matrix, Part 3 of 4 . . . . . . . . . . 257
52 Operation Cobra Defensive Lethality Matrix, Part 4 of 4 . . . . . . . . . . 258

# LIST OF FIGURES


1 Notional fleet mix evolution example . . . . . 5

2 DoD Decision Support System, reproduced in [63] from [132] . . . . . 19

3 JCIDS Process & Acquisition Decisions [19] . . . . . 20

4 Fleet plan evolution by OEC . . . . . 24

5 Overall evaluation criterion example measures . . . . . 25

6 Fleet plan evolution, options . . . . . 26

7 Notional fleet plan adaptability vs. acquisition decision . . . . . 27

8 Notional fleet plan adaptability vs. design decision . . . . . 28

9 Defense Acquisition System [2] [19] . . . . . 36

10 Acquisition Life Cycle [132]. . . . . . 40

11 Relationships of Strategy, CONOPs, JOpsC, CBAs and JCIDS. [48] . . . . . 41

12 Outline of Stovepiped CBA-Based Acquisition Processes, reproduced from [47] . . . . . 42

13 Pre-MDD Fleet-wide CBA-Based Acquisition Processes, reproduced from [47] . . . . . 45

14 IPPD for Fleet Mix [33] . . . . . 46

15 Robust fleet decision tree by Wesolkowski, et al. [140] . . . . . 49

16 Somboonwiwat's Grouping Flow Chart [126] . . . . . 52

17 Adaptable fleets by Wesolkowski, et al. [140] . . . . . 61

18 Adaptable fleets with more variance and demand, by Wesolkowski, et al. [140] . . . . . 62

19 Ford's Interoperability Character Identification . . . . . 73

20 Ford's 'System Instantiation' . . . . . 73

21 Ford's 'Performance-Enhanced System Instantiation' with Data . . . . . 74

22 Summary of Jones-Wyatt Interoperability Method [78] . . . . . 75

23 Trapeze Model of SoS Engineering [105] . . . . . 79

24 Hybrid of Trapeze [105] and traditional wave model, created by [35] . . . . . 79

25 Fleet Battle Experiment Delta [7] . . . . . 82

26 Overview of modeling types characterized by fidelity and discreteness [18] 84
27 System dynamics model of Lanchester's laws with fatigue [10] . . . . . . . 85
28 Example Block for a Strike Asset in Sample Modeling Approach . . . . . . 88
29 Combustion Reactor Network Shown in [104] . . . . . . . . . . . . . . . . 105
30 Comparison of reactor network and mission network . . . . . . . . . . . . 107
31 Depiction of full fleet mix planning methodology, with modified steps. . . . 119
32 Notional value functions for capability and budget. . . . . . . . . . . . . . 123
33 Phase two: Alternative generation. . . . . . . . . . . . . . . . . . . . . . . 124
34 Phase three: Fleet mix planning. . . . . . . . . . . . . . . . . . . . . . . . 131
35 Fleet Battle Experiment Delta results [7] . . . . . . . . . . . . . . . . . . . 136
36 Friendly (attacker) casualties versus force-wide interoperability level . . . . 139
37 Enemy (defender) casualties versus force-wide interoperability level . . . . 140
38 Friendly (attacker) casualties versus force-wide interoperability level, reduced defender numbers . . . . . . . . . . . . . . . . . . . . . . . . . . . 141
39 Enemy (defender) casualties versus force-wide interoperability level, reduced defender numbers . . . . . . . . . . . . . . . . . . . . . . . . . . . 141
40 Figure 38, Zoomed . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 142
41 Fleet paths shown by fleet ID No. . . . . . . . . . . . . . . . . . . . . . . . 149
42 Fleet paths shown by fleet ID no., colored by criterion ranking . . . . . . . 150
43 Normalized fleet performance, colored by criterion ranking . . . . . . . . . 150
44 Total occurrence of various paths in the top 20 most adaptable paths, under each of 5 different weighting scenarios. . . . . . . . . . . . . . . . . . . . . 153
45 Total occurrence of fleet mixes associated with top the 20 fleet paths under each of 5 different weighting scenarios. . . . . . . . . . . . . . . . . . . . . 154
46 Total occurrence of various paths in the top 20 most adaptable paths, under each of 100 randomized weighting scenarios. . . . . . . . . . . . . . . . . 155
47 Total occurrence of fleet mixes associated with top the 20 fleet paths under each of 100 randomized weighting scenarios. . . . . . . . . . . . . . . . . 155
48 Fixed-interoperability case with distance threshold of $\$1 \times 10^8$, all paths plotted . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 161
49 Fixed-interoperability case with distance threshold of $\$5 \times 10^8$, only 1 in 100 paths plotted . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 161

50 Variable-interoperability case with distance threshold of $\$1 \times 10^8$, all paths plotted . . . 162

51 Variable-interoperability case with distance threshold of $\$5 \times 10^8$, only 1 in 100 paths plotted . . . 162

52 Variation of adaptability in the variable-interoperability case, plotted against path step and ranking. Colored by adaptability criterion value. . . . 163

53 Variation of adaptability in the fixed-interoperability case, plotted against path step and ranking. Colored by adaptability criterion value. . . . 163

54 Simplified instantiation of methodology for purposes of demonstration . . . 166

55 Notional chart of fleet mixes ranked by some OEC and connected via lines of cost sufficiency, i.e. is the cost difference smaller than some incremental budget increase. . . . 167

56 Potential way to investigate the effects of acquisition decisions on fleet mix adaptability. . . . 168

57 Potential way to investigate the effects of increasing interoperability in one system on fleet mix adaptability. . . . 168

58 Adaptability of fixed- and variable-interoperability fleet paths, Y-axis starts at 3.8 . . . 173

59 Adaptability of fixed- and variable-interoperability fleet paths, colored by interoperability, Y-axis starts at 3.8 . . . 174

60 Adaptability of fixed- and variable-interoperability fleet paths, colored by various design variables . . . 175

61 All variables plotted against adaptability, for variable-interoperability case . 176

62 Actual by predicted plot for variable-interoperability case, with $R^2$ = 0.71 . 177

63 Actual by predicted plot for fixed-interoperability case, with $R^2$ = 0.48 . . . 178

64 Effects screening for parameters in variable-interoperability case . . . 178

65 Effects screening for parameters in variable-interoperability case . . . 179

66 Any fleet paths without high interoperability and good adaptability are grayed out . . . 181

67 Any fleet paths with low interoperability are grayed out . . . 183

68 Any fleet paths with low average cost are grayed out . . . 184

69 Average path adaptability versus average path interoperability, colored by average path cost . . . 185

70 Variable-interoperability cases with good adaptability and bad interoperability . . . 187

71 Variable-interoperability cases with good adaptability and high interoperability . . . 188

72 Enemy (defender) casualties versus force-wide interoperability level . . . 197

73 Normalized fleet performance, colored by criterion ranking . . . 199

74 Simplified instantiation of methodology for purposes of demonstration . . . 201

75 Adaptability of fixed- and variable-interoperability fleet paths, colored by interoperability . . . 202

76 Repeated figure: Hand-crafted fleet paths. . . . 259

# SUMMARY

This thesis develops a proof of concept methodology for the rapid assessment of fleet-wide requirements by enabling the creation of fleet mix plans that are adaptable to given budgetary uncertainty and to multiple mission preference weightings. The methodology is used to test the ability to understand the effects, on strategic-level variables, of infusing interoperability into a fleet. The methodology utilizes an optimization-guided exploration that iterates different asset types and fleet configurations over multiple missions to determine fleet performance. Utilizing a novel fleet scaling approach developed by analogy to chemical reactors, the methodology avoids modeling an entire fleet of thousands of system types, instead opting to use missions as building blocks to scale up the fleet. After the costs and performances of the various candidate fleets have been determined, the methodology transitions into a standard fleet mix planning problem. However, this problem is modified to quantify the adaptability of those fleet plans to changes in budget and mission weightings, and to create multiple potential adaptable fleet plans. Adaptability is quantified via an adapted approach from other fields that incorporates the difference and number of fleet options available along a given purchasing plan.

This methodology is motivated by multiple issues identified in the current requirements development portion of defense acquisition, in the face of uncertain future missions and budgets. Acquisition programs meant for a future of highly-interoperable system operations are developed using capabilities-based assessments, but these assessments are not conducted in the context of the entire defense system of systems and thus can either duplicate capabilities or create capabilities that are not optimal or necessary. Furthermore, as the strategic environment becomes more volatile, uncertain, complex, and ambiguous, decision

makers must increasingly choose between focusing the military force to get excellent performance in one mission type, or hedging their bets by allowing a more diverse capability set. To address this, the developed methodology deals with some of the key issues involved in assessing the adaptability of force acquisition plans for an interoperable force.

The primary structure of this methodology is that of a fleet mix planning problem, with an alternative generation phase and a planning phase. The first phase involves using an optimizer to explore optimal locations of the system quantity, functional characteristics, and interoperability space. Evaluation of the relevant system of systems (SoS) is done via mission modeling, with the SoS evaluated against each potential mission. After this is done for the entire design space with some stopping criteria, the SoS for all missions are scaled up to a full-size fleet by a simple scaling method that consults the strategic performance requirements on the fleet to determine the number of simultaneous operations of each mission type that a given fleet could perform, given how many systems are required for each mission by any one SoS. Consideration is also given in the case where systems are not necessarily additive across missions because two different missions may use the same exact system.

Once full-size fleet alternatives are generated, the methodology proceeds to the fleet mix plan development phase. In this phase, existing methods for developing fleet mix plans are employed in order to compute a plan of purchases based on potential budgets and mission weightings. However, a further step is added in order to determine not just the robustness of the individual fleets within a given plan, but the flexibility of the entire plan relative to other plans. For this, a fleet plan flexibility criterion is developed based on a modification of a flexibility or adaptability measure from existing literature. This flexibility criterion accounts for the number of alternate branches available at each time step of the fleet purchasing plan, as well as the "distance" or similarity of each of these alternate fleets to the one proposed by the plan. This is done to preserve choice and adaptability for the decision maker at every point along the fleet plan, such that the fleet can be readily changed to perform other missions with sufficient efficacy if the budget and mission scenario changes.

This methodology is instantiated with various methods from a set of alternatives, and tested via a two-step approach. The first step tests the chosen mission modeling method, the chosen interoperability modeling method, and the chosen fleet scaling method. Experiment set 1 first involved testing an OMAHA beach landing combat scenario by assessing whether the mission model replicates historical data with reasonable accuracy, and extend this scenario to a brand new combat scenario in World War II.

Next, experiment set 1 tested the chosen interoperability method by assessing whether the combat model reproduces real-world experiments showing that interoperability improves combat effectiveness. Experiment 2 performs the proposed fleet-scaling operation on the OMAHA mission SoS to compare it to the real-world Normandy beach landing force.

Experiment 3 tested the fleet mix planning aspect of the methodology against multiple possible budget and mission scenarios by comparing the generated fleet mix plans. This includes a qualitative comparison of the fleets' robustness ratings, for all budget scenarios, under the new flexibility criterion developed and robustness and flexibility criteria from other research.

Finally, step two involved testing whether an interoperability-enabled fleet-planning methodology provides improved robustness for generated fleet mix plans, as a whole, than a methodology without such a capability. This was done by constraining the interoperability of assets during the space exploration portion to a fixed number. The results were that there is sufficient evidence that interoperability, out of all of the other functional characteristics, has a significant effect on fleet plan adaptability. As a result, interoperability should likely be included in future analyses to test the strength of this effect.

As a whole, this methodology presents a first step to dealing with the question of how best to plan a force for defense applications. However, assumptions made during the development of this methodology mean that the issue is not settled and there is more work to be done to definitively meet this need. Combat and mission modeling advances, such as con-ops modeling, modularity, and ballistics, would allow for more realistic mission modeling. Expanding the modeled interoperability types to other types of interoperability, such as command and control, would hopefully expand the conclusions made in this study to interoperability in general. Other enhancements include assessing the problem of fleet plan selection from the point of view of real options, incorporating asset availability, reliability, and maintenance into mission modeling, scaling, and fleet planning, and developing costing methods for interoperability and functional characteristics in general.

# CHAPTER I

# INTRODUCTION

## *1.1 Motivation*

The strategic decision making community has become aware, in the last 20 years, of how the strategic environment has changed. It is now more volatile, more uncertain, more complex, and more ambiguous. This concept, referred to as the VUCA (Volatile Uncertain, Complex, Ambiguous) environment, is now mentioned in leadership primers [89] and other strategic planning literature [99].

The US Army War College Strategic Leadership Primer defines these terms as following:

> **Volatility**: the rate of change of the environment. Volatility in the Information Age means even the most current data may not provide an adequate context for decision making. Beyond an ability to accurately assess the current environment, leaders must anticipate rapid change and do their best to predict what may happen within the time scope of a project, program, or operation. Volatility in the environment coupled with the extended timelines of modern acquisition programs creates a special challenge for strategic leaders and their advisors.
>
> **Uncertainty**: the inability to know everything about a situation and the difficulty of predicting the nature and effect of change (the nexus of uncertainty and volatility.) Uncertainty often delays decision-making processes and increases the likelihood of vastly divergent opinions about the future. It drives the need for intelligent risk management and hedging strategies.
>
> **Complexity**: the difficulty of understanding the interactions of multiple parts

> or factors and of predicting the primary and subsequent effects of changing one or more factors in a highly interdependent system or even system of systems. Complexity differs from uncertainty; though it may be possible to predict immediate outcomes of single interactions within a broader web, the non-linear branches and sequels multiply so quicklyand double back on previous connectionsso as to overwhelm most assessment processes. Complexity could be said to create uncertainty because of the sheer volume of possible interactions and outcomes.
>
> **Ambiguity**: describes a specific type of uncertainty that results from differences in interpretation when contextual clues are insufficient to clarify meaning. Ironically, ambiguous is an ambiguous term, whose definition changes subtly depending on the context of its usage. For our purposes here, it refers to the difficulty of interpreting meaning when context is blurred by factors such as cultural blindness, cognitive bias, or limited perspective. At the strategic level, leaders can often legitimately interpret events in more than one way and the likelihood of misinterpretation is high.

While tackling ambiguity is traditionally an organizational challenge, and untangling complexity is often the role of the apparatus of government (the State Department, intelligence agencies, etc.), uncertainty and volatility seem to doubly pertain to acquisition programs and by extension to engineering.

It is instructive to deal with this matter in terms of broad 'capabilities' first. Given that the role of a strategic decision maker (SDM) is to align the capabilities of their organization with expected capability needs[89, 99], they are faced with a few challenges: First, it is likely that there exist a few possible scenarios, among which the capabilities required will vary drastically. These scenario capabilities will be hard to estimate, but SDMs have teams and organizations that try to foresee future trends in technology, world politics and economics, and adversary capabilities. Next, SDMs must select one or more scenarios which appear(s) to be most likely to occur. In the event that more than one scenario is likely, SDMs must hedge their bets or perhaps count on the Theory of the Lesser Included Case, where they can assume that one scenario is less difficult to achieve than another.

From an engineering point of view, this is akin to attempting to align functional characteristics with uncertain requirements, guaranteeing that within a certain range the design will still perform adequately. Two concepts come into play here: robustness and adaptability. Robustness is defined by the IEEE Glossary of Terms [69] as "the degree to which a system or component can function correctly in the presence of invalid inputs or stressful environmental conditions." In our problem this would imply a sudden, large, yet short-term shift in the threat environment. Importantly, robustness is closely related to the inherent capability of a fleet - that is to say, a fleet can be considered robust to a particular scenario if it can perform adequately in that scenario "as is", or without modification to its structure or mix. Adaptability or flexibility is defined by the Glossary of Terms as "the ease with which a system or component can be modified for use in applications or environments other than those for which it was specifically designed" [69], and by others as "[the property of only requiring] a small infusion of money in order to address effectively a large number of distinct scenarios. It is unlikely that any cost-constrained [body] will be able to address every scenario. Scenarios that a [body] cannot address (adapted or otherwise) pose a unique risk to that particular [body]." Here there is an implication that perhaps this "use" is more long-term; the application is a new one. In our problem this would imply that the entire organization must be flexible enough to allow an easy shift to a different threat environment. Combined, we would have an organization that is both robust to rapid shifts in the short term and flexible enough to change easily to deal with unforeseen long-term issues.

The organization that will be dealt with in this dissertation is a strategic military "force", which is defined in further detail later in the chapter. Military forces must be able to handle multiple different mission types, and have assets specifically suited to handling those missions. However, increasingly frequently, the VUCA environment is subjecting those forces to more uncertain, and volatile requirements [89]. One day a force must handle a counter-insurgency mission, and the next day deterring a peer adversary. This flexibility is highly important in this day and age. Unlike in previous decades, there is growing recognition that US defense budgets will likely be challenged in the future. In announcing the Third Offset Strategy, then-Secretary of Defense Chuck Hagel said that "continued fiscal pressure will likely limit our militarys ability to respond to long-term challenges by increasing the size of our force or simply outspending potential adversaries on current systems, so to overcome challenges to our military superiority, we must change the way we innovate, operate, and do business" [64]. This continued fiscal pressure has a direct effect on adaptability - it limits the degree of change that is permitted for each time period if the strategic scenario changes.

To remain flexible, acquisitions must be made that do not lock-in the force to expensive changes down the line, should threat environments change. Thus, not only is the adaptability of a force important, but also the adaptability of a force purchasing plan, i.e. the entire set of acquisition decisions made over some period of time, each of which in effect creates a new force in time. It is the resultant adaptability of this decision set that is of interest, more-so than any one force or decision within the set. As a justification for this, one can imagine that a single force can be adaptable to multiple different scenarios by the infusion of a small number of assets. This tradeoff is reflected in Figure 1.

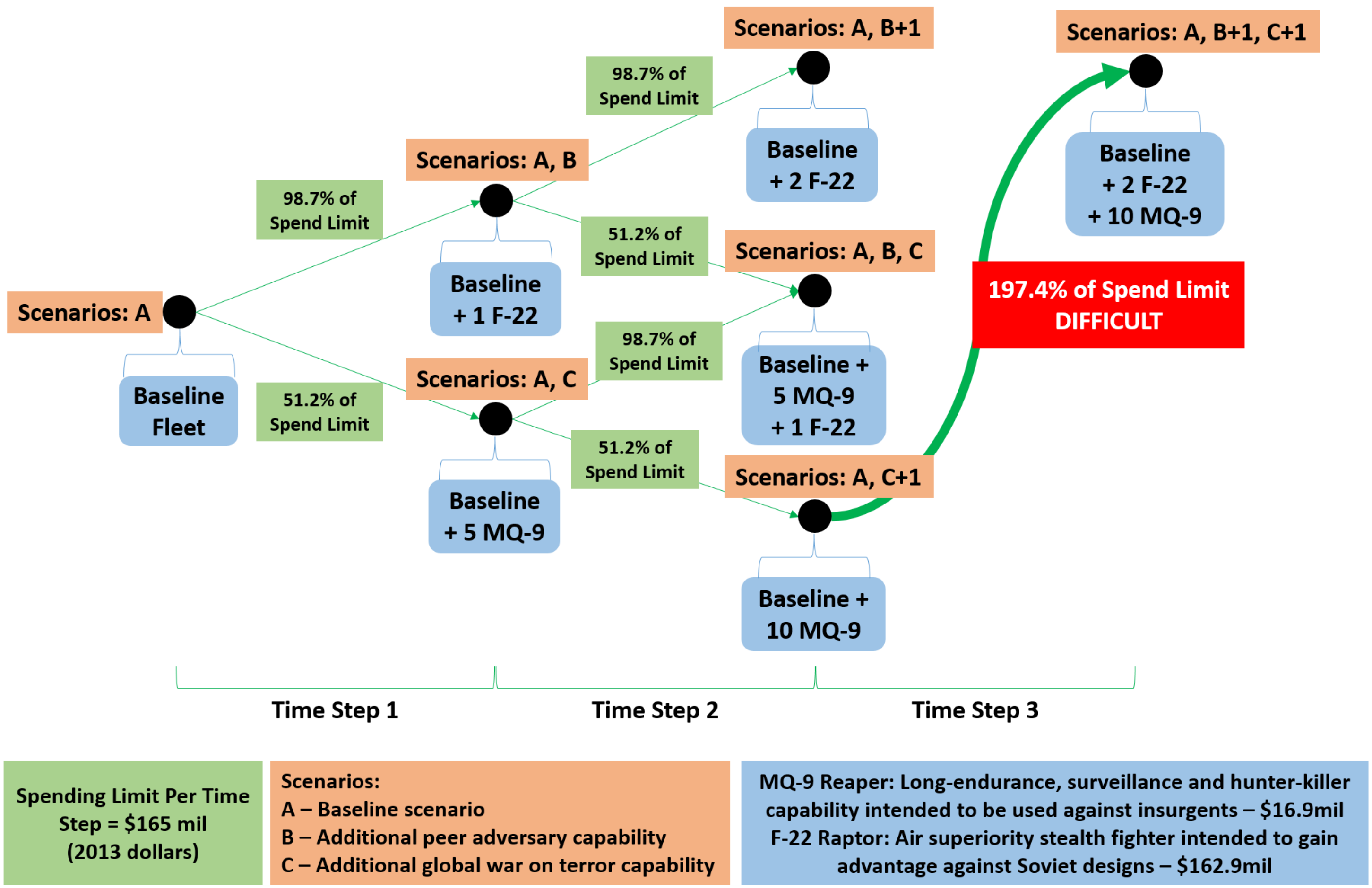



Figure 1: Notional fleet mix evolution example

Notional fleet mix evolution options, with tradeoffs between an F-22 fighter and an MQ-9 remotely-piloted aircraft (at notional 2013 costs) for two general scenario capabilities - peer adversary capability and war on terror capability. Highlighted is the difficulty in rapidly transitioning from a global war on terror capability to a peer adversary capability within the alloted budget: this is a reflection of adaptability in the traditional sense.

In this chart, we begin with some sort of baseline capability A provided to us by a baseline fleet mix (that has a baseline operational cost, of course). At each acquisition time step (be it a year, 5 years, etc.) we can make a purchase of new systems for a certain notional cost per time step, based on the budget alloted by Congress. Depending on whether we desire some of capability B or capability C, we purchase some of one or the other system. Systems can have varying costs that take up a varying amount of budget. In the event that budgets were restricted or increased, this would have an effect on the paths open to us. Furthermore, we can try to hedge our bets regarding which capability we need by perhaps purchasing some of one system in one time step, and some of the other in the next time step. Or we can double down and gain a +1 capability by purchasing more of the same system. However, if we proceed down some double-down path (such as investing in 10 MQ-9 reapers) and we suddenly require B+1 capability due to a volatile world or simply because threats have changed with time, we are less able to make such purchases and must acquire B+1 capability in 50% chunks or request more money from Congress. On the other hand, had we proceeded in the opposite direction (acquired B+1 capability first) we could have acquired 90% of the capability acquired in the C+1 case (9 drones would have cost us $152.1 million).

Of course, this is a highly simplified problem, not least because sometimes the decisions we make can (effectively) permanently exclude us from making other decisions, in terms of R&D costs required, the costs of restarting a manufacturing line (and perhaps re-acquiring all tooling or at least training employees), etc., especially when we consider that some decisions might be time-dependent. For example, restarting the manufacture of the F-22 in 5 years might not provide as much benefit because the aircraft will be that much older technologically and therefore provide that much less utility compared to enemy assets than if it had been fielded in greater numbers initially. Furthermore, the problem complexity increases even more when the decisions are taken at the joint level and decision makers must decide between acquiring the full spectrum of joint capabilities including naval, air, and land, as opposed to simply intra-air decisions as shown in the figure.

One potential aide in this problem is the concept of interoperability [32]. Defined in a later section, it is sufficient for now to say that interoperability will be used in the sense of the ability of two assets to exchange resources. One of its main benefits is its ability to potentially allow forces to create more ad-hoc connections [121] which could improve their adaptability at the strategic-acquisition level we are concerned with. If the exchange of a resource is performed smoothly and the resource is a needed one, then the assets have used their interoperability to operate more effectively. This ability is highly relevant to a VUCA environment. That is because a volatile strategic environment may require that non-standard missions suddenly have strategic priority. If assets that were designed independently of each other must suddenly be used together in an unanticipated way, high interoperability may be preferable.

However, with high interoperability necessarily comes complexity in terms of both the design, implementation, and operation of those assets. This also means an increase in cost. As ever, it is necessary to determine the proper amount of interoperability and which assets could most benefit from it. In the context of improving the strategic adaptability of a set of force acquisition decisions this idea becomes even more important - it may be important to determine which assets' improved interoperability would lend the most adaptability to the decision-set.

Finally, when the decision makers of a military branch conduct analyses to determine what collection of systems must be present in their force in order to conduct future operations, they are in essence solving a type of problem called a fleet mix planning problem. However, this is often not done via a unified, cohesive and integrated methodology but as a set of disparate studies [131, 106]. The great benefit to be gained by moving from the status quo to a methodology that can be instantiated in the form of, e.g., a computer program, is that analyses can proceed much more quickly, methodically, and holistically. That is, there is no longer a set of separate studies that assess each aspect of the problem - instead, the computer program can simply output all results of interest.

Due to the lack of existing literature dealing with how best to handle these issues, a methodology is developed to assess this problem. This methodology is then applied towards acquiring evidence for the position that the increasingly interoperable forces used by the US are at least partially a solution to the need for robustness and flexibility in a VUCA strategic environment. This is one of the main hypotheses of the dissertation:

> **Hypothesis 1:** If a methodology is developed that incorporates interoperability modeling into a traditional fleet mix planning approach, and if the adaptability of fleet mix plans to budgetary and capability uncertainty can be quantified, then the effects of interoperability on fleet mix plan adaptability can be investigated.

## *1.2 Terminology*

### 1.2.1 Interoperability

Interoperability has had many definitions[21], owing to the many applications where interoperability challenges have arisen. As there is sufficient overlap among them and they are too numerous to list out completely, only a few will be noted. Many sources including [21] and [79] cite the following:

1. The IEEE definition: "The ability of two or more systems or components to exchange information and to use the information that has been exchanged" [69].
2. The DoD Dictionary of Military and Associated Terms definition[44], which cites two other joint publications:
   (a) "The ability to operate in synergy in the execution of assigned tasks."
   (b) "The condition achieved among communications-electronics systems or items of communications-electronics equipment when information or services can be exchanged directly and satisfactorily between them and/or their users."

Furthermore, the Defense Acquisition University's Glossary of Defense Acquisition

Acronyms and Terms[38] uses the same definition as Chairman of the Joint Chiefs of Staff Instruction 3170.01I[132]: "The ability of systems, units, or forces to provide data, information, materiel, and services to and accept the same from other systems, units, or forces and to use the data, information, materiel, and services so exchanged to enable them to operate effectively together. National Security System (NSS) and Information Technology System (ITS) interoperability includes both the technical exchange of information and the end-to-end operational effectiveness of that exchanged information as required for mission accomplishment."

With these definitions, [21] and [79] arrive at two definitions:

"The ability of a collection of communicating entities to (a) share specified information and (b) operate on that information according to an agreed operational semantics." [21]

"The ability of two or more systems or components to exchange resources in the form of data, information, materiel, and services, and to use the resources that have been exchanged to enable them to operate effectively together." [79]

Both definitions share similarities - they specify that interoperability must have an aspect of action to it. However, as the first definition defines interoperability as an ability possessed by communicating *entities*, it leaves open the possibility of organizations [46]. While an important and valid form of interoperability, organizational interoperability will not be considered a part of this dissertation, although it is quite relevant to how the armed services operate. The first definition also specifically focuses on information, while the second adds materiel and services. While the second definition is perhaps more complete in this separate regard, for the sake of simplicity only data and information will be considered a part of interoperability. Finally, the second definition more explicitly states that interoperability must lead to more effective operation. If two systems exchange information that leads to worse performance, then the interoperability of this system-pair is compromised. Thus, the effective operation aspects implies some sort of manipulation of the data or information that transforms it into a state that facilitates ease of use.

Thus, the second definition from [79] will be modified slightly into the following form and used as the working definition for this dissertation:

"The ability of two or more systems or components to exchanges resources in the form of data, information, or materiel and to use the resources that have been exchanged to enable them to operate effectively together."

### 1.2.2 System of Systems

The DoD defines a system as: "functionally, physically, and/or behaviorally related group of regularly interacting or interdependent elements; that group of elements forming a unied whole" [42]. Many other definitions exist, yet they all touch on the same subjects. However, system of systems (SoS) is a more nuanced, vague, and contested term.

The Chairman of the Joint Chiefs of Staff Instructional 3170.01I[132] defines a system of systems (SoS) as: "A set or arrangement of interdependent systems that are related or connected to provide a given capability. The loss of any part of the system will significantly degrade the performance or capabilities of the whole."

From Maier [90]:

> A system would be termed a "system of systems" or a "collaborative system" when:
>
> 1. Its components fulfilled valid purposes in their own right and continued to operate to fulfill those purposes if disassembled from the overall system, and
> 2. the components systems are managed (at least in part) for their own purposes rather than the purposes of the whole.
>
> Moreover, ... commonly cited characteristics of systems-of-systems (complexity of the component systems and geographic distribution) are not the appropriate taxonomic classifiers. The principal reason is that there are design guidelines that address those demands that apply differently for systems within and

without the proposed class.

Finally, [70, 105, 16] collectively create this list of differentiating features of a SoS from a system:

1. Are larger in scope and more complex
2. Can have fuzzy boundaries between systems
3. Possess a higher degree of uncertainty and risk
4. Evolve more continuously and have elements of differing life-cycles
    (a) Involve continuous systems engineering that is never finished
5. Can have more than one management/acquisition entity
    (a) Can have a broader range of stakeholders
6. Have elements not designed to t the whole that are integrated post-design and deployment
    (a) Have constituent elements which possess operational independence
    (b) Have a focus on data, information, and resource flow between systems which were not necessarily designed to be interfaced
7. Have emergent behaviors
8. Can have ambiguous capability or mission requirements
9. Can be geographically distributed
10. Testing, evaluation, and validation can be very difficult due to nebulous performance criteria and sheer size and number of systems

SoS can take many forms and can be extremely complex to manage [119]. One author notes the applicability of SoS analysis to transportation and traffic [40]. Defense systems are another common SoS [105]. Due to the ability of a SoS to show emergent behavior, this term will be used exclusively to refer to a subset of the full military force. Specifically, the subset that is operating a single mission together. If assets do not operate together, they are not part of the same SoS.

### 1.2.3 Fleet Mixes and Force Mixes

The usage of the term “fleet” in this dissertation will not follow the military usage, which is defined by the Department of Defense Dictionary of Military and Associated Terms[44] as “an organization of ships, aircraft, Marine forces, and shore-based fleet activities all under a commander who may exercise operational as well as administrative control” or numbered fleet, defined as “a major tactical unit of the Navy immediately subordinate to a major fleet command and comprising various task forces, elements, groups, and units for the purpose of prosecuting specific naval operations”. Under these definitions, a fleet is simply a larger tactical organizational unit of ships, aircraft, and personnel.

The definition used in this dissertation will be closer to that used in literature for various problems such as the vehicle fleet sizing and mix problem [4, 13, 33, 34, 53, 120] and many others. In this context, the fleet is simply the collection of all systems under consideration. Although this is a somewhat nebulous description, it allows for flexibility for a potential practitioner to define their fleet in multiple different ways, e.g. the entire collection of aircraft controlled by the Air Force, one (or all) of the Navy’s fleets, or indeed the entire collection of systems operated by the United States Armed Services. Furthermore, “fleet mix” or “force mix” will be used interchangeably with “fleet” and “force”, however the former terms highlight the multi-asset nature of fleets. Specifically, the mix refers to the particular proportion of each asset type - “what percent of the mix of assets does this asset constitute?”

However, it should be noted that a fleet must represent some significant collection of the stakeholder’s assets or systems. For example, referring to 10 F-35 aircraft operating in a mission together as a fleet would not be accurate, unless those aircraft represent, for example, the full collection of F-35 aircraft purchased by a smaller country. As such, it would be accurate to say that a fleet must be large enough to affect the *strategic* decisions of stakeholders. Furthermore, the greater the number of system types encompassed by a fleet, the better. In this sense, the usage of the term “fleet” is closer to the military concept of a “force”, defined as “An aggregation of military personnel, weapon systems, equipment, and necessary support, or combination thereof” [44] with the additional restriction of being strategically significant.

The use of “strategic significance” will be kept intentionally vague. This is because different numbers of assets can be strategically significant for different types of organizations. As mentioned before, the purchase of 20 additional jets for a country like Israel, which plans on having a number on the order of 75 to 100 [52] constitutes a significantly more strategic decision than it would for the US, which plans on eventually having numbers in the low thousands [88]. Similarly, the US Navy has 10 aircraft carriers which could themselves be considered strategic-level assets.

### 1.2.4 Fleet Purchasing (or Mix) Plan

With the above definition of fleets and fleet mixes, we can define the fleet mix plan (or purchasing plan) as a vector of fleet mixes (themselves vectors) through time. At each time step (or step in the plan), the fleet mix will change in some way, e.g. number and therefore proportion of fighter aircraft will increase.

At each step in the plan, the cost of the fleet may fluctuate based on changes in the costs of assets in the mix. Furthermore, the capabilities of the mix may change as well, since each asset contributes its own capabilities. Furthermore, in order to perform specific missions, systems of systems can be synthesized from some number of assets within the fleet mix. These SoS of course provide both emergent capability as a whole, as well as individual capability from each asset within the SoS. Thus, the fleet mix as a whole can be taken to have a certain amount of emergent capability that is more than the sum of its assets capabilities.

The process of determining which assets to buy, how many, and when, over multiple planning periods, is called a fleet mix planning problem in the literature [143]. When decision makers plan their acquisitions, they are in effect solving fleet mix planning problems, whether explicitly or not. These methods must therefore be examined to determine whether they are sufficient to meet the needs outlined in the motivation.

### 1.2.5 Threat Environments, Scenarios, and Missions

This dissertation will maintain the assumption that the full set of missions operated by a force is known and model-able. This assumption has many difficulties associated with it: mission modeling as a whole is of course a work in progress with varying levels of fidelity depending on the complexity of the mission and of the modeler's needs. Combat modeling in particular is fraught with difficulties due to the chaotic, highly "human"-dependent nature of combat, in which training, morale, and experience all contribute greatly to the result [37]. Furthermore, important variables such as terrain, ballistics, and concepts of operations currently demand higher-fidelity approaches. Abstracting combat to a higher level therefore results in a great loss of fidelity. However, modeling single engagements is not the purpose of this dissertation: in general, we are only interested in aggregate effects that are more easily capture-able in lower-fidelity combat models. Therefore it is at least sensible to start with this assumption, and roll it back in future work.

Secondly, the assumption requires that the full set of missions is known. This may not be the case in the real world. However, if true, it is no doubt a useful exercise for SDMs to go through the process of enumerating all mission types in detail such that they can be quantitatively modeled. If some mission cannot be modeled, perhaps the decision maker can determine if the Theory of the Lesser Included Case applies - in other words, whether that mission is similar but less difficult to operate than some other mission.

Threat environments and scenarios are terms that will be used interchangeably. In this dissertation, they will mean "priority weightings on the full set of missions a force can perform", meaning that a counter-insurgency threat environment will prioritize counter-insurgency missions over, e.g., mine countermeasure (MCM) or ballistic missile defense (BMD) missions. However it is important to note that because different scenarios are merely shifts in mission priority, there is still a demand for the other mission types - it is merely lessened. Thus, a force operating in a counter-insurgency threat environment will de-prioritize MCM or BMD missions but will still need a few assets to operate them. This implies that perhaps the effectiveness in these de-prioritized missions are not as important and they can be performed at a lower required capability level.

The usage of this term shifts the conversation from merely being robust to different mission types, which is a more SoS-centric conversation (i.e. “can my counter-insurgency SoS perform MCM?”) to a force-centric conversation (i.e. “can a force whose acquisitions for the past 20 years have focused on dealing with near-peer adversaries effectively handle a counter-insurgency environment at a certain capability level?”). Immediately, the shift from operational to strategic decision making is now obvious: if the force cannot operate counter-insurgency missions well, it means the SDM ought to have hedged their bets e.g.*20 years prior* in order to better align the organization.

## 1.3 Military Strategic Decision Making

The US Army War College has defined strategic leadership as “the process used by a leader to affect the achievement of a desirable and clearly understood vision by influencing the organizational culture, allocating resources, directing through policy and directive, and building consensus within a volatile, uncertain, complex, and ambiguous global environment which is marked by opportunities and threats” [89]. The US Army War College’s Strategic Leadership Primer [89] lists a number of aspects of the strategic environment that leaders must look to.

1. Threats
2. International alliances
3. National culture
4. Military-industrial complex
5. Public opinion

6. Federal budget
7. Technological factors
8. Federal government
9. Private organizations
10. Internal environment

Of these many strategic dimensions, three are particularly relevant to engineering: threats, budgets, and technological factors. These three can be tightly coupled - the threats present can influence the budget required to meet them due to the technology available. Technology available to the enemy affects the types of threats the enemy offer, similarly for budget. Finally, a lower budget can affect the types of technology that can be used to meet threats, and can increase the number of threats the nation may have to face due to deterrent effects (the inverse of this is the *Pax Americana* [94]).

Furthermore, these three factors can be quite volatile. As the primer indicates, volatility is one of the chief aspects of the external environment, together with uncertainty, complexity, and ambiguity. "Volatility in the Information Age means even the most current data may not provide an adequate context for decision making. Beyond an ability to accurately assess the current environment, leaders must anticipate rapid change and do their best to predict what may happen within the time scope of a project, program, or operation. **Volatility in the environment coupled with the extended timelines of modern acquisition programs creates a special challenge for strategic leaders and their advisors**" [89] (emphasis added).

## *1.4 Interoperability as a Complicating Factor*

Utilizing both the concepts of interoperability and system of systems, Net Centric Warfare is a doctrine proposed to advance the state of the military to better-utilize information technology and sensors in the defense SoS. Rising to prominence in the 1990's, the primary promise of net centric warfare is to quicken the speed of command, and to allow military forces to be better self-synchronized [26], which is to say that the SoS must operate together more cohesively and effectively. This implies that, when operating together, assets will become more capable than ever before, both because they are allowed more information and because they will have more ability to act on that information [26, 7, 6]. Additionally, it was hoped that net-centric warfare would also have the benefit of reducing reliance on systems with custom capabilities and reducing the number of assets required to achieve a task, resulting in reduced cost [25]. And although net-centric warfare's popularity has dropped off, many of its ideas live on in the form the other service initiatives that will be discussed later, such as the 3rd Offset Strategy or NIFC-CA.

Unfortunately for net-centric warfare and many of its descendants and in contrast to what is seen in consumer electronics, interoperability between military assets is often piecemeal [25]. Many examples exist of assets that require upgrades in order to become interoperable with other assets, either as part of a shift in strategy or tactics, or an improvement in technology or standards [71, 144, 27, 122, 103]. As the defense community attempts to work towards greater interoperability, it has been hampered by a few challenges unique to defense systems and their acquisition. Firstly, agreeing to a definition for interoperability can be difficult, as it is a relevant principle for both organizations, assets, and subsystems. Given a definition, establishing standards represents the next difficulty, since defense systems come in all shapes and sizes with all manner of requirements ranging from man-portability to power usage, durability, or range (not to mention that many of these systems are already in operation and can utilize different standards) [121]. Adding interoperability into every new asset is a great cost to the taxpayer, especially since some assets may never need to interoperate in real operations [45]. Therefore, a decision must be made for each asset regarding whether it is to interoperate, and with which other assets.

The DoD has already implemented the concept of the Net-Ready Key Performance Parameter (KPP) [61]. This assessment of net-ready capability is determined by the operational impact the asset's net-readiness has. The Net-Ready KPP is tested by the Joint

Interoperability Test Command for any new asset being developed [136]. However, with how important good interoperability can be to future assets, interoperability can no longer be considered primarily a property of the asset under consideration, but a tune-able property of the overall SoS [25]. Of course, tuning this parameter is precisely the job of the strategic decision maker, in addition to tuning the number of assets, the type of assets, and their concept of operations [89].

## *1.5 Defense Acquisition*

Currently, defense acquisitions only occur after a long process of requirements (or capability) examination. This process begins all the way at the strategic level, where the President's office releases the National Security Strategy. This flows into the Department of Defense's National Defense Strategy, which flows into the military's National Military Strategy. The documents serve as forecasts of what capabilities will be required, what challenges will be present, and generally serve as the strategic decision makers' views and visions of the future [5].

From these documents, the three Department of Defense decision-support systems, Figure 2, take over. These are the Joint Capability Integration and Development System (JCIDS), the Defense Acquisition System [134], and the Planning, Programming, Budgeting, and Execution (PPBE) process. JCIDS identifies, assesses, validates, and prioritizes joint military capability requirements. the Defense Acquisition System takes capability requirements and converst them to materiel capability solutions. PPBE supports the two previous processes by enabling funding, operations, and support [15].

JCIDS was created with the view that capabilities ought to matter more than requirements. The reason for this, as Secretary of Defense Rumsfeld stated in 2002, "It is pretty clear [the previous Requirements Generation System] is broken, and it is so powerful and inexorable that it invariably continues to require things that ought not to be required, and

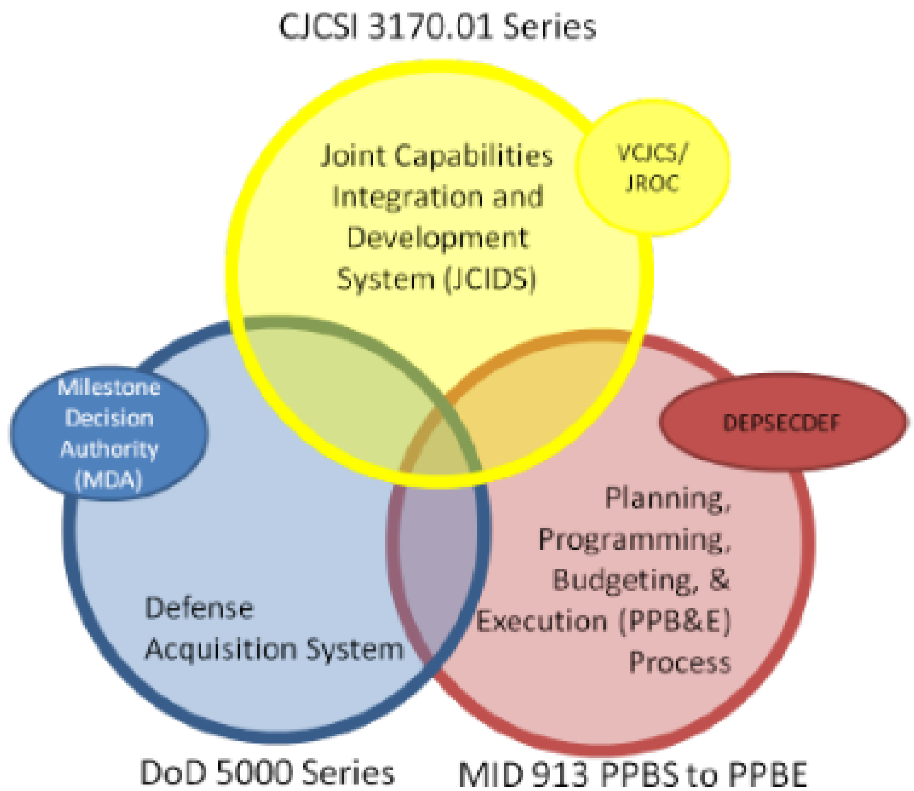



Figure 2: DoD Decision Support System, reproduced in [63] from [132]

does not require things that need to be required" [117]. There was an increasingly recognized view that designing to a system's requirements may not be the same as improving the operational objectives [63]. Requirements needed to stem from mission objectives and mission capabilities in a traceable form, otherwise systems were less likely to operate well in the missions they would be used in. Furthermore, JCIDS allows decision makers to determine which existing capabilities may be suited to meeting the required capability. The end result is that, once desired capabilities are enumerated, JCIDS ought to be able to arrive at the most applicable way to meet those capabilities.

One of the primary ways that JCIDS proceeds is through the Capabilities-Based Assessment (CBA). Griendling [63] summarizes [132, 72] nicely:

> The CBA focuses on determining potential solutions across the doctrine, organization, training, materiel, leadership and education, personnel, or facilities

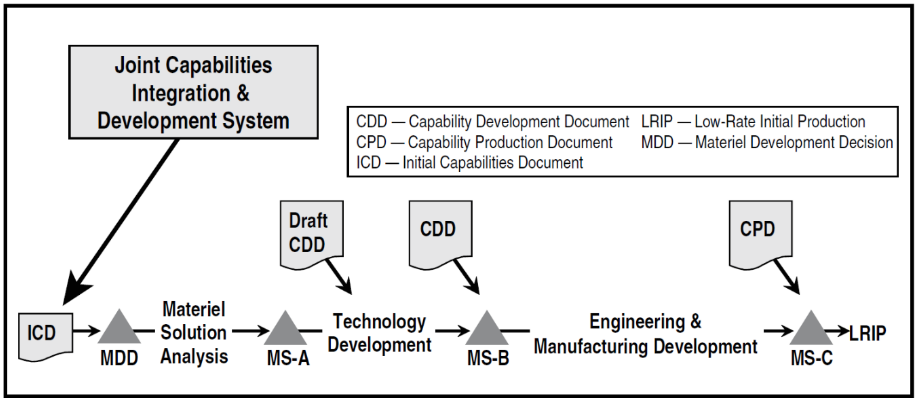



Figure 3: JCIDS Process & Acquisition Decisions [19]

(DOTMLPF) spectrum to fill capability gaps. A CBA identifies the mission to be studied, the capabilities required to perform that mission, the operational characteristics and attributes of each capability, existing capability gaps and operational risks, an assessment of the viability of non-materiel solutions, and, if needed, a recommendation on the type of materiel solution to be pursued. A CBA also justifies that a solution is needed for the identified gaps, as opposed to accepting the operational risk and making no changes. A materiel solution can fall into one of three categories: transformational, evolutionary, or information technology. The CBA results in two documents, depending on the approach recommended. If a non-materiel solution is recommended, a DOTMLPF Change Recommendation (DCR) is created instead. If a materiel solution is indicated, an Initial Capabilities Document (ICD) is presented to the Joint Requirements Oversight Committee (JROC) for review. Once the ICD is approved, it is sent to the Milestone Decision Authority (MDA) to determine the scope of the analysis of alternatives (AoA) that follows, as well as designating the lead components in the Materiel Development Decision (MDD). This leads to a materiel solutions analysis phase, which, in conjunction with the ICD, supports entrance into JCIDS Milestone A. Because the CBA is the kickoff to the JCIDS process, doing a poor job on a CBA is likely to lead to solutions that are not affordable, untimely, or ineffective.

However, the JCIDS process is not perfect. For one, there are issues with beginning projects with immature technologies, as highlighted by [62]. Furthermore, as many sources [47, 63, 1] have noted, the Capabilities-Based Assessments which form one of the primary components of JCIDS have shortcomings, including being limited to a single mission, and not adequately assessing the needs of the entire force as opposed to the needs of the mission. CBAs are supposed to be informed by the high level strategy documents mentioned earlier, but there does not seem to be any literature at the time of this writing regarding methods that allow this linkage to take place. This is one of the roles that the methodology aims to fulfill.

## *1.6 Observations, Problem Formulation, and Primary Research Objective*

### 1.6.1 Summarizing Observations

To summarize the issues identified in the above sections, it has become clear that strategic decision-makers, involved in converting the president's National Security Strategy into action and acquisition, require a holistic way to manage development of the military's forces. This means an effective method or methodology for requirements generation that combines threat projections, budgetary projections, and asset technology or capability. The purpose of this method would be to function as a tool for decision makers at the strategic level, a way to analyze alternative future forces at various points in time and chart a course through time for the existing force, where we say that a force consists of asset types, the number of each type, the capabilities associated with each type, etc.

Wherever stochastic variables are involved in engineering design, some sort of robustness characterization is often used. The significant emphasis placed by the strategic leadership community on the volatility of threats and budgets implies that a sort of force robustness metric ought to be considered as an important output of the method, thus allowing leaders to potentially weigh force metrics against each other when deciding on the path to take, e.g. one acquisition path resulting in a more expensive robust force while another results in a slightly cheaper force more specialized for taking on peer adversaries. These types of high-level decisions are exactly the ones that strategic leaders ought to be making as they attempt to align their respective organization with their vision of the future. Using this hypothetical method as a capability gap generation tool, decision makers could determine that the best path to take involves increasing some capabilities of assets in air superiority, for example. The rest of the acquisition process, including JCIDS, could then take over - using CBAs to determine whether a new asset must be acquired or existing assets can be upgraded, whether a non-materiel solution can be employed, etc. Importantly, although the idea behind the analyses is similar, the traditional CBAs used in JCIDS would not suffice because they deal with specific capabilities, not the identification of force-wide capabilities (or force-wide requirements).

The following observations can be gleaned from the previous sections:

1. Future threats are volatile - cannot be predicted with certainty
2. Future budgets are volatile - cannot be predicted with certainty
3. Strategic decision-makers need a rapid quantitative long-term force planning method or methodology
4. It is possible that a measure of robustness to uncertain threats and budgets will aid in planning the long-term development of a force
5. Assets in an interoperable force are more easily able to make ad-hoc connections with each other to address new problems
6. Too much interoperability is expensive, complex, and overwhelming - it is important to determine how much interoperability is enough to accomplish some goal
7. Determining the requirements of the force in the long-term allows existing DoD processes to take over the task of determining how these requirements will be met

Of course, this list of desirements is hardly exhaustive for the type of strategic tool envisioned. Many technology trends aside from interoperability exist in the defense community, for instance modularity. Furthermore, mentioning threats without mentioning the fact that many threats can often be addressed with a change in force structure or concepts of operation would be missing the whole picture. Other factors exist that are highly important to a military operation: logistics, weapon ballistics in modeling and simulation, etc. Ideally, these factors would also be implemented into the method. However, although they will be kept in mind while developing the thesis, for the sake of keeping the dissertation to a manageable scope they will not be investigated at the present time and will be left as future work.

### 1.6.2 Goal Capability

The goal capability is for a group of analysts to conduct this sort of analysis every so often in order to ensure that the joint force structure is on track to meet its required capabilities and that the acquisition plan is adaptable to volatile changes in capability requirements. At the conclusion of each analysis, either a decision-support environment or some results would be sent to a decision maker, and perhaps these results will be investigated with higher-fidelity methods prior to decisions being made.

There are a few things that ought to be compared against each other in this case. The first is the overall quality of each fleet mix plan within the set of possible alternatives. This ought to take into account cost as well as the performance in every mission the fleet mixes are capable (or incapable) of conducting. The second is the adaptability of the plans - this ought to take into account the number of other options available in the whole decision set, as well as any other desired metrics that adaptability ought to capture. Next, because the fleet plans vary by the types of assets included in them, comparisons must be made within fleet plans and across fleet plans to understand how the assets in them differ.

In Figure 4, notional fleet plans are ranked by an Overall Evaluation Criterion (OEC) that sums the performance across all missions (as well as the cost) and weighs them by

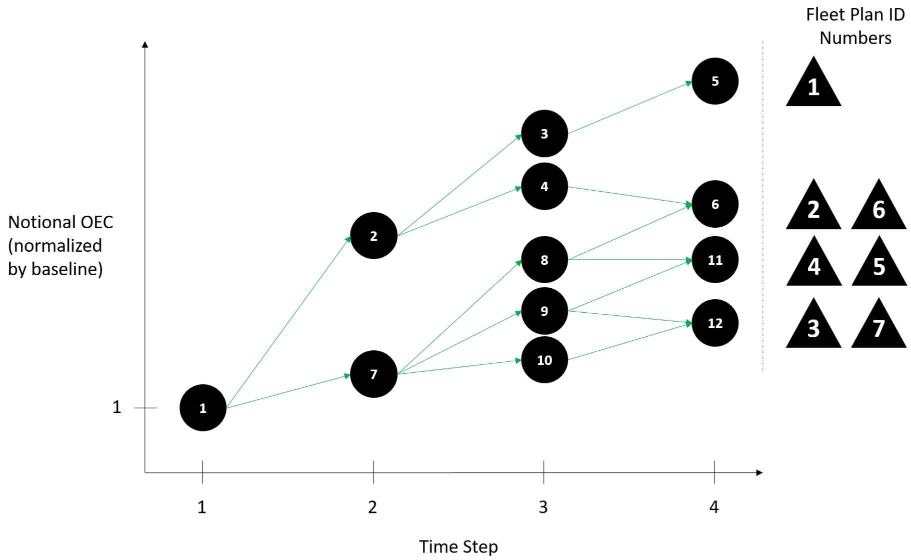



Figure 4: Fleet plan evolution by OEC

Notional chart of fleet mixes ranked by some OEC and connected via lines of cost sufficiency, i.e. is the cost difference smaller than some incremental budget increase.

decision maker preference. This OEC is normalized by the OEC value of the baseline fleet (Fleet 1). Furthermore, only fleets that are an acceptable cost distance away from each other are shown. In this figure, we could expect to want to choose the higher branch, consisting of selecting fleet 2 over fleet 7 for the first decision.

However, the issue is not necessarily that simple, as seen in Figure 5. We can see that despite Fleet 2 being ranked higher in the OEC than Fleet 7, Fleet 7 has the better cost performance (it is less expensive) and is a little better in two missions. Of course, this is a natural result from using an OEC - weightings will give preference to fleets the decision maker thinks they care about more.

The decision support step could aide the decision maker in understanding the impacts of their preferences. For example, in Figure 4, nearly each step in the lower-performing branch has more options for decisions than the higher-performing branch. This implies that choosing the higher-performing branch could make the fleet less adaptable. Coloring each path (the lines connecting the fleet mixes of each path) by its adaptability, for example, could give the decision maker a quick understanding of the impact of their decision by

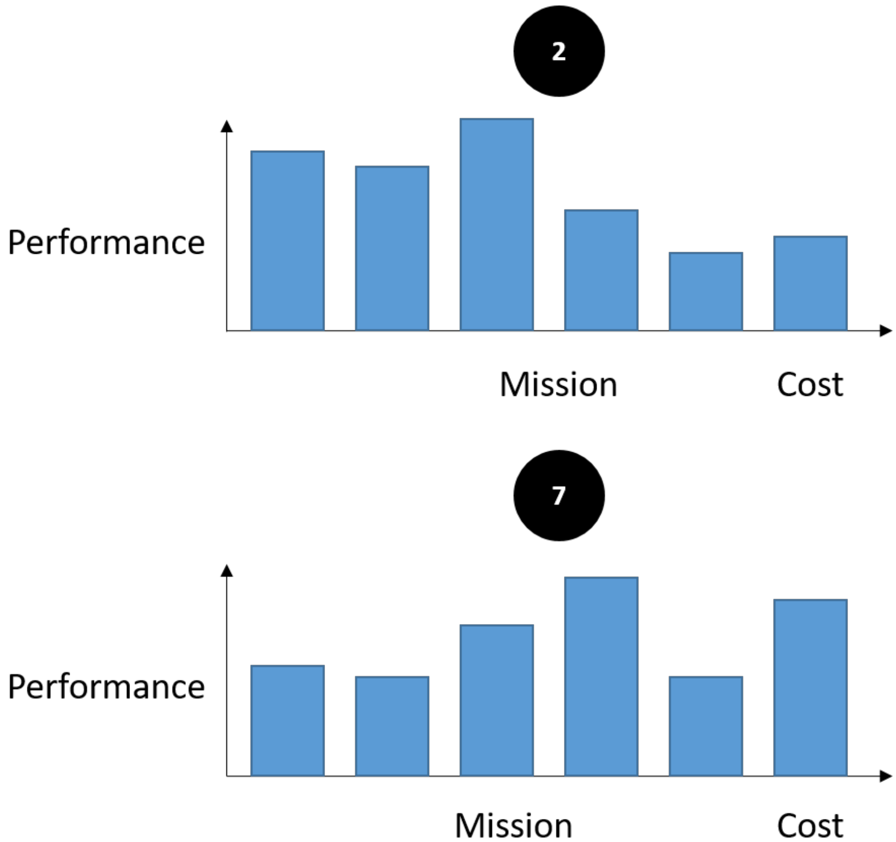



Figure 5: Overall evaluation criterion example measures

Overall evaluation criteria can both simplify the problem and mislead. In this case, the better ranked fleet from Figure 4 is only better in a few missions and is worse in cost.

quantifying resultant adaptability.

Finally, highlighting how fleet plan adaptability is affected by system design variables or acquisition decisions is another important use. For example, perhaps the decision-maker is considering adding a purchase of aircraft carriers in the third time step, and an upgrade to interoperability in step 4, as seen in Figure 6[1]. Figure 7 shows a potential visualization of the effects on overall plan adaptability of adding varying numbers of aircraft carriers to the force at step 3 of the plan. Potentially, one can identify a knee in the curve and downselect a few fleet mix plans for further analysis, such as plans 2, 3, 4, 5, and 7. One can also use this for verification or for understanding the design space, e.g. "why does adding 4 aircraft carriers in plans 1 and 6 hurt adaptability so much? What is special about 2 aircraft carriers

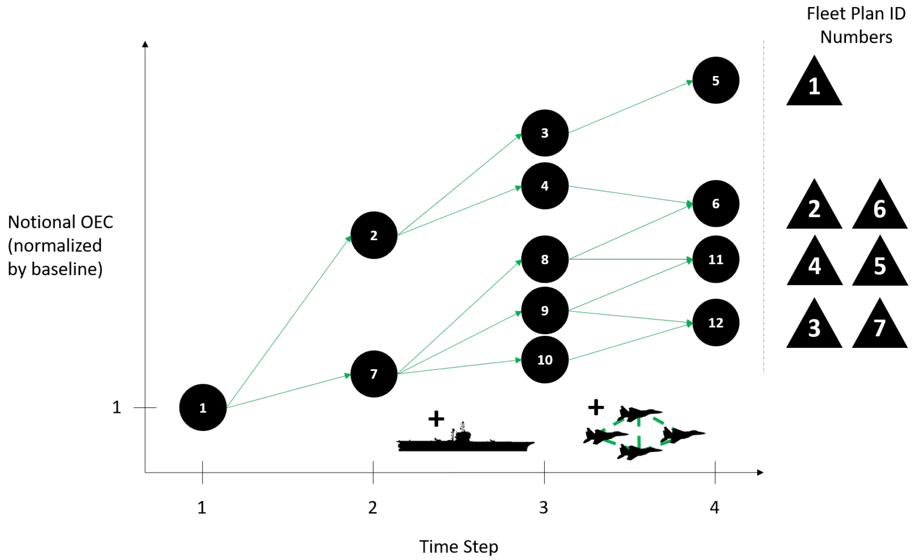



Figure 6: Fleet plan evolution, options

Fleet plan evolution, showing the changes considered in step 3 and step 4. The difference between the fleets in time step 3 is the number of aircraft carriers, while the difference in step 4 is the degree of interoperability in a specific asset type.

versus 1 or 3 that allows plans 4 and 7 to be even more adaptable?" Similar questions can be asked for the effects of design variables on interoperability or any other system design variable or functional characteristic.

[1]License: https://creativecommons.org/licenses/by/4.0/, Pages: http://www.supercoloring.com/silhouettes/aircraft-carrier, http://www.supercoloring.com/silhouettes/fighter-jet

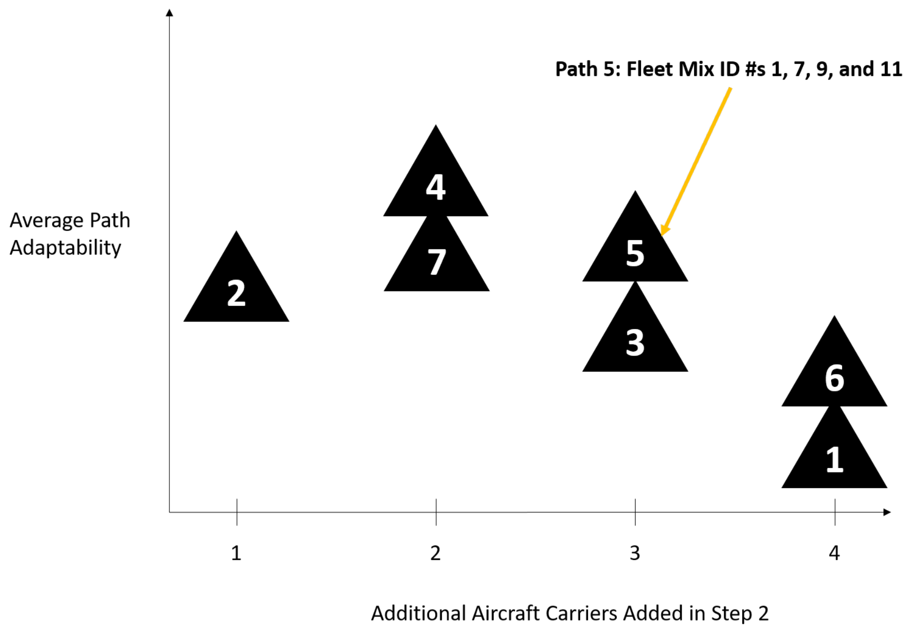



Figure 7: Notional fleet plan adaptability vs. acquisition decision

Potential way to investigate the effects of acquisition decisions on fleet mix adaptability.

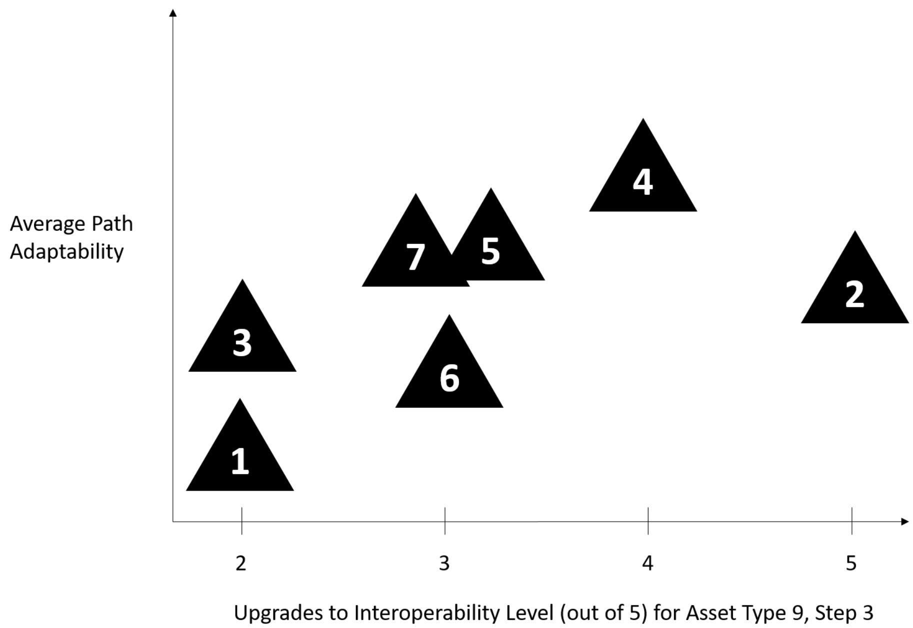



Figure 8: Notional fleet plan adaptability vs. design decision

Potential way to investigate the effects of increasing interoperability in one system on fleet mix adaptability.

Figure 8 shows a potential investigation of how upgrading the interoperability of some asset at a specific point in time can affect the average adaptability of each fleet path (fleet mix plan). We can see that in this situation, there is little risk to adaptability from improving interoperability to level 4 (out of 5 levels; to be discussed in the next chapter). Improving interoperability to level 3 produced better adaptability in two cases and worse in another case - the causes for this would need to be investigated before considering improving interoperability even further. Additionally, this type of study would not give any information regarding *how* interoperability would be improved - merely that this improvement could be related to better adaptability.

In our example, the decision maker would likely retain fleet plans 4, 5, and 7 for further analysis. In our limited case, perhaps the question of "what is special about 2 aircraft carriers versus 1 or 3 that allows plans 4 and 7 to be more interoperable" is answered by the fact that the fleet plans with 2 aircraft carriers also happened to have relatively good interoperability in step 4. Thus, those fleet plans as a whole were more adaptable to multiple future scenarios as compared to the rest. However, it should be noted that these fleet plans are also towards the bottom of the group in terms of OEC, meaning that they are less capable in the various missions than other fleet plans. These types of decisions - the acquisition and design decisions that comprise the force structure planning problem, are the focus of this work.

### 1.6.3 Problem Formulation and Primary Research Objective

For this dissertation, certain assumptions will be made regarding who the user of the methodology will be and what information is available to them. This methodology is targeted at strategic decision makers and the analysts who support them. Any organization or group of organizations responsible for forecasting future threats, needs, and resources and modeling them is a potential user of this methodology. In the United States Joint Chiefs of Staff, for example, one such user could be the J-8 Directorate, whose job is to "[evaluate] and [develop] force structure requirements. It develops, maintains, and improves the models, techniques, and capabilities used by the Joint Staff and combatant commands to conduct studies and analyses for CJCS" [76]. A co-user could be the J5 Directorate whose job is Strategic Plans and Policy: "Joint Staff J5 proposes strategies, plans, and policy recommendations to the CJCS to support his provision of "best military advice" across the full spectrum of national security concerns to the President and other national leaders and to ensure those recommendations are informed by a larger strategic context coordinated with interagency and alliance partners, account for the view and requirements of the combatant commanders, and assess risk in executing the national Military Strategy" [75].

The assumptions made are as follows:

1. All relevant missions can be modeled
2. There exist forecasts of uncertainty ranges for all mission performance or capability

requirements, and these can be mapped to mission model outputs.

3. There exist forecasts of uncertainty ranges for future budgets available.
4. For asset modeling in missions, asset performance or functional characteristics exist and can be modeled.
5. for asset modeling in missions, decision makers are interested in at least one of the following:
   (a) One (or more) asset(s) whose acquisition is under consideration, with defined functional characteristics and performance and defined ranges of potential acquisition quantities.
   (b) A to-be-designed asset whose desired functional characteristics and performance are being explored, with defined ranges of potential functional characteristics, performance, and quantities.

Armed with this information, the user ought to have enough information to begin the analysis in question, though of course the complexity and scope of the analysis can be improved and will then require even more information. It is expected that in the case of the US armed forces, J5 and J8 together will have the required information to perform this analysis.

Proceeding to create a concise primary research objective, we first condense the stated observations into one concise overarching need. This need is to enable decision makers to "quantitatively perform long-term planning of a military force while accounting for uncertain threats and budgets via a single method or methodology". This means that we are chiefly seeking a force planning method that accounts in some way for budgetary and threat uncertainty. Furthermore, we would like to investigate whether a force development plan adaptability criterion is used in existing force planning methods and if not, create one. Either way we will investigate whether such a criterion enhances the decision-maker's ability to select an acquisition plan. Finally, assuming we have a criterion that suffices, we would like to include interoperability into the force planning method to test whether increased interoperability impacts the force robustness, and if not then why not.

> **Primary Research Objective:** Develop a methodology to perform system requirements development based on strategic force-level adaptability analysis. Account for purchasing budget, multiple uncertain scenarios, interoperability, and SoS. Provide meaningful, realistic solutions in a reasonable amount of time.

This primary research objective implies certain goals for the methodology. It is desired for a decision-maker to be able perform force-level analyses such as planning out force acquisitions based on force requirements over some window of time. The analysis must allow the user to account for each SoS operating in its mission, for multiple missions of varying levels of uncertain importance. To do this, the methodology must model assets' functional characteristics and account for their cost. To allow for force planning, budgetary uncertainty over this same time period must be considered *alongside* the desired performance or capability of a candidate force. Interoperability must be accounted for in mission modeling to accumulate evidence regarding the central thesis of the dissertation. Finally, a 'reasonable amount of time' must be determined. With these thoughts in mind, research questions will be developed to determine which fields should be investigated for relevant information.

# CHAPTER II

# BACKGROUND

## *2.1 Research Question Development*

In the previous chapter, it was ascertained that there is a gap in the methods supporting the DoD's current acquisition process. This gap was determined to be related to the DoD's ability to trace individual capability gaps up to the fleet level in a way that accounts for interoperability while remaining robust to budgeting and mission changes for individual assets. Although there is a JCIDS requirement for CBAs to remain cognizant of capabilities already developed or in development across the Joint Force, this is not the same as mandating CBAs with a cognizance of the entire fleet from the top down. Furthermore, since CBAs are often related to only one acquisition, any overall fleet gap must be analyzed and addressed at a higher level before reaching the CBA level.

The first step is to select a proper structure for the methodology. This must be based on the methods selected according to their ability to meet the needs of the objective, as well as where in the acquisition process this methodology fits in conceptually. Choosing an appropriate structure, steps, and inputs and outputs thus cannot precede other research questions, but as this step is of high importance it is discussed first. A further need is to ensure that traceability and transparency have been guaranteed throughout the structure of the methodology such that there is no ambiguity in the results and they can be reused when iterating on the analysis is required. Questions such as what how is an optimal fleet determined, and how is an optimal fleet schedule selected are all highly relevant to the objective and the structure of the methodology. The structural problem, and selection of an appropriate fleet mix planning skeleton, constitutes Research Question 1:

**Research Question 1.1:** Given a fleet sizing and mix method, how should the overall methodology be structured?

**Research Question 1.2:** What fleet sizing and mix method is sufficient for testing this methodology?

A gap that will be discussed in Research Question 1 is the incompatibility of current fleet mix planning method assumptions with defense applications. Research Question 2 will address how the definition of 'fleet' in the fleet mix planning problem class can be translated to the usage of fleet or force in this dissertation:

**Research Question 2.1:** What method is best suited for taking a set of disparate SoS operating different missions and rapidly scaling them up or unifying them into a full force?

The issues of robustness and adaptability are of paramount importance to this methodology. Robustness is used to describe the capability of a force to meet varying changes in scenarios. Flexibility is used to describe the ability of a force plan to be adapted over time to shifting scenarios. How have these topics been treated in relevant fields, and are any conclusions or methods transferable to this problem? How must threat environments and budgets be formulated to best suit a calculation of these metrics? These topics are addressed in Research Question 3:

**Research Question 3.1:** What method is best suited for defining and calculating adaptability of a plan (not just a set point in time) or a set of plans?

**Research Question 3.2:** How should shifting budgetary and threat priorities be represented to best capture uncertainty and volatility for calculation of adaptability and robustness?

Without interoperability, a SoS cannot effectively operate together, and this affects mission performance. Being able to model an asset's degree of interoperability, or lack thereof, is critical to success of the methodology. Which types of interoperability should be investigated for inclusion into the methodology? If multiple types *can* be included in the model, should all of them be modeled, or is it sufficient to simply model one type? What methods exist to describe interoperability and what types of interoperability do they account for. What criteria ought to be used to select an interoperability modeling method, and which of the researched methods meet these criteria? These questions constitute the investigation collectively designated Research Question 4:

> **Research Question 4.1:** Which types of system-to-system interoperability should be included in the model?

> **Research Question 4.2:** What methods are sufficient for modeling the given interoperability types?

> **Research Question 4.3:** Which method should be chosen for the purposes of a demonstration of the methodology?

After a determination or creation of a sufficient model for interoperability, it is necessary to determine the other side of this equation: modeling the missions. Specifically, once available methods in the literature have been outlined, they must be compared against each other and against certain criteria in order to determine whether any of them is sufficient to meet the needs of the research objective. Coupled with this analysis is whether the chosen interoperability model can be readily integrated into the chosen mission modeling method in a traceable, transparent, and realistic way. Together, these topics constitute Research Question 5:

> **Research Question 5.1:** For evaluating force plans with and without interoperability, what are the necessary criteria for a mission model that evaluates force effectiveness?

**Research Question 5.2:** What mission models exist that can accommodate the criteria of this methodology, and which should be chosen?

**Research Question 5.3:** What missions should be modeled in order to gain confidence in the results of the methodology?

## 2.2 *Defense Acquisition*

Acquisition is defined by the United States Department of Defense (DoD) as including the design, engineering, testing and evaluation, production, operation, and support of defense systems [19]. The United States Department of Defense has a long and detailed process for acquisition of new systems and processes. This process, called the Defense Acquisition System, encompasses all requirements, budgetary, and management aspects of acquisition, called the Decision Support Systems (DSS). Created in 2003 and updated in 2012, the Joint Capabilities Integration and Development System (JCIDS) is one of the three DSS that makes up the Defense Acquisition System[77], shown in 9. Examination of JCIDS and the steps leading up to it will be useful for the purpose of this dissertation, as these processes outline when and how requirements are developed for a new acquisition. This includes what methods are used to determine whether there is a need for such an acquisition, whether it ought to be a materiel acquisition or something else in the Doctrine, Organization, Training, Materiel, Leadership and Education, Personnel, Facilities, and Policy (DOTMLPF-P) set of options, and what potential solutions are [77] [132].

### 2.2.1 The Current Approach

With the Navy as an example, current force structure assessments (FSAs) are created in the following way [131]:

> [the] Navys Force Structure Assessment (FSA) was developed in an effort to determine the right balance of existing forces, the ships we currently have under construction and the future procurement plans needed to address the

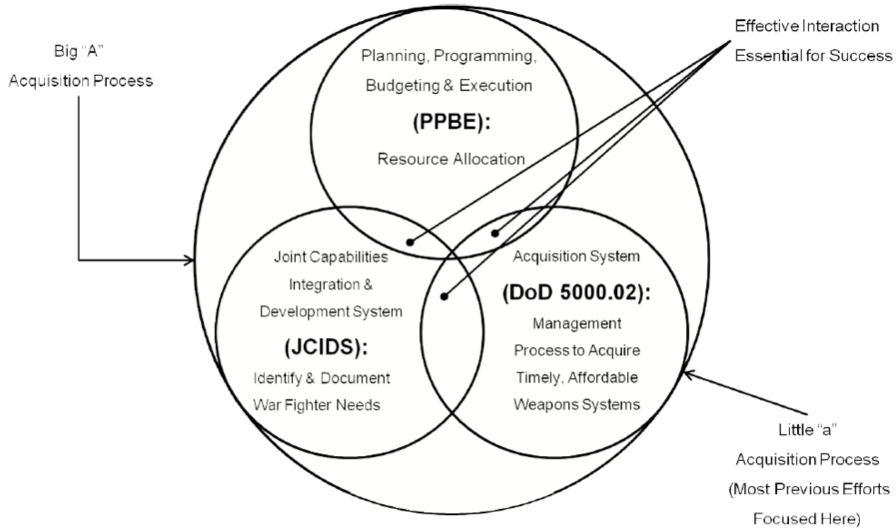



Figure 9: Defense Acquisition System [2] [19]

ever-evolving and increasingly complex threats the Navy is required to counter in the global maritime commons....

The number and mix of ships in the objective force, identified by this FSA, reflects an in-depth assessment of the Navys force structure requirementsit also includes a level of operational risk that we are willing to assume based on the resource limitations under which the Navy must operate. While the force levels articulated in this FSA are adjudged to be successful in the scenarios defined for Navy combat, that success will likely also include additional loss of forces, and longer timelines to achieve desired objectives, in each of the combat scenarios against which we plan to use these forces. It should not be assumed that this force level is the desired force size the Navy would pursue if resources were not a constraintrather, this is the level that balances an acceptable level of warfighting risk to our equipment and personnel against available resources and achieves a force size that can reasonably achieve success....

In January, the 2016 FSA started with a request to the Combatant Commanders (CCDRs) to provide their unconstrained desire for Navy forces in their respective theaters. In order to fully resource these platform-specific demands, with very little risk in any theater while still supporting enduring missions and ongoing operations, the Navy would be required to double its current annual budget, which is essentially unrealistic in both current and expected future fiscal environments.

After identifying instances where forces were being requested for redundant missions or where enduring force levels were not required, while also looking at areas where we could take some risk in mission success or identify a new way to accomplish the mission, we were able to identify an FSA force level better aligned with resources available....

In order to assess warfighting risk and identify where margins existed that could be reduced, we did an in-depth review and analysis of what it takes to win, on what timeline, and in which theater, for each major ship class. The goal of this phase of the analysis was to determine the minimum force structure that:

1. complies with defense planning guidance directed combinations of challenges for force sizing and shaping;
2. meets approved Day 0 and warfighting response timelines;
3. delivers future steady state and warfighting requirements, determined by Navys analytic process, with an acceptable degree of risk (e.g. does not jeopardize joint force campaign success)

As the Congressional Research Service noted [106]:

Section 1067 of the FY2016 National Defense Authorization Act (S. 1356/P.L. 114-92 of November 25, 2015) required the Secretary of Defense to provide for three independent studies on alternative fleet platform architectures for the Navy in the 2030 time frame, and to submit the results of each study to the congressional defense committees. The three studies were completed in 2016

> and reviewed at a March 8, 2017, hearing before the Seapower and Projection Forces subcommittee of the House Armed Services Committee. The results of the three studies are summarized in Appendix F. The Navy states that the FSA that led to the 355-ship plan “assumes that the future plans for our Navy, in ship types and numbers of ships, continues to replace the ships we have today with ships of similar capability and in similar numbers as we transition to the future Navyit does not address potential options that may come out of the ongoing review of the potential Future Fleet Architecture studies that were directed by Congress [in the FY2016 NDAA] and completed in October 2016. As we evaluate the options presented in these studies and move to include them in our plans for tomorrows Navy, this FSA will need to be updated to reflect those changes that are determined to be most beneficial to meeting the Navys missions of the future. [131] ”

What the above quotation implies is that there is no integrated approach to developing a force mix plan (force structure plan). Force architectures, force structures (or force mix plans), and force capability assessments all consist of separate processes that are sometimes undertaken together or separately depending on the need of the assessment. Furthermore, force adaptability would likely be calculated via this same approach - a request would be sent out to combat commanders to assess what sorts of threats they might see developing in the future. Then force structures would be developed for these separate assessments and compared to the current shipbuilding plan. This would be a time-consuming process that could be simplified by accounting for these types of variables up front. Finally, this solution mode of separate studies is exacerbated by how the military actually conducts its acquisitions.

### 2.2.2 JCIDS Overview

As stated by the Office of the Chairman of the Joint Chiefs of Staff (CJCS), "the key objective of the JCIDS process is to facilitate the JROC and its subordinate boards... to manage and prioritize capability requirements within and across the capability requirement portfolios [132]." JCIDS essentially requires that requirements be validated throughout the acquisition process based on previously outlined capabilities. As outlined in in CJCS Instructional 3170.01I[132], it consists of crafting and comparing three capabilities documents. The Initial Capabilities Document (ICD) is the first document and highlights the capabilities required to complete the mission, the gap in capabilities, and what can be done to address the gap. The Joint Requirements Oversight Council (JROC) can accept the ICD and thereby validate one of three courses of action, among which is recommendation to create a materiel solution to address the gap. The Capability Development Document (CDD) follows an analysis of alternatives (AOA) step and is created after the draft CDD is approved at Milestone A. It outlines the requirements needed in terms of key performance parameters (KPPs), schedule, technology maturity, and thereby affordability of the proposed alternative. Finally, the Capabilities Production Document (CPD) is created created pre-production and is there to ensure that the proposed solution does indeed meet all required capabilities[132].

JCIDS exists in the form of several documents in the DoD. There is the JCIDS Manual, which gives an overview of the JCIDS Process, instructions accompaying this overview, and multiple enclosures which detail steps in the process more thoroughly. There is also the JCIDS Process Flow Chart, a very large document which takes a user step by step through the JCIDS process and documents every decision and step that must be performed for any type of activity that falls under the purview of JCIDS. Together, these documents outline the following overall acquisition lifecycle, shown in 10 in simplified form.

Additionally, prior to JCIDS, the DoD takes into account strategic guidance, Concepts

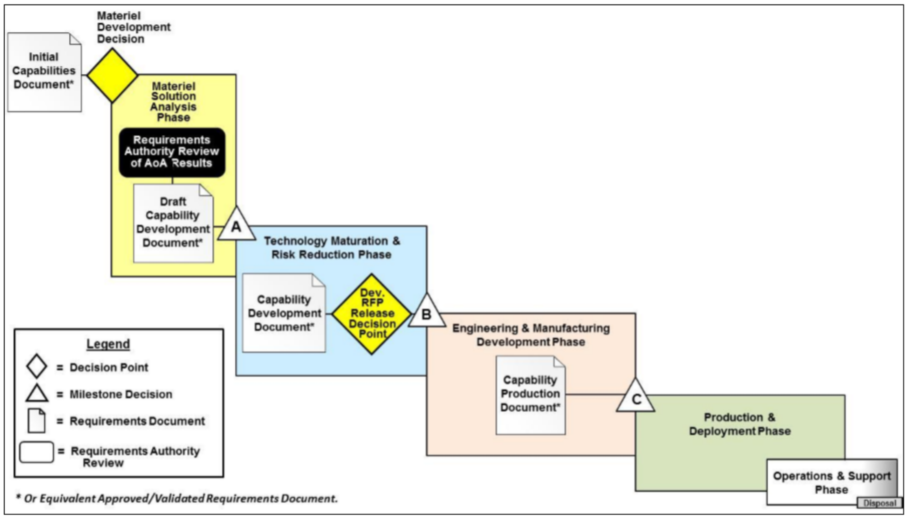



Figure A-4. JCIDS and DAS Process Interactions (Deliberate Process)

Figure 10: Acquisition Life Cycle [132].

of Operation (CONOPs), and Joint Operations Concepts (JOpsC) to create Capability-Based Assessments (CBAs) which determine whether there is a capability gap that needs to be filled [132]. Although the most recent relevant CJCS Instructional Report (CJCSI 3170.01I) does not show this diagram, the general process as depicted in Figure 11 is still valid.

The highlight of the pre-JCIDS process is the CBA. CBAs act as the analysis that analyses the mission and the capabilities required to complete it, which capabilities can be addressed with current solutions and therefore which cannot, and a solution recommendation.

On the whole, performing CBAs before entering JCIDS is an improvement. This is because implementing capabilities-based assessments theoretically prevented over-prescribing of engineering solutions. Thus, engineers would free to suggest a greater variety of solutions to meet capability requirements instead of being told that they must build an airplane with range X and top speed Y to meet the DoD's requirements. Capability-based thinking changed the thought process of the DoD, meaning engineers were only told that there was a need for ordnance to reach location Z within time T, and engineers could suggest various

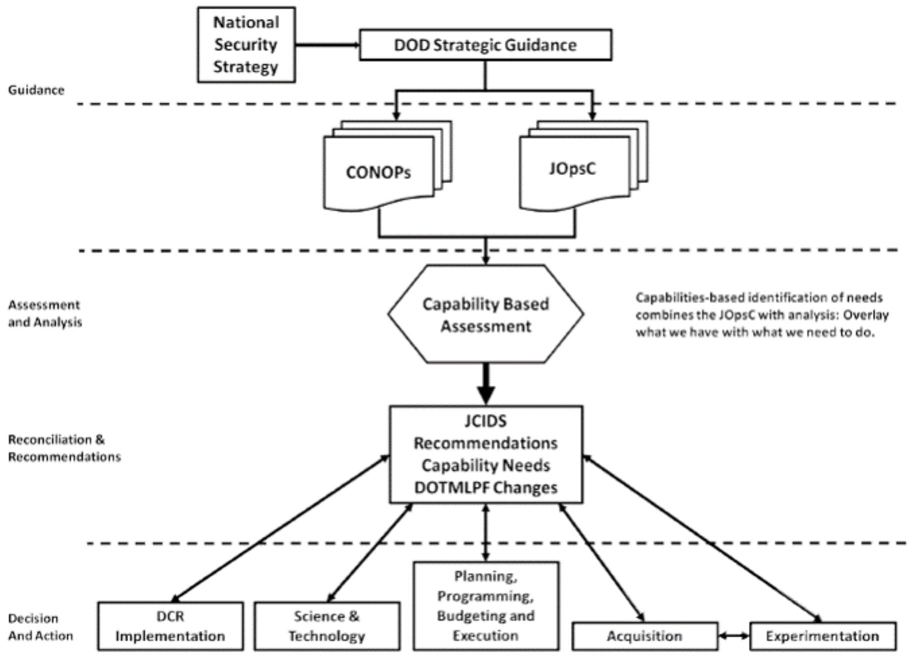



Figure 11: Relationships of Strategy, CONOPs, JOpsC, CBAs and JCIDS. [48]

ways to do this. Furthermore, JCIDS allows for *joint* capabilities assessments, meaning greater inter-service cooperation.

### 2.2.3 Problems with the Acquisition Process

Certain problems have been identified with the current acquisitions process. Specifically, Doerry and Fireman [47] identify issues with the AOA and CBA processes. They note that for a few acquisition projects, “the final alternative implemented (after much delay) was not part of the recommended solution set coming out of the AOA. For CG(X) the final acquisition alternative has not been selected almost a year after the originally scheduled completion of the AOA... AOAs sufferred from the lack of a well defined fleet architecture where the role and needed capabilities of these individual ships were clearly articulated and prioritized within the context of total fleet affordability.”

They add that the Navy therefore needed a pre-AOA process to define fiscally-constrained fleet requirements. ”The current acquisition process... is reactionary in that materiel solutions are not studied or explored in any level of detail until a capabilities gap is identified

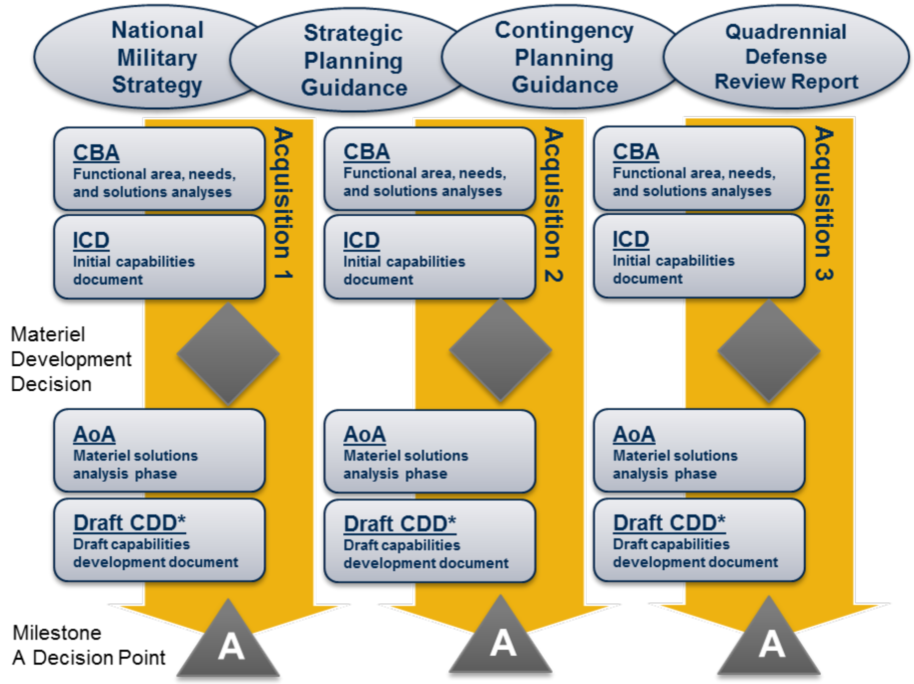



Figure 12: Outline of Stovepiped CBA-Based Acquisition Processes, reproduced from [47]

as part of the JCIDS process. Materiel solutions are developed to specifically address each individual capabilities gap independent of other gaps or consideration of overall fleet or systems architectures. **The fleet is currently designed one acquisition program at a time...**". More generally, the need for an SoS-level requirements allocation process has been noted previously [54, 63]. Doerry and Fireman's version of the current acquisition process is highlighted in Figure 12.

From Doerry and Fireman it is clear that there is likely a mismatch between how JCIDS is intended to be implemented and how it is being implemented. Theoretically, the type of pre-AOA process they describe is supposed to have happened at the strategic level. Thus, all CBAs stem from already highlighted mission needs. Furthermore, in the acquisition process CBAs are supposed to be evaluated in the context of other previous or current acquisitions and CBAs, thus enabling more of what Doerry and Fireman envision and helping to reduce stove-piping[77]. A similar study to the one they describe was performed ad-hoc in 2006-2007 by Naval Sea Systems Command (NAVSEA) in order to meet the Chief of

Naval Operations' (CNO) proposed ship building strategy. This study involved the following [60]:

1. Buying the right level of capability and preventing requirements-creep. The CNO created and empowered the Navy Capabilities Board (NCB) and the Resources, Requirements and Review Board (R3B) to review requirements that drive costs in ships, aircraft and weapons.
2. The Navy has clearly delineated a long-range shipbuilding plan. We must now commit to and remain on track toward a 313-ship force structure so our shipbuilders can make appropriate long-term investments in skilled workers and infrastructure.
3. Naval Sea Systems Command (NAVSEA) is exploring reduction of types and models of ships to reduce nonrecurring costs and increase learning benefits. This includes maximizing reuse of ship designs, components, use of open architecture and mission systems modularity.
4. The acquisition community and industry are exploring alternative acquisition strategies where we segregate risk and purchase material strategically, increase leverage and reduce risk in contracting.

Among the tools used were risk analysis and mitigation, capability analysis, and reduction of ship types and models. These tools would also complement the three phases of Naval planning methodology outlined in the CNO's 30 year plan developed in the early aughts, highlighted in [60] and explored further in [47]:

1. Near-term. This period includes the current budget year and future years defense plan (FYDP). During this phase, the Navy endeavors to minimize adjustments to the plan to balance the mix of ships, unit cost and resources available in the budget, while addressing industrial and

vendor base concerns. Given known requirements, return costs on ships in construction and quantities, the cost estimates are reasonably accurate.

2. Mid-term. This period is beyond the FYDP out to 10 to 15 years. Requirements are based on Defensewide planning scenarios and incorporate intelligence assessments of future threats and operating environments. Cost estimates are parametrically derived from analogies to current ship classes.

3. Far-term. This period begins 15 or more years into the future. Because requirements are not fully recognized, the number and types of ships are rough targets based on joint and Navy analytical models and are focused on capability sufficiency and potential fleet architectures. Cost estimates are notional rough order of magnitude because of the uncertainties.

Essentially, these phases can be described from far-term to near-term as: Expectation, Planning, Stabilization. Long-term fleet planning depends on rough estimates of expected threats with vague requirements, and on maintaining multiple potential options for fleet architectures.

Doerry and Fireman[47] propose that the current mismatch is related to improper planning at the far and mid term. CBAs are performed on a single capability area and not on the design of the entire fleet, as shown in 12. By deriving gaps directly from NSS and the DoD Strategic Guidance, the DoD could standardize the spirit of the studies the Navy performed in 2006 and create a process more similar to 13.

## *2.3 Fleet Planning Problems*

### 2.3.1 Fleet Sizing and Mix

The Fleet Sizing and Mix (FSM) Problem has received a significant amount of attention in the literature, with applications in military [34, 58, 140, 143, 111] (and modular [141]), shipping [95], and transportation fleets [120, 53, 56, 67, 17, 59], among others. Fleet mix


Figure 13: Pre-MDD Fleet-wide CBA-Based Acquisition Processes, reproduced from [47]

planning is the problem of determining the proper proportion of assets in a fleet based on that proportion's effectiveness, according to given measures of effectiveness [143]. Furthermore, a fleet mix plan will have a time component which accounts for when assets are procured or retired, and at what rate. The sizing aspect of the problem implies that not only the proportion but also the number of each asset must be determined as a natural extension of attempting to quantify the effectiveness of the fleet mix.

Structurally, the problem consists of a few key parts:

1. The potential assets in the fleet and their properties.
2. The models, simulations, or equations by which potential fleets are evaluated (generally including missions and cost).
3. The measures of effectiveness that allow for evaluation.
4. The decision criteria for picking between a few "good" fleets.

Firstly, evaluating too large a number of potential fleets can become expensive if the generation of results is not nearly-instantaneous. This is compounded by situations where MOEs must be checked at multiple points in time to ensure they do not deteriorate, potentially necessitating even more "function evaluations." The optimization methods for such problems varies. More traditional methods revolve around integer linear programming or mixed integer linear programming [53, 34, 58], while newer methods utilize multi-objective genetic algorithms [142] including NSGA-II [127]. Potentially other types of optimization algorithms can also be used so long as they satisfy the criteria, e.g. multi-objective mixed

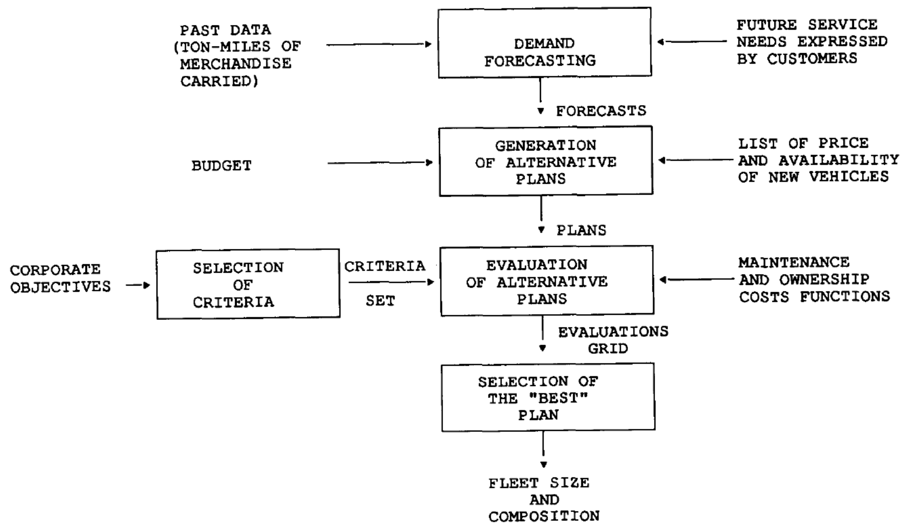



Figure 14: IPPD for Fleet Mix [33]

integer linear programs [9, 51], or others [101] which carry a more explicit form of uncertainty into the problem, which can be advantageous for probabilistic mission models.

In some cases, measures of effectiveness (MOEs) are calculated via system dynamics models [17] or other optimizers [50]. However, MOEs can often be nontrivial to generate. If multiple MOEs exist, potential fleet mixes can become non-dominated with respect to some measures but not others, meaning that a decision-support system or process must be implemented in order to arrive at one solution [33, 13], e.g. an Overall Evaluation Criterion, Analytical Hierarchy Process, TOPSIS, etc.

### 2.3.2 Fleet Mix Scheduling

Fleet mix scheduling problems already address some of the problems faced by military decision makers, mainly in that they offer a cohesive methodology for assessing future force structures. Fleet mix scheduling describes the problem of determining the evolution of a fleet of assets over time, when subject to budgetary, performance, and/or risk constraints. In essence, the goal is to connect the baseline fleet to all of the options enumerated by the optimizer. Depending on the number of time steps desired, multiple further connections can be made. Typically, the only limitation to whether two fleets can be connected is the cost difference between the fleets. A simplified summary follows:

The first decision that must be made in this case is what cost distance threshold should be used to connect fleets to each other. This decision has a pronounced effect on the outcomes, as it can substantially reduce the number of options. Some, such as [140], use a percent increase from the cost of the baseline fleet in order to develop the fleet. Depending on the fleet options available, however, the exact number requires some amount of decision maker input in order to determine what a reasonable cost difference is.

Once this is done, fleet mix schedules can be constructed in any number of ways. Different methods have different ways to do this, but in general the difference between fleets is calculated as a "cost distance". The simplest calculation of cost distance is merely a Euclidean distance of the unit cost of each asset multiplied by how many of said asset is included in the fleet.

However, another potential metric that can be used is called the "city block distance", or a Minkowski generalized distance that is computed with a Minkowsky parameter of 1. This type of distance can be used to account for the fact that the fastest path between two fleets is not along the hypotenuse, but along the dimensions that differ. This means that the "city block distance" can more realistically account for purchases when the difference between two fleets is concerned, since that difference is essentially the number of unit purchases (or retirements) that must be made in order to turn one fleet into another. Purchases cannot be hybridized in some way such that they travel "through a city block."

However the distance is calculated, the result can essentially be summarized as an n by n triangular matrix, where n is the number of fleets and each element in the matrix is the distance from one fleet to the next. These distances are then used to create the fleet paths in a number of different ways, typically based on the threshold mentioned earlier. However, in literature there many different approaches to fleet mix scheduling, some of them relying on creating new fleets, for example, and others not relying on cost as the sole metric by which to group fleets. These various methods are highlighted here:

An older method by Brown et al. [20] utilizes a high-level approach to fleet mix scheduling. They abstract the modeling and simulation aspect seen in other methods, leaving the user to input into their PHOENIX optimization model such variables as the minimum and maximum number of operational aircraft required in the fleet performing misison m in year t, minimum fraction of those aircraft required to be of high technology, annual survival rate of aircraft, etc. While it is quite difficult to estimate some aspects of the fleet mix scheduling problem such as cost without more advanced techniques, newer methods have at least attempted to take advantage of the power afforded by modern computing in order to perform more modeling of missions and performance.

A group at the Aerospace Systems Design Lab (ASDL) utilizes a physics-based pollution simulation, noise modeling, as well as supply and demand factors, to inform a system dynamics model that plans the purchase of assets in a fleet [67] [109]. The group also studies technology infusion problems with using this same framework [110] . This problem benefits from the fact that the fleet performance models could be fitted to second order quadratic polynomials and other surrogate models. In situations where the model is more complex, a significantly number of model runs would be necessary to create mathematical representations. However, if this could be done, then fleet mix scheduling problems could be addressed via methods such as system dynamics or optimization, as is done in other cases.

Two attempts by Barlow et al. [11] and Wesolkowski et al. [140] generate paths through fleet alternatives based on either the cost of adding new assets in the case of Wesolkowski, or risk minimization in the case of Barlow. Both of these methods also demonstrate more enhanced mission modeling capabilities. Barlow uses an agent-based model to analyze Military Operations in Urban Environments (MOUT) in the WISDOM-II model. Barlow then utilized a multi-objective evolutionary algorithm to derive suitable force structures under cost, casualty, and effectiveness constraints, simulating each of the 1100 possible force structures in three different environments with 100 repetitions a piece in order to capture

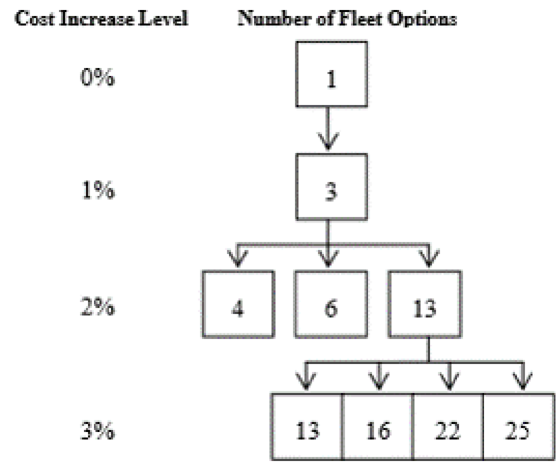



**Figure 3:** Number of options which an example fleet has for growth at each cost level

Figure 15: Robust fleet decision tree by Wesolkowski, et al. [140]

stochastic effects in the risk facing the blue force. Barlow generates paths of minimum risk for two different types of force structures based on this evolutionary approach.

Wesolkowski uses the SaFE model (a Monte-Carlo simulation of various tasks needing to be accomplished, sampling from ranges of possible completion times per asset [139]) to estimate shipping times for a year. Then, the NSGA-II algorithm is used to generate "optimal fleets with respect to platform cost and mission duration". Once this was done, Wesolkowski used the following to compare the fleets:

1. For each scenario: $(i = 1, , Y)$
   (a) For each fleet:
      i. For each scenario: $(i = 1, , Y)$
         A. Compare the fleet to every fleet in the k-th scenario
         B. If the fleet contains one of the fleets in the k-th scenario, then the fleet can accomplish the k-th scenario
      ii. Assign the fleet a score based on the percentage of scenarios it can accomplish

Wesolkowski did this with an initial population of 500 fleets on 100 scenarios for 100 generations, with a total resulting fleet count (after removal of duplicates) of 45,495 fleets.

After this, the method of scheduling was as follows: “An example fleet was chosen, and for each scenario that it could not already accomplish, the costs required to adapt the fleet were calculated. The costs of the different platform additions were organized according to the percentage of the original fleets cost.” This is essentially implying a calculate of the cost distance of each fleet to each other fleet, where the dimensions consist of the total cost of each type of asset in the fleet.

A method by Abbass et al. [4, 3] utilizes multiple novel methods in approaching fleet mix scheduling. First, Abbass investigates scenario modeling from the point of view of scenario planning [124, 3]. Abbass critiques traditional probabilistic approaches:

1. ‘A large amount of data must be collected, maintained, and updated to manage these distributions.’
2. ‘Inability to account for emotions, feelings, and complex human behavior. Socio-technical interface is critical in strategic security and defence planning exercises.’
3. ‘Only one type of uncertainty can be handled: branching points - the planned uncertainty that we understand well and can map onto a set of probability distributions. Shocks, surprises, discontinuities in systems, can’t be accounted for. These include collapse of the Soviet Union, rise of China, etc.’
4. ‘Use of historical data to generate probability distributions, assuming continuity of trends.’

Instead, Abbass proposes building a data base of future scenario structures by using creative thinking methods to identify deep uncertainties. These structures are used to generate alternative scenarios that are mapped onto a set of required mission tasks. Abbass then models these missions via the WISDOM model (related to the WISDOM-II model used by Barlow from the same group) using the required tasks calculated from the scenarios generated and the modeling of those tasks in WISDOM. Once this is done, Abbass uses NSGA-II with a population of 50 and 100 generations to create potential fleets that can address the scenarios. The non-dominated solutions to each scenario and problem instance are extracted, then their performance for in each other scenario is calculated, so that each fleet has performance characteristics for each scenario. However, the fleet is only guaranteed to be non-dominated for one scenario.

Finally, the fleet mix schedule is developed via k-centroid clustering of all non-dominated solutions based on the cost of each solution, such that "the distance between two weighted solutions represent the Euclidean distance between the cost vector of two possible fleet mixes. The threshold $theta_1$ - taken in this study to be \$0.5b - represents the difference in total costs for which two solutions are seen to be invariant or similar in terms of their budget." The disparate solutions thus clustered are then combined into a single fleet by taking the 'ceil' of all fleets, such that the resulting fleet has the minimum number of vehicles required such that the "fleet can perform all problem instances that generated the solutions in that cluster." Once the 'ceil's are created, they clustered once more, effectively creating a hierarchy of clustering. This repeats until the stopping criterion is met. The result is a hierarhy of clusters that can successively complete more and more problem instances.

A final note stems from a fleet mix planning problem outline for the US Coast Guard [13], which deals with how decision support systems (DSS) can be leveraged for the fleet mix planning (FMP) problem and what challenges existed at the time. The primary differentiating factor in this paper is the that the author notes that the "FMP problem has many characteristics of problems that decision support systems have been defined to handle. (I.e., it is unstructured, involves several models and lots of data, and requires non-trivial mechanisms for the presentation of data and models.) It then follows that a typical DSS would be able to solve the FMP problem, or else that the FMP problem is one that a DSS ought to be able to solve. And a DSS that works well for the FMP problem can well be considered a standard for decision support systems." If indeed the FMP problem is so amenable to DSS, it is important that any methodology constructed permit the creation of a DSS from methodology inputs/outputs.

### 2.3.3 Fleet Grouping and Scaling

To address the problem noted earlier, mainly that the SoS defined in other problems is not necessarily large enough for the sort of strategic analysis required, a literature search was done to discover whether any other methods in related fields addressed this. While not exactly the same, the problem of fleet group replacement has literature that touches on similar topics. Somboonwiwat [126] develops a grouping scheme to treat vehicle types in a fleet as members of one or another group based on functional characteristics, and optionally creating sub-groups based on cost. Somboonwiwat then provides two different integer programming models based on whether the replacement is inter-group (replacement of groups within a fleet) or intra-group (replacement of systems within a group).

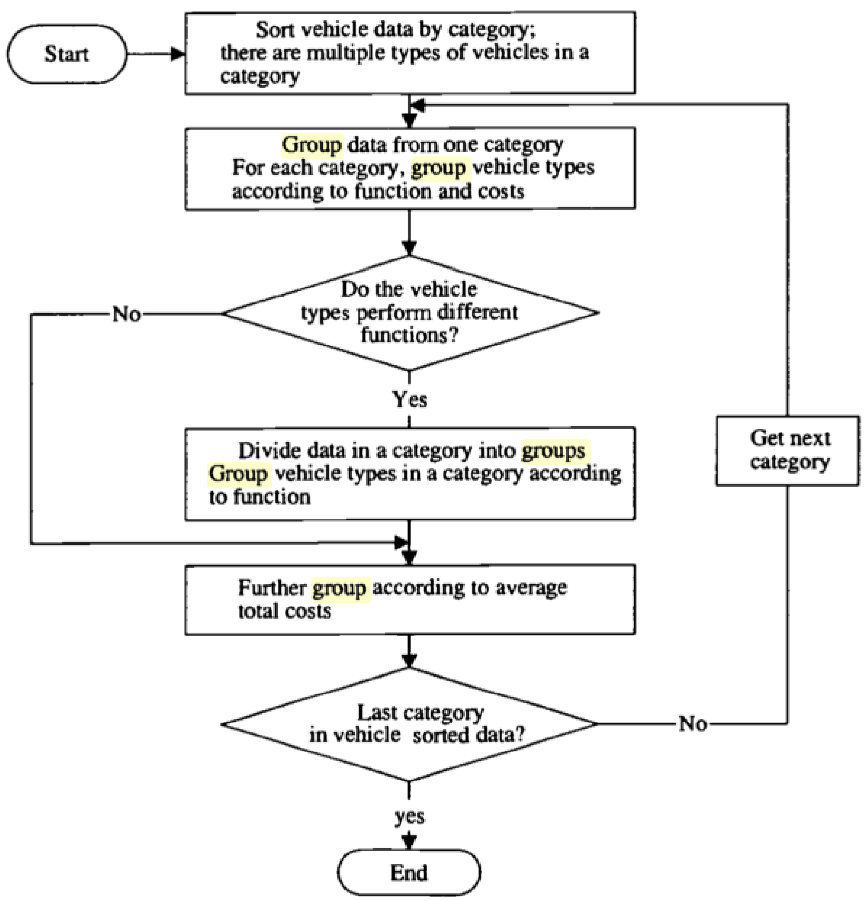



Figure 16: Somboonwiwat's Grouping Flow Chart [126]

The example given is grouping all vehicles in the "transport" category by function, which could include "equipment transport, passenger transport, etc.". However, in defense applications, systems are increasingly becoming multi-role. The concept of operations for many stealth fighters involves expending ordnance as per normal operations, and then remaining behind as an ISR platform. This can present challenges for Somboonwiwat's method, as a vehicle's function can change depending on mission, or even within a mission. Even if such problems could be overcome, it is not immediately obvious how to then link mission modeling to this grouping, since the number of systems operating in a mission would only be a subset of the overall group (e.g. "fighter", "multi-role"). Any solutions to this would likely obviate the need for a functional grouping of the sort Somboonwiwat suggests for civilian fleets.

A related method in fleet mix planning comes from Ghanmi et al. [58]. Here, the focus is on addressing the problem of multi-role assets. Attempting to optimize a fleet of tactical vehicles for special forces operators, the authors begin with a set of tactical vehicles and a set of missions. They enumerate all the roles the vehicles can perform, and map which mission has which roles. The rest of the analysis proceeds as any fleet mix optimization problem may, where instead of missions the roles are used. These steps are shown in Tables 1 - 3:

Table 1: Ghanmi Multi-Role Vehicle Tasking, Mission-to-Role Mapping

| | Vehicle Role j, Role weightings | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Mission i | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| 1 | 0.2 | | 0.4 | | 0.1 | | | 0.3 |
| 2 | | 0.3 | 0.2 | | | 0.3 | | 0.3 |
| 3 | 0.3 | 0.2 | | 0.1 | 0.2 | | 0.1 | 0.1 |
| 4 | 0.4 | | 0.3 | | | 0.2 | | 0.1 |
| 5 | | 0.2 | | 0.2 | 0.3 | | 0.2 | 0.1 |

Table 2: Ghanmi Multi-Role Vehicle Tasking, Role-to-Requirements Mapping

| | Role requirements | | | | |
|---|---|---|---|---|---|
| Role j | Pax | Payload | Volume | Mobility | Survivability |
| 1 | 15 | 15 | 12 | 3.1 | 2.2 |
| etc. | | | | | |
| 8 | 14 | 26 | 14 | 2.4 | 2.1 |

Table 3: Ghanmi Multi-Role Vehicle Tasking, Vehicle-to-Requirements Mapping

| | | Vehicle performance | | | | | |
|---|---|---|---|---|---|---|---|
| Vehicle k | Cost | Pax | Payload | Volume | Mobility | Survivability |
| A | 150 | 5 | 2 | 2.1 | 3.6 | 3.8 |
| etc. | | | | | | |
| E | 140 | 8 | 2.8 | 2.7 | 3.2 | 3.5 |

In the method, each vehicle is mapped to a specific role in each mission and missions cannot be performed simultaneously. Thus in effect, the roles stand in for the traditional definition of "mission" and thus the rest of the analysis proceeds as a somewhat-multi-mission process. However, this approach has several challenges for actually producing a strategic-level fleet.

The enumeration of mission-level performance requirements greatly simplified the computational burden of the method. However, while the method may work well for more high-level mission models where evaluating a strategic-level fleet is roughly as fast as evaluating a smaller fleet, some mission models may require more complex modeling, e.g. combat. For these models, evaluating 1,000 assets or 100 assets greatly affects the computational burden.

Furthermore, the models described in [58] do not include other assets. The model was proposed for a tactical vehicle fleet. However combat is typically the domain of SoS, where emergent effects of the interactions between multiple different asset types are revealed. The lack of an ability to model the interplay between different assets, especially as interoperability will be considered, creates a significant setback to using this method.

To summarize, the main issues identified can be combined into one generalized problem. This is the problem of how to scale a mission-level-size SoS to a full strategic-fleet-size SoS. This scaling must account for multi-role assets but also multi-asset missions. Finally, the method should not contribute to the already significant computational complexity of modeling combat missions at any significant level of fidelity.

### 2.3.4 Discussion of Fleet Mix Problems

Fleet mix problems are decomposed into two essential problems - what is the best fleet mix and size, and how do these change with time, subject to budget and mission constraints. It should be noted that the FSM problem is a subset of the fleet mix scheduling problem, and thus the latter will be treated as the primary issue to address. Other types of issues in this problem class include how to deal with uncertainty and how to handle mission modeling.

In recent years, mission modeling has been performed either during an optimization (thus informing the optimizer on which direction to proceed), or after a set of potential fleets has already been identified. Many of the fleet mix scheduling approaches involve more simplified models (though some, such as the MOUT model used in WISDOM-II, do not) or models that were not published with the paper. However, so long as the method can incorporate non-mathematical models for performance (or rather, so long as the method can incorporate mission modeling or simulation), it should suffice for the purposes of this methodology.

The second issue in this problem class, as mentioned previously, is how to deal with budget and mission constraints. There are two types of ways to deal with this. These are essentially the two ways that Wesolkowski [140] and Abbass [4] deal with the problem, which are not altogether distinct. Both methods cluster fleets together, with Wesolkowski merely checking if fleets contain other fleets, and Abbass eliminating duplicates and grouping fleets by cost similarity.

Wesolkowski's approach takes each of the fleets from the NSGA-II algorithm, determines how many scenarios the fleet cannot do, and determines what the cost to add that capability is (to add the assets necessary to be able to do that scenario). These additional costs were organized according to their percent increase to the original fleet cost. This organization generates the purchasing plan for a given initial fleet.

Abbass, on the other hand, successively groups fleets by k-centroid clustering of their cost, takes the ceiling of this number, and treats this new rounded number as a new fleet and grouping it in a subsequent cluster. Thus, purchasing plans are created via grouping hierarchies.

Unfortunately, both Abbass's and Wesolkowski's fleets are only operationally significant, unless each asset is a placeholder for multiple assets or unless the entire strategically-significant fleet is used to perform only one mission at a time, which is not realistic. Thus there is no guarantee of strategic significance from these methods. Somboonwiwat's method is directly relevant to this question, but is lacking in a few regards. Given that the definition of fleet for this dissertation is a grouping of assets with strategic significance, there may be a gap in the literature for how to address this.

Wesolkowski and Abbass both deal with budgets, but do not necessarily attempt to discuss robustness in such a great extent. This is a topic that will need to be investigated further.

## *2.4 Robustness, Adaptability, and Flexibility*

Wesolkowski says that "fleets that can effectively accomplish a set of mission scenarios are said to be robust to that set of scenarios. To evaluate robustness we examine all fleets generated by the MOOs for all scenarios and determine the supersets of the fleets generated by any given scenario" [140], summarizing both his and (effectively) Abbass's views on fleet mix robustness to missions.

However, one can imagine two different kinds of fleet robustness. The first is the robustness of each fleet to each scenario. The other is the robustness of the purchase plan to changes in scenarios, i.e. the robustness of the decision to proceed with a certain plan. RAND Corporation has espoused 'robust decision-making' as a way to make decisions in a world full of deep uncertainty. RAND defines several principles for robust decision-making [114]:

1. Reason over multiple scenarios. The set of plausible futures expressed in the scenarios should be diverse, in order to provide sufficient challenges against which to test alternative near-term policies. These scenarios can also facilitate group processes designed to elicit information and achieve buy-in to the analysis from stake-holders with very different values and expectations.
2. Seek robust, rather than optimal, strategies that do well enough across a broad range of plausible futures and of alternative ways of ranking the desirability of alternative scenarios. Robustness provides a useful criterion for organizational decision-making under uncertainty because it reflects both the normative choice required, while requiring specificity in characterizing the nature of good enough, and the approach many decision-makers actually use under such conditions.
3. Employ adaptive strategies to achieve robustness. Adaptive strategies change over time in response to new information; the predict-then-act framework takes little cognizance of this possibility.
4. Use computers to characterize uncertainties by their relevance to the selection of robust strategies. Predict-then-act analyses begin with consensus on a model for how actions are related to consequences and on specific probability estimates of risks. In contrast, robust decision-making seeks to identify strategies whose acceptable performance is largely insensitive to the wide ranges of uncertainties characteristic of many problems. It then characterizes a small number of key, irreducible trade-offs inherent

> in the choice among such robust strategies. Predict-then-act methods use the computer as a calculator to yield best strategies contingent upon selected assumptions. Robust decision-making uses the computer as a tool for interactive exploration to discover and test hypotheses about robust decisions.

There are a few relevant take-aways from these principles: Multiple scenarios, the need for robust strategies that do well enough across a broad range of plausible futures, and the need for adaptiveness. In fact, multiple scenarios (although not necessarily in the way envisaged) and adaptiveness are already part of the fleet mix planning methods. Abbass[4] has cited many of these same scenario-planning principles in his work.

In "High-Performance Government" [114], RAND never defines robustness, although the principles outlined above imply that a robust decision is not necessarily an optimal one, but performs better across a wider set of alternatives than does the optimal one. However, other RAND sources give definitions [87] such as: robust strategies, that is, ones which will reduce vulnerabilities by performing well compared to the alternatives across a wide range of scenarios.

Weigel and Hastings[137] define a robust space system architecture as one that "must successfully weather any changes that may occur during the course of the system development or operation." To analyze the robustness of architectures they create a real options-based approach that determines the cost of transitioning to a new architecture versus maintaining the current one in the face of budget reductions. However, they leave to the designer or project manager the task of calculating the commonalities between the initial architecture and the potential new architecture. This approach has benefits for planning out architectures, or in the case of this dissertation, fleet compositions. However, it is not in and of itself a way to categorize which fleet plan would be most robust to such budgetary swings.

Still other sources use a different term altogether for this same general idea. For example, owing to its similarity with problems in decision theory, some authors [112, 91] refer to this characteristic as the flexibility of a plan, and when it is coupled with the "goodness" or value of each decision in the plan it is referred to as plan robustness.

Overall, robustness to various missions and budgets seems to be addressed to a greater or lesser extent, but not robustness or flexibility of the fleet plan.

### 2.4.1 Fleet Sizing and Mix Adaptability

Wesolkowski [140] differentiates this type of robustness, which he calls adaptability, from the robustness of a single fleet:

> We want to find out how well a fleet is strategically positioned, i.e. how well can it adapt to potential future scenarios. An adaptable fleet will only require a small infusion of money in order to address effectively a large number of distinct scenarios. It is unlikely that any cost-constrained fleet will be able to address every scenario. Scenarios that a fleet cannot address (adapted or otherwise) pose a unique risk to that particular fleet. Hence, each particular fleet configuration will have a unique profile of scenarios for which it is robust, adaptable, or risky."

Wesolkowski sets up a set of fleets and missions for transportation. The missions are combined into scenarios of various mission task characteristics and frequencies, and the fleets are then optimized with an NSGA-II algorithm. However, [140] did not deal with fleet mix scheduling explicitly because no fleet mix schedule is developed. Instead, adaptability is determined as in the above example:

> Each fleet in each scenario was compared with the fleets in every other scenario to determine each fleets capabilities. For a fleet X of scenario A, if one of the fleets optimised for scenario B is a subfleet of X, then X is capable of performing B. Each fleet was assigned a fleet-capability score based on the percentage of scenarios which it could accomplish, for cost increases of up to 1%, 2%, 3%, 4%, and 5% of each fleets original cost. The minimum cost

required to increase each fleet such that it contained at least one other fleet in every other scenario were calculated, and fleet-capability scores were assigned to these increased fleets.

Then, a few experiments are performed with the above adaptability definition in mind. First, the cost available to adapt each fleet (aka the allowable cost threshold) is increased by 1%, from 1% to 5%, and the analysis is re-run to determine what percentage of the fleets can accomplish how many of the scenarios and how adaptable they are (i.e. are they within X percent of a fleet that can accomplish those scenarios). The results are shown below:

Second, the mission frequencies were multiplied by a random number from 1 to 2 for each scenario, thereby increasing the demand and the variance in demand. Furthermore, cost increases were now 5%, 15%, 25%, 35%, and 50%. The results are shown in Figure 18.

Wesolkowski concludes the experiments by observing that when modeling adaptability, it is important to use realistic representations of all possible future scenarios, as the scenarios can have serious impacts on adaptability. This can be seen by contrasting Figure 17 and Figure 18, where even a 5% increase in budget in the latter does not produce the same kinds of effects as seen in the former due to the much more demanding scenarios.

However, Wesolkowski's analysis, while helpful, does not take into account the adaptability of fleet plans explicitly. As such it would require some re-work in order to adapt to our situation.

#### 2.4.2 Graph and Network Adaptability

Byrne et al [23] discuss the effects of algebraic connectivity on graph robustness. Algebraic connectivity is defined as second eigenvector of a connected graph, i.e. one in which there is a path between all pairs of vertices, whereas a complete graph is one in which exactly one edge connects every pair of vertices. They discuss the mistaken notion that increasing algebraic connectivity increases the robustness of the graph, where robustness is defined

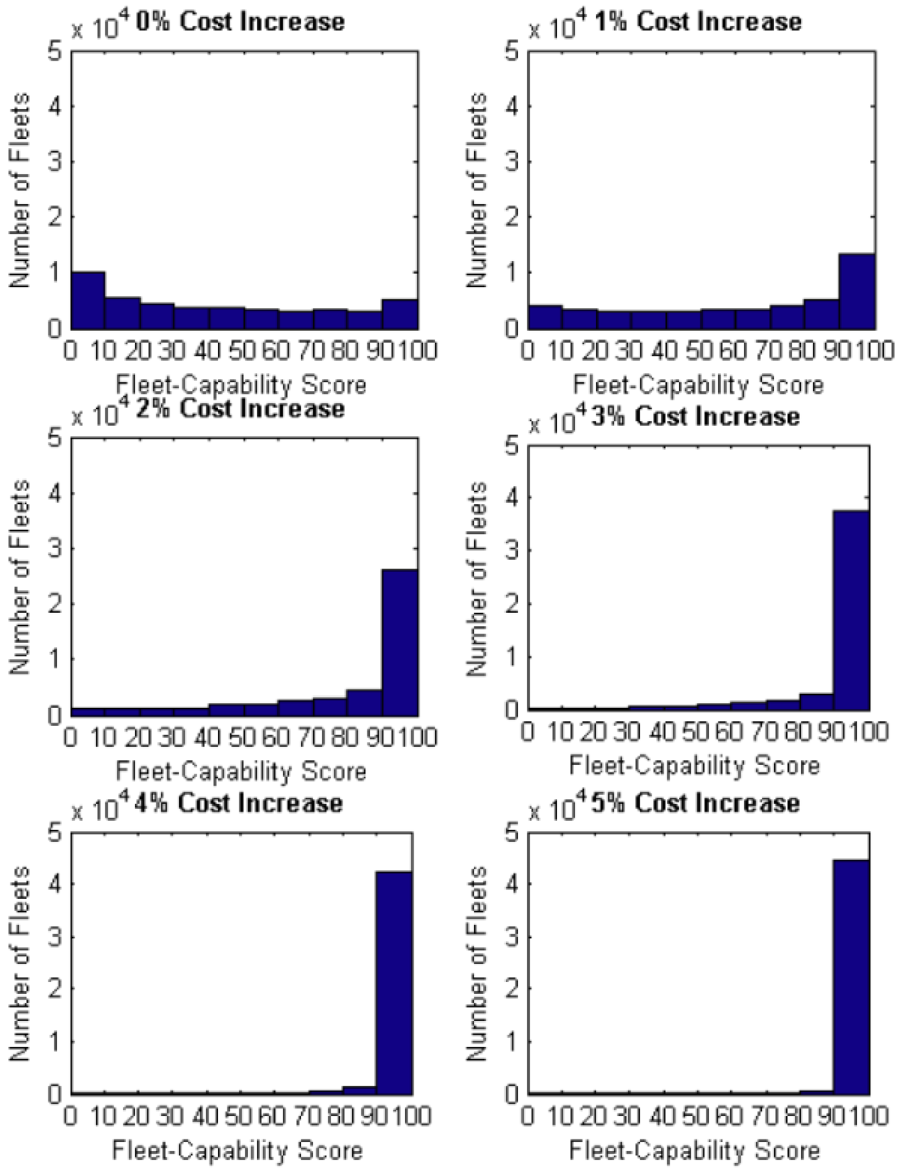



Figure 17: Adaptable fleets by Wesolkowski, et al. [140]

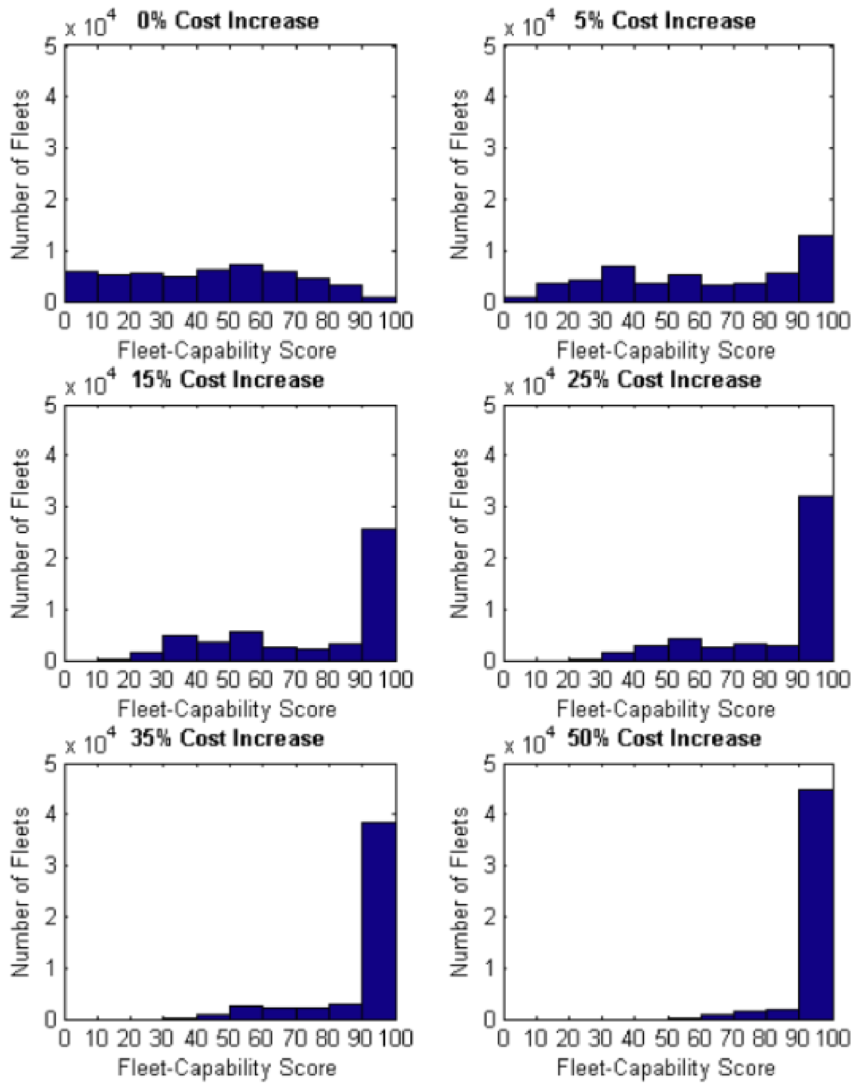



Figure 18: Adaptable fleets with more variance and demand, by Wesolkowski, et al. [140]

as the resistance of a graph to becoming disconnected. On the topic of disconnection, the node and edge connectivity are discussed [39]. Node and edge connectivity are simply the number of nodes or edges that must be removed in order for a graph to become disconnected, i.e. for one connected graph to become two. Byrne et al show that increasing the algebraic connectivity of a graph can reduce the node and edge connectivity, even though the former forms a lower bound on the latter two.

Kadono et al [80] discuss an ant colony optimization approach to ad hoc GPS network routing that is based on the robustness of the networks. Where $g(\nu_j, \nu_{j+1})$ is the robustness of link $(\nu_j, \nu_{j+1})$, the robustness of a path $\nu_1, \nu_2, ..., \nu_k$ is defined as:

$$G([\nu_1, \nu_2, ..., \nu_k]) = \min\{g(\nu_j, \nu_{j+1})\} \quad 1 \leq j \leq k-1$$

For $g(u, v)$ they defined two possible measures of robustness, which are related to the distance, range, and velocity vectors of the two nodes of the link. Both $g$ functions take values of real numbers from 0 to 1.

### 2.4.3 Decision-Theoretic Approaches to Flexibility in Industrial Decision Making Applications

Decision-theoretic approaches generally follow the same overall process. The goal is to outline the set of possible options, then determine some sort of probability associated with those options while accounting for the number of options at the next phase. Two sources that are instructive in these approaches are by Pye[112], and Mendelbaum and Buzacott [91].

Pye determines the entropy of a probability distribution for a given uncertainty in the choice. He defines flexibility as “the entropy of the distribution of probabilities concerning the d.m.’s future decision”, and says that the flexibility retained after making a choice $a$ is $U(prob(\, c_i \, is \, chosen \,|\, a)_{i=1}^{M})$, which is maximized if the probability for each choice $c_i$ is $1/M$. Thus the maximum value for flexibility in Pye’s formulation of the uncertainty

$\sum_{i=1}^{M} p_i log_2(p_i)$ is $log_2 M$, since each choice is equally likely. Pye then proceeds to offer a similar treatment to the case where the decision maker and 'nature' are playing a game (in game theoretic terms) and after the decision maker's first choice $a$, nature may make a choice before the decision maker acts next.

Pye highlights a few different types of situations - ones in which probabilities with nature's choices cannot be determined and ones in which they can (unforeseeable and foreseeable risk, or aleatoric and epistemic). He points out that in the case where the risk is unforeseeable, only the number of options can be calculated, whereas when the uncertainty is foreseeable probabilities for those options can be calculated. He then proceeds to define the term robustness as one which combines the flexibility of a decision and its value in various ways depending on the properties of the value function.

Mandelbaum and Buzacott take a somewhat different though related approach. They highlight the difference between the "true model" of the decision, where probabilities and values are perfectly understood, and an "original model" which is perhaps incomplete or not wholly accurate in its estimations of the true model. They point out that the concept of flexibility is far more relevant because we possess only original models, not true ones. They then proceed to describe the expected losses of a decision, or the estimation of the most likely loss given uncertainty around the true loss.

Mandelbaum and Buzacott define flexibility for each choice as simply $n$, the number of options available for the subsequent choice after initial choice $a$ is made. They then discuss estimation of the losses according to each model, where the losses for the true model for choice $a$ given some uncertainty $I$ is

$$\mathcal{L}(a \mid I) = E\left[\min_{b \in B(a)} \{L^0(a,b)\} \mid I\right]$$

. This value can be calculated with the following equation.

$$\mathcal{L}(a \,|\, I) = \alpha + \int_{\alpha}^{\infty} \prod_{b \in B(a)} P\left[L^0(a,b) > y \,|\, I\right] dy \tag{1}$$

Where $\alpha$ is the lower bound on the distribution and $\beta$ will be used later for the upper bound.

They determine that flexibility, i.e. more options, decrease the difference between the expected losses from the original model and the expected losses from the true model, as shown (for a uniformly distributed loss function) in the following equation:

$$\mathcal{L}(a \,|\, I) = L^*(a) - \frac{\beta - \alpha}{2} + \frac{\beta - \alpha}{n(a) + 1} \tag{2}$$

Where $n(a)$ is used as the number of options after decision $a$ has been taken and $L^*(a)$ are the losses associated with $a$ for the original model (not the true model). Buzacott and Mandelbaum point out that as the number of options increases, the limit of the third term goes to 0, though of course the marginal benefit from each additional option decreases as well.

Both of these methods are largely similar. However the Mandelbaum and Buzacott method provides slight advantages in that it it is somewhat simpler to compute given relatively little information about the problem.

## *2.5 Interoperability*

### 2.5.1 Interoperability Criteria

A common feature in advanced conceptual design is the need for rapid analysis to explore a wide variety of alternatives. In traditional design this analysis can be conducted with historical regressions of trends. However in advanced design, no such regressions exist and everything must be model-based. Thus a common feature is to explore functional requirements first, and then evaluate how those requirements may be met.

Criteria will now be developed to determine whether any potential interoperability measures meet the needs of the research objective. From the success criteria for the objective, multiple criteria can be pulled down to the level of interoperability as well: The interoperability measure must be as realistic as possible or have imperfections that can be mitigated, and be as rapid as possible to assess. The measure ought to be quantitative because it must potentially interface with quantitative mission models. Since interoperability was defined as both the ability of two systems to exchange resources, *and* to use the resources that have been exchanged to operate more effectively together, the measure adopted ought to have applicable effects in mission modeling. The measure ought to be flexible and scalable, since the dissertation is dealing with SoS. Finally, the methodology must enable a requirements exploration process to evaluate various fleet alternatives, which means determining functional requirements before physical requirements. A high fidelity subsystem-to-subsystem model of interoperability will likely not be fast enough nor, by the same token, flexible enough, to enable rapid assessment of SoS.

This problem is complicated by the fact that for long-term forecasting of the type we are dealing with, any interoperability technology being modeled today may be obsolete by the time the assets utilizing it are fielded. Thus, an alternative is to model options in lower-fidelity models and select the best of those to model in a more time-consuming, higher-fidelity technology assessment approach.

### 2.5.2 Interoperability Types

#### *2.5.2.1 Physical Interoperability*

Physical interoperability is the term we will be using to describe interoperability among physical interfaces. This type of interoperability is used for modular sub-systems, for support (such as catapult hooks for naval aircraft), and for logistics (common refueling standards, ammunition). Modeling this type of interoperability is desirable, because in the case of modularity - there is resurgent interest in how and where best to implement it, while in the case of support and logistics - these are factors that have a profound impact on military operations. [12]

Modeling this type of interoperability at a high fidelity would require knowledge of the physical interfaces required of or available to assets that either exist or are in the conceptual design phase and may be decades from production. On the other hand, determining high-level requirements for modularity may be possible and desirable as it would inform conceptual design for assets. However, modeling at a high-level presents challenges when assessing the impacts of modularity on asset effectiveness. One possible solution is to assume that modularity has no impact on asset effectiveness - in this way, mission models are independent of modularity. If this assumption is made, modularity only has a logistical impact - ships must travel to port in order to exchange modules and the problem becomes planning out the best mix of module placement both in port and on ship. This is essentially a separate logistics problem that could be solved as an additional mission, where time to target and standing capability gaps are the measure of effectiveness. Or this problem can be interjected as an intermediate layer between the mission models and the optimizer, acting as a damper that decreases the number of available assets to each mission model.

Either way, this type of interoperability is somewhat separate and likely has a lesser effect on mission effectiveness (the primary means of assessing fleet effectiveness in the literature) than do other types of interoperability.

#### *2.5.2.2 Data and Communications Interoperability*

Signals interoperability is the type described in by the exchange of data and communications, whether it be targeting information, status information, locational information, etc [7]. Like physical interoperability, this type of interoperability is highly technical in nature, thus limiting the fidelity that can be used at the level of analysis with which we are concerned. Indeed, high-fidelity modeling of interoperability may include all the various physics of signal transmission, bandwidth, metadata and metadata handling between assets, standards and protocols, and security [8, 24, 25]. However, these methods can be time consuming. Furthermore, modeling them could require modeling things such as terrain and air quality, all of which can change depending on where the mission is conducted [78]. It is easy to see that the needs of such a model begin to quickly increase and complicate the scope of the dissertation especially given that the aim is to develop functional requirements for a fleet that's presumably operating in all or most scenarios, at least at the stage of the analysis where we are concerned.

Another important consequence of this is the current inability to model limitations associated with an increase in use of interoperability [6, 45]. This is an important factor to keep in mind while designing an interoperable SoS [25]- limitations can include increased latency, diminished bandwidth, and increased signal interference in addition to complexity. These factors are necessarily more difficult to manage as the interoperability model becomes more and more abstracted from the physics and programming inherent in the problem. This is considered a topic for future work and improvement, however. For now it will be assumed that a decision maker will choose the minimum viable interoperability given the constraints on the fleets.

Despite these limitations, there do exist methods to model signals interoperability at a high level. Furthermore, unlike physical interoperability, it seems more difficult to assume away the effects of signals interoperability at the mission level, given the results from experiments [121] [102].

#### *2.5.2.3 Modeling Command and Control (C2)*

Command and control covers a wide variety of actions. Interoperability of command and control can mean either organizational interoperability, which is outside the scope of this dissertation, or of command and control systems to enable better battle management. Part of this question is the matter of C2 architectures, i.e. centralized vs. decentralized command and control, and how it affects or is affected by the information sharing protocol, which can also be centralized or decentralized. This is also affected by network security.

Some work on modeling command and control architectures and comparing them to information sharing architectures is found in [130]. However, C2 will not be in the first instantiation of this methodology. This is partly because, as stated by Builder, et al.,[22] network-based models of command and control processes can still miss very significant parts of the problem because command and control is such a human-centric activity. As an example, frequent successes and failures of command and control are more a result of whether subordinate forces have been adequately briefed as to the commander's intention and whether the commander's intention properly reflects the facts on the ground [22]. This is not likely to be captured in a simple network-based model. It is likely that more study is required in order to implement a command and control model that takes such factors into account such that they properly affect combat missions. On the other hand, it can be an open question whether modeling proper and improper command and control ought to be a part of a strategic fleet planning methodology. Answering this question and the challenges associated with modeling C2 is left to future work due to scoping reasons.

#### 2.5.2.4 *Selection of Interoperability Type*

By way of demonstration of the capabilities of the methodology, a higher priority will be given to signals interoperability. This is largely due to its greater effects on mission performance as opposed to the effects of physical interoperability, which is most felt prior to or after any given mission. For a more final instantiation, physical interoperability will also need to be incorporated. However, there is likely future work involved in enabling this due to the level of abstraction that is required of a model for incorporation into the methodology.

### 2.5.3 Qualitative Interoperability Methods

The need for interoperability is not new. It was needed, even before the advent of the net-centric warfare concept, in order to provide accurate, timely, and secure communications or targeting data [121]. The DoD has created multiple organizations and standards to attempt to address and guarantee interoperability where relevant [100]. However, previously, this was the domain of systems engineers responsible for communications or sensor systems that had to interface with other existing assets as part of satisfying the project's requirements [136]. SoS-level modeling requires interoperability modeling and simulation for the purpose of determining whether a new system should be interoperable, and to what degree, with an arbitrary number of existing systems.

Many previous attempts to capture types of interoperability have been insufficient due to their qualitative nature [78, 55]. This made them difficult to incorporate in a quantitative model or simulation of asset cooperation without a degree of subjectivity. Part of the issue is that answering the question of ”What is interoperability” is a non-trivial process, since interoperability can mean different things to different organizations [78, 55]. However, as the need to empower the decision maker through ever more complex modeling and simulation increases, enabled by increased computational power, creating more quantitative representations of interoperability between assets has received more attention in the literature [78, 55].

Older attempts at abstractions of interoperability attempted to categorize the types of interoperability based on their characteristics, or at the level at which they occurred. Examples of these types of models are given below, in Table 4.

Table 4: Comparison of Qualitative Interoperability Methods

| Name | Variable Type | Interop. Type | Insight [55] | Author |
|---|---|---|---|---|
| LISI | Rank 0-4 | Collaborative | Impacts of interoperability | [41] |
| OIM | Rank 0-4 | Organizational | Organizational interop is unique | Clark, et al. [29] |
| NCW | Rank 0-4 on Matrix | Operational-Organizational | Lack of interop reduces mission effectiveness | [6] |
| LCIM/LCI | 9 Levels | Operational-Organizational | Smooth transition from operational to organizational | [129, 135] |
| SoIM | 2 Ranks, 1-4, 1-6 | System-centric | Measure interop. with levels | [85] |
| QoIM | MoE/MoP, Matrix | Comprehensive | Simulate to correlate interop. to MoEs | [96] |
| MCISI | Distance matrix | Comprehensive | Predict degree of interop. via system difference | [8] |
| IAM | Varied | Comprehensive | Describe multiple types of interop. | Leite |
| Stoplight | 2x2 Matrix of 0,1 | Operational | Acquisition affects interop. | [66] |
| SoSI | 3 Levels | Operational-Organizational | Need to manage program interop over all lifecycle | [100] |

However, many of these models are not very amenable to quantitative studies. This is because they mostly *rank* interoperability based on certain criteria. Ranking can become subjective, and furthermore can create difficulties for a user when a system is somewhere on the boundary of two rankings. Other methods in Table 4 mostly deal with organizational or collaborative interoperability, which is outside the scope of this dissertation. Mensh et al [96] made an attempt to quantify interoperability by breaking it down into multiple different components and correlating these components to simulation and operation data - however, they admitted that more data had to be collected, and not much more work seems to have been done in this regard [55].

Two remaining interoperability quantification methods exist then: Ford's Similarity-Based Interoperability Measurement method [55] and Jones-Wyatt's Reliability-Based Interoperability Method for system of systems [78]. These two methods will be briefly outlined to showcase their strengths and weaknesses.

### 2.5.4 Similarity-Based Interoperability Method

Ford [55] approaches the problem of interoperability from a somewhat linguistic point of view, beginning by noting that sentences involving any sort of interoperability often have all relevant information in them, such as the system, the type of information the system is sending, where the system sends that information to, and how. Thus, Ford defines a series of variables that capture the systems involved ($S$), the 'interoperability characters' that relate the systems ($X$), and whether the systems possess those interoperability characters (or to what degree) ($C$). For example, the sentence "The long train expeditiously transports raw material down the tracks to the factory" is characterized as in 19, where each subsequent characteristic of *how* the train transports raw material is a new 'interoperability character'. If a characteristic is mono-directional, i.e. a system can only transmit this resource but cannot receive it, then $X$ will include both a transmission character and a receipt character.

A more concrete example is show in 20. This figure shows both the variables Ford

$$S = \{train, material, tracks, factory\}$$

$$X = \begin{Bmatrix} Transport, \\ Transport.Material, \\ Transport.Material.onTracks, \\ Transport.Material.onTracks.Expeditiously \end{Bmatrix}$$

$$C = \{0, 1\}$$

Figure 19: Ford's Interoperability Character Identification

$$S = \{Laptop, PDA\}$$

$$X = \{Comm.USB, Comm.WiFi, Comm.Serial, Comm.GSM, Comm.Bluetooth\}$$

$$C = \{0, 1\}$$

$$\Sigma = \left[\begin{array}{c|cccccc} & USB & WiFi & Serial & GSM & IR & Bluetooth \\ \hline Laptop & 1 & 1 & 1 & 0 & 0 & 0 \\ PDA & 1 & 1 & 1 & 1 & 1 & 1 \end{array}\right]$$

Figure 20: Ford's 'System Instantiation'

uses, as well as the 'instantiation' of those variables in the form of the $\Sigma$ variable, which is essentially just a matrix of systems by interoperability protocols, which has a boolean for every interoperability protocol the system does or does not possess.

20 can be modified to include data rates instead of boolean values based on the respective implementations of the interoperability protocols in each of the systems (WiFi 802.11g vs. 802.11b, for example, have different maximum download speeds). This is shown in 21. After a system-set has been instantiated, Ford proposes the axiom that "If a pair of systems is instantiated only with system interoperability characters, then the measure of their similarity is also a measure of their interoperability." Ford then proceeds to measure this

$$\Sigma_P = \left[\begin{array}{c|cccccc} & USB & WiFi & Serial & IR & GSM & Bluetooth \\ \hline Laptop & 480 & 54 & 0.02 & 0 & 0 & 0 \\ PDA & 480 & 11 & 0.250 & 0.271 & 1.152 & 2 \end{array}\right]$$

Figure 21: Ford's 'Performance-Enhanced System Instantiation' with Data

similarity by using a weighted similarity function, where $\sigma'$ and $\sigma''$ are system instantiations, $n$ is the length of $X$, $c_{max}$ is the largest character state value, and r is the Monkowski parameter owing to the equation modified by Ford. This function is shown in Equation 3.

$$I = \Big[\frac{\sum_{i=1}^{n}\sigma'(i) + \sum_{i=1}^{n}\sigma''(i)}{2nc_{max}}\Big]\Big[1 - \Big(\frac{1}{\sqrt[r]{n}}\Big)\Big(\sum_{i=1}^{n} b_i {\frac{\sigma'(i) - \sigma''(i)}{c_{max}}}^{r}\Big)^{1/r}\Big] \tag{3}$$

This equation is applied to each system-pair, and the value $I$ of that pair is the interoperability of that system pair (via its assumed surrogate, similarity). Importantly, a system cannot be interoperable with itself, and thus its value is 0 for itself.

### 2.5.5 A Reliability-Based Interoperability Methodology

Jones-Wyatt provides a relatively straightforward chart for navigating the reliability-based methodology, shown in 22. Immediately apparent from this chart is that there are many layers to to the method, ranging from a system-pair exchanging a single resources, to how all resources are being exchanged across the range of systems, moving into interoperable all systems are with each other, and finally into the interoperability of the entire SoS. The first and last measures are both represented with scalars, while the intermediate steps are represented via matrices - with resources described by multiple matrices and systems described by one. Transitioning between these levels is the primary crux of Jones-Wyatt's method[78].

Jones-Wyatt first begins with the reliability-based aspects of the method. They pertain to reliability of resource exchanges, where reliability is defined to include transmission, translation, and quality of translation. Thus the reliability of translation is calculated as

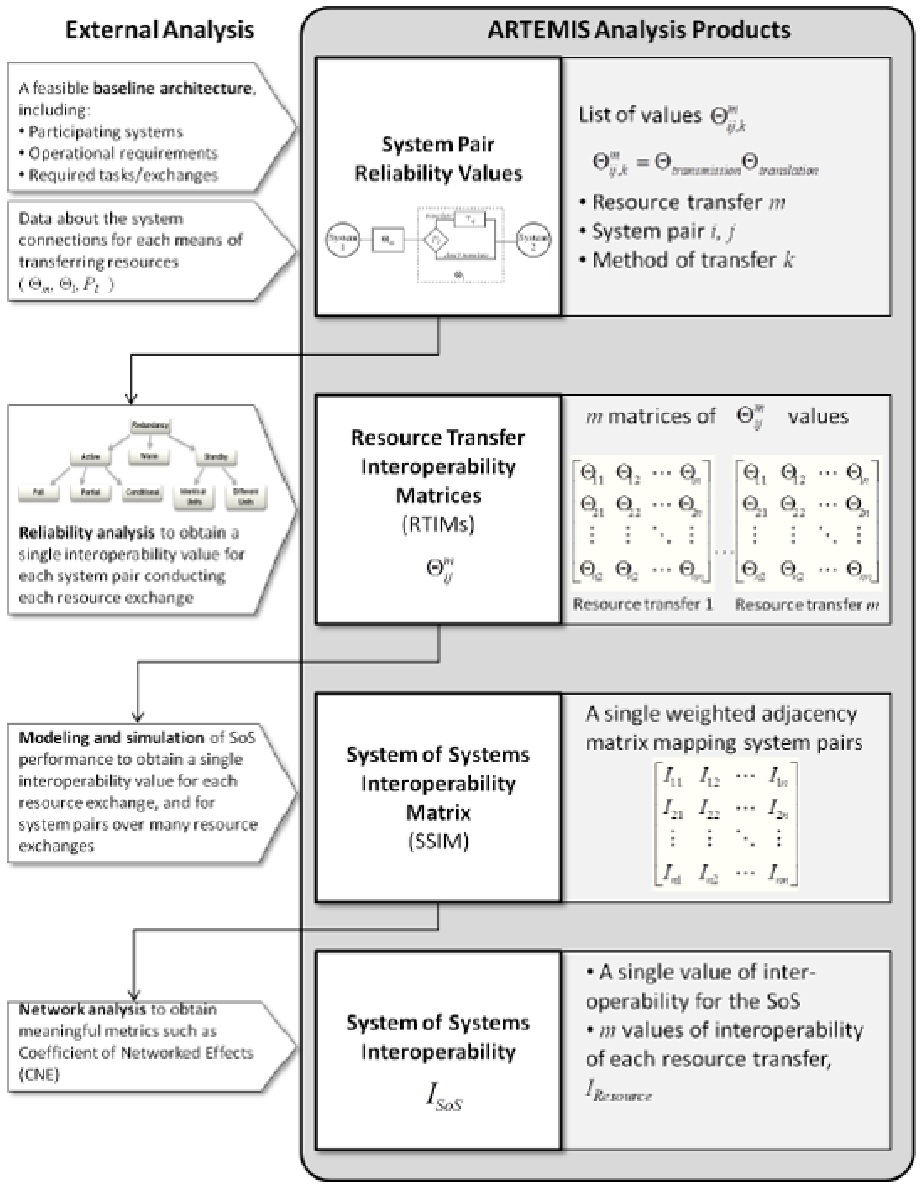



Figure 22: Summary of Jones-Wyatt Interoperability Method [78]

$\Theta_l = P_l\tau_q + (1 - P_l)$ (where $\tau_q$ is the quality of translation and $P_l$ is the probability of requiring translation) and the total interoperability for system-pair i,j is calculated as $\Theta_{i,j} = \Theta_m\Theta_l$, where $\Theta_m$ is the transmission reliability. When there is redundancy in potential resources, this is calculated as $\Theta_{i,j,\forall k} = 1 - \prod_{k=1}^{m}\Big(1 - \Theta_k\Big)$.

Moving on to the system-pair interoperability over all resources, this is calculated simply as $I_{ij} = \prod_{k=1}^{m}\Theta_{ij}^{k}$, and the SoS interoperability value is $I_{SoS} = \prod_{i,j=1}^{n} I_{ij}$.

While this methodology is certainly scalable and quite simple, it can suffer from sensitivity to the input values, especially if such values are not substantiated by simulation or real-world data. Jones-Wyatt also acknowledges this, and derives her interoperability values in her test case from simulation.

### 2.5.6 Discussion of Interoperability Methods

The criteria developed in section 2.5.1 are presented again.

1. Realistic
2. Rapid
3. Quantitative
4. Facilitates mission modeling
5. Flexible and scalable
6. Functional, not physical

Simply by the third criterion, none of the qualitative measures would suffice. However, both of the quantitative measures for interoperability provide good enough capability to be considered for use with the methodology. While Ford's method is somewhat more realistic since it can accommodate data transfer rates directly, data transfer rates (or standards) alone do not dictate the full extent of interoperability of two systems [65]. Furthermore, working off of existing protocols presents challenges for a methodology dealing with longer time spans, as many of these protocols and standards are liable to change. Both methods are relatively rapid to evaluate once inputs have been provided, and being quantitative, they can both be adapted to impact mission modeling in some way. Jones-Wyatt's method is slightly more scalable, since it encourages system-type interoperability pairings while Ford's method assumes that a such a pairing is self-interoperability, i.e. a system interoperating with itself as opposed to with a system of the same type. However, this reliability method requires its inputs to be provided via simulation or something similar. A final reminder is that these methods do not take into account the limitations associated with an increase in use of interoperability. Again, this is considered a topic for future work and improvement and for now it will be assumed that a decision maker will take this into account when making the choice [84].

Overall, both methods could be adapted for use in the proposed methodology, as both of their weaknesses could be avoided with clever approaches. Furthermore, as improved methods come about there is no reason they cannot be integrated instead. However, the weaknesses of the reliability-based interoperability method can be overcome for now by analyzing the interoperability value at many different settings and commenting on the trends. For setting requirements, this is sufficient, since a later simulation of outputs from this methodology can return whether any particular interoperability value is feasible given the assets and constraints involved.

## *2.6 System of Systems*

### 2.6.1 System of Systems Design

With the term SoS defined defined in the previous chapter, the next step is to ask how design in the context of such complex systems is performed. Dahmann et al. [35] discuss key differences between traditional systems engineering (SE) and SoS SE. Mainly:

> Since "many models of SE are based on the ability of the systems engineer to define boundaries and requirements clearly and to control the development environment so that requirements can be optimally allocated to components based solely on SoS technical trade analyses. ... Because SoS systems engineers frequently use existing systems as their 'components', they are faced with an allocation of functionality and implementation details that cannot be made optimal to meet SoS user needs. In addition, the lack of control over the development of the component systems with independent ownership, funding, development processes and, in some cases, different operational missions, requires the systems engineer to acoommodate considerations beyond the technical when evaluating capability objective options. Finally, unanticipated changes in the external environment may occur during development (e.g., changes in national priorities, funding, threat assessments, and magnitude or nature of the demands placed on SoS capabilities), and they may have an overriding effect on user capabilities required or able to be delivered, further complicating the work of the systems engineer."

There are multiple design ideas based on these differences. One of them is the Trapeze Model [105] shown in Figure 23. Dahmann, claiming that this model made it difficult for practitioners looking to chart a course for an SoS program, 'unwinds' the trapeze model into a modified wave model, one of the traditional SE tools for project management. The SoS wave model is shown in Figure 24. Key features of this model relate back to the differences discussed by Dahmann et al., mainly the concept of continuity of the SoS and the lack of control over the individual 'components' by practitioners.

In terms of simulations, there have been multiple methods that attempt to take into account SoS impacts on the system level. Some of these methods are aimed squarely at defense applications [68] while others are simply related to defense [63], as well as collaborative SoS [98, 49]. A common feature of these methods is the need to model the

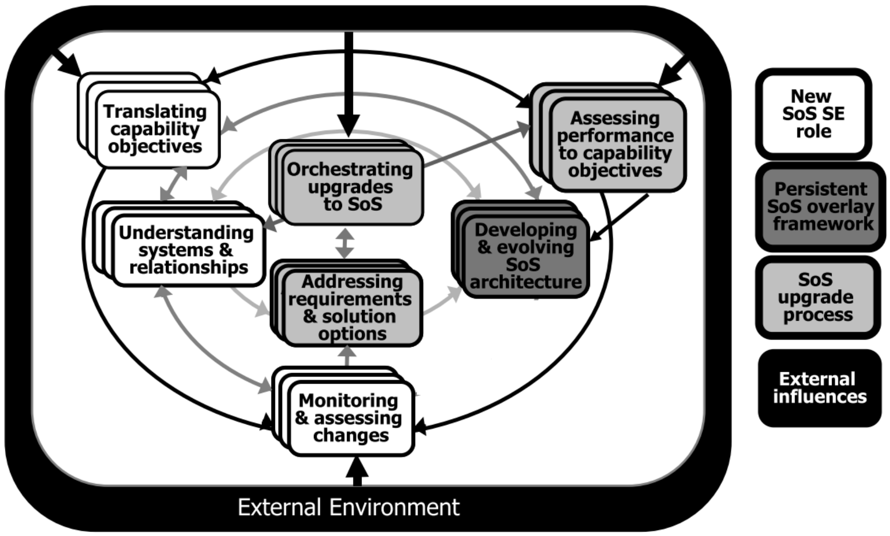



**Figure 4-1. Core SoS SE Elements and Their Relationships**

Figure 23: Trapeze Model of SoS Engineering [105]

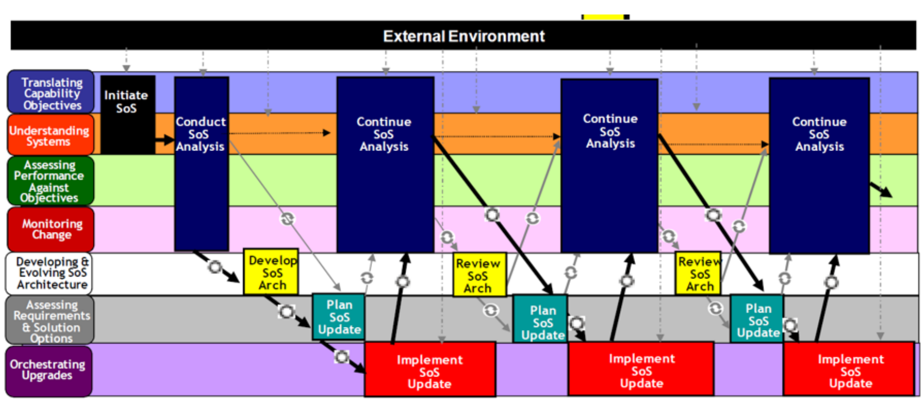



Figure 24: Hybrid of Trapeze [105] and traditional wave model, created by [35]

SoS operating at the mission level in addition to modeling each asset in the SoS. This may seem obvious, but can be computationally expensive as mission models begin to account for more and more assets. However, this is currently the only way to understand SoS-level impacts.

### 2.6.2 System of Systems Performance

The term system of systems has been defined in the previous chapter to mean "a set or arrangement of interdependent systems that are related or connected to provide a given capability. The loss of any part of the system will significantly degrade the performance or capabilities of the whole," as per the CJCSI 3170.01I[132]. Furthermore, SoS have certain characteristics differentiating them from systems. However, it is not at all clear how the performance of SoS ought to be judged.

In the DoD's Systems Engineering Fundamentals[133] chapter titled "Metrics", certain metrics are highlighted as being important to a manager when assessing performance of their product. Starting from highest level to lowest, these are Measures of Effectiveness (MOEs) or Measures of Suitability or Success (MOSs), Measures of Performance (MOPs), and Technical Performance Measurements (TPMs). The examples provided are as follows:

1. **MOE:** The vehicle must be able to drive fully loaded from Washington, DC, to Tampa on one tank of fuel.
2. **MOP:** Vehicle range must be equal to or greater than 1,000 miles.
3. **TPM:** Fuel consumption, vehicle weight, tank size, drag, power train friction, etc.

MOEs are a logical starting point for measuring system of systems performance, as they inherently contain some aspect of the mission in them, and SoS perform missions together. Thus, extending an MOE out to the SoS level would involve specifying "percentage of trips from Washington, DC, to Tampa made on one tank of fuel," or translating the overall needs of the mission into a quantifiable metric. For example in an air-to-air combat situation, the MoEs might be "percent of enemy systems shot down", "percent friendly losses", and "time until mission completion". However, it is apparent that this immediately necessitates some sort of mission modeling capability - this will be discussed in a later section.

### 2.6.3 Net Centric Warfare, and the Future of Warfare

While the term net-centric warfare may have fallen a bit out of vogue[30], the idea of networked systems increasing their overall effectiveness is very much still a priority for the DoD. One need not look further than the existence of the F-35 program for this [107], as that jet's interoperability is rapidly allowing much greater networking capability. Furthermore, this concept of warfare is continually evolving or changing names, from the 'Combat Cloud' [83] to 'Naval Integrated Fire Control - Counter Air' [93]. What is clear is that networking systems together to allow them to share information can have a big impact on their effectiveness [6].

This is most clear in two situations: the Air Force found that networking F-15Cs together improved their kill ratio by over 100 percent [7] over un-networked F-15Cs. As Alberts states, "this increased combat power resulted from the significantly enhanced battlespace awareness that was provided to the pilots operating with tactical data links. Components of awareness included weapons loading of the blue force, real-time position of the blue and red force, and status of blue engagements." [7].

Furthermore, the Navy's Fleet Battle Experiment series also provides a trove of information on how networked systems may operate. Fleet Battle Experiment (FBE) Delta showed that networked assets can provide far more effective and faster capability against enemy targets [7], while as a whole FBEs Alfa-Echo demonstrated the "Ring of Fire" concept, a "joint distributive fires network" where firepower is allocated instead of the system from which it emanates, allowing platforms to perform multiple missions [102].

What must be made clear is that, in addition to being necessary from the point of view of standard operations, interoperability is also the most significant enabler of this type of futuristic battle capability. The ability of systems to self synchronize via a high battlespace

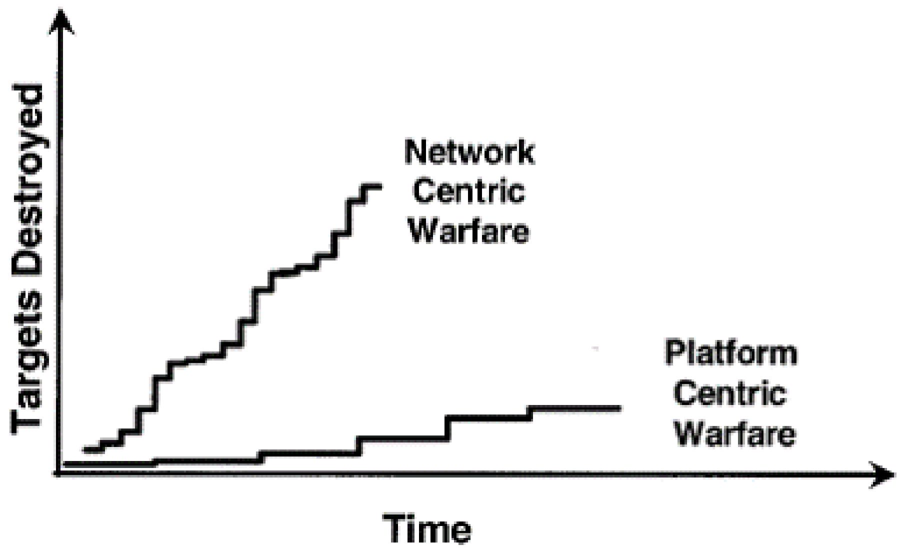



Figure 25: Fleet Battle Experiment Delta [7]

awareness and to form ad hoc connections to each other, interoperating in ways not originally anticipated, is what could create the sort of force the military envisions [121, 26].

### 2.6.4 Networked Effectiveness

Bridging the discussions of SoS and interoperability, it becomes necessary to discuss how a networked, interoperable system behaves and how to asses the effectiveness of such a system.

Domerçant discusses the effects of collaborating systems in the ARCNET tool[49]. This tool modifies a method used by Perry that is based on information theory and Shannon entropy (information entropy), as well as reliability, to create a system-wide collaboration factor. In the application of two systems searching a space, this is done by first creating a normalized knowledge function based on some expected distribution for the search. The system-wide collaboration function is then $K_M(t) = 1 - \prod_{[i,j]} K_{ij}(t)$. This is used to calculate the system-wide collaboration effects $K_C(\lambda) = K_M(t)[1 - K(\lambda)] + K(\lambda)$ where $\lambda$ is the probability distribution parameter for a Poisson-distributed random variable. Furthermore, Domerçant proposes a potential complexity factor that can be included in the calculation.

## 2.7 *Mission Modeling*

Mission modeling has taken many forms over the years. The topic is quite complex, as there are numerous challenges associated with modeling missions with any degree of fidelity. A discussion of mission and combat modeling must invariably first acknowledge that these issues exist. Davis and Blumenthal of RAND wrote about such problems in a 1992 [37] white paper. They identified issues with the attitudes toward models, content in models, and the process of modeling and analysis:

1. Minimal empiricism
2. Parochialism and ignorance
3. Dubious acceptance criteria
4. Phenomena omitted or buried (e.g. soft factors)
5. Teaching the wrong lessons
6. Mirror-imaging the opponent
7. Inconsistent assumptions
8. Models implicitly tied invalid assumptions
9. Failure to converge
10. Pro-detail bias
11. Aggregated analysis issues
12. Confusion of bureaucratic "approval" with "validation"

For more detail on each of these factors are found in [37]. The unfortunate truth is that, given that this thesis deals with the development of a methodology, the development of a holistic, realistic, appropriate combat model of the sort desired by Davis, Blumenthal, and indeed the DoD is outside the scope of this work. It is hoped that such issues are eventually resolved, thereby improving the efficacy of employing the methodology developed in this dissertation.

Nevertheless, the current work will still be investigated, as it constitutes what is currently available to the engineering community in academia and beyond.

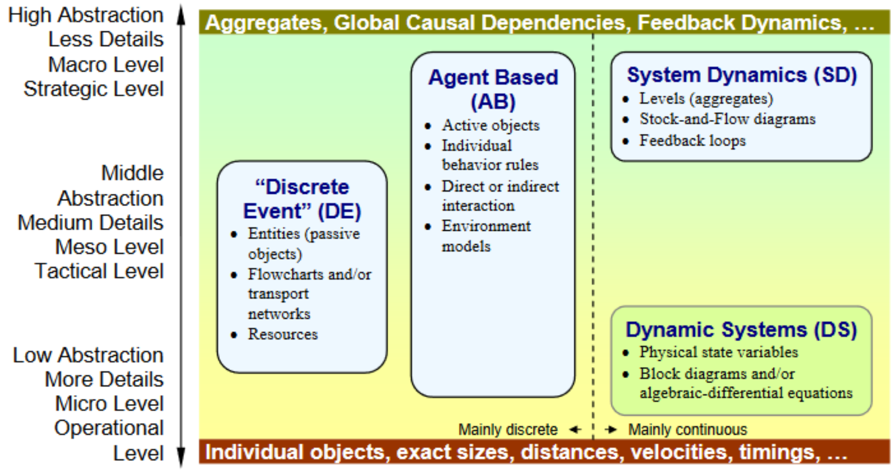



**Figure 3: Approaches (Paradigms) in Simulation Modeling on Abstraction Level Scale**

Figure 26: Overview of modeling types characterized by fidelity and discreteness [18]

### 2.7.1 System Dynamics and Lanchester's Laws

Lanchester's laws are perhaps the earliest form of combat modeling, developed in 1916 by Frederick Lanchester [81, 10]. For 'modern combat' with long-range weapons such as firearms, this method is merely a set of partial differential equations that relate the attrition rates of a force of attackers and a force of defenders based on their numbers.

$$\begin{aligned} dA/dt &= -\beta B \\ dB/dt &= -\alpha A \end{aligned} \tag{4}$$

As Lanchester's square law is a partial differential equation, work has been done to model it in a system dynamics-type model. System dynamics is a modeling approach based on a system of coupled, nonlinear, first-order differential or integral equations [128]:

$$\frac{d}{dt}x(t) = f(x, p) \tag{5}$$

Where $x$ is a vector of levels (stocks or state variables), $p$ is a set of parameters, and $f$ is a nonlinear vector-valued function. System dynamics solves these systems via $dt$ intervals. This modeling approach stems from the work of Jay W. Forrester and continues to be relevant today in many different fields [128, 18].

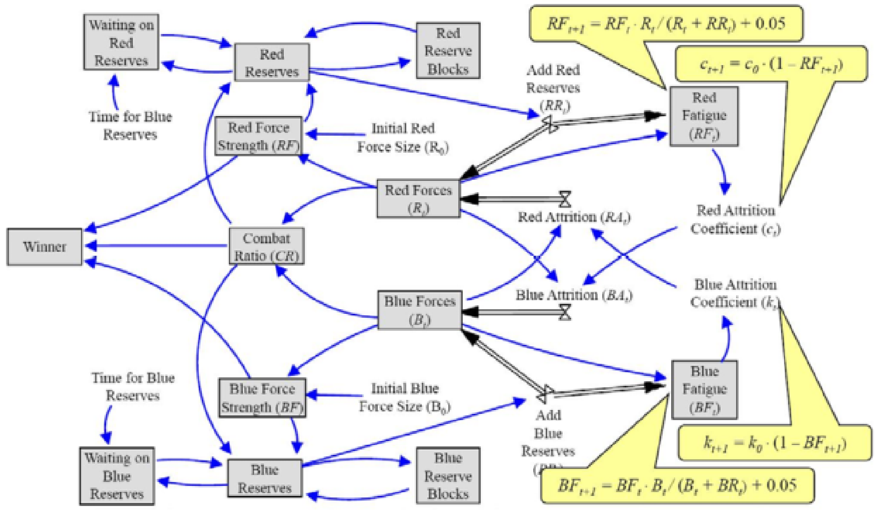



**Figure 7**: System Dynamics Model with Fatigue

Figure 27: System dynamics model of Lanchester's laws with fatigue [10]

Comparing the equations of Lanchester's laws and system dynamics, it is easy to see how the law might be modeled as a system dynamics model, especially since system dynamics can accommodate feedback loops. The numbers of troops, equipment, or materiel present at any point in the model would constitute the levels, while rates would include troop losses, equipment expenditure, and failure rates [10].

Artelli models Lanchester's laws with increasingly complex system dynamics models, eventually working up to a system dynamics model that incorporates fatigue (Figure 27), showing that the model with fatigue creates greater losses of troops in the same period of time, thereby leading to a faster victory.

### 2.7.2 Agent-Based Models

Agent-based models (ABM) are a common modeling technique in many fields ranging from ecology, game theory, and SoS design [18]. These types of models are quite natural for SoS design due to very similar founding principles, e.g. the idea that emergent behavior appears when many systems operate together [28].

The general idea of agent-based models is to describe the simple behavior of various types of low-level individuals with a set of rules, then instantiate many of these individuals and watch how their interactions affect the various variables of interest over discretized time-steps[138, 28, 18]. Jennings identifies four major characteristics for multi-agent systems: each agent has restricted capabilities and incomplete information, system control is distributed, data is decentralized, and computation is asynchronous [73]. Agent-based models have been used to model predator-prey relationships based solely on the behavior of the predator, the behavior of the prey, and their respective quantities [18]. Borshchev refers to agent-based modeling as 'decentralized' and 'bottom-up' [18].

Agent-based models have numerous relevant features for combat modeling [28], because it is conceptually simpler to define the logic of individual soldiers on the battlefield, as well as how they interact. However, once agent-based models increase in complexity and number of agents modeled, they can require high performance computers in order to run, limiting their usefulness [28, 116]. ABMs can take a few seconds to run at the lower levels for systems with order(100) agents, and increase in run times from there [113, 18].

### 2.7.3 Other Approaches

Many other modeling types exist. In other fields, models combine previously discussed paradigms together, for example modeling the problem at a higher, aggregate level, as well as a lower, agent-based level [18, 123] in the case of supply-chain management. However, there are other potential ways to model combat aside from these, based various other modeling methods.

A model has been developed in separate work that simulates combat based on discrete-time Markov chain (DTMC) states. In DTMC, states transition to each other with certain probabilities with every change in time [97]. This concept is used in many statistical models, as it has certain properties that distinguish it. First is the Markov property - that the state of a process is independent of its past states [97].

$$P(X(t_n) = j_n | X(t_{n-1}) = j_{n-1}, ..., X(t_1) = j_1) = P(X_n = j_n | X(t_{n-1}) = j_1)$$

Furthermore, a Markov process can be time-homogeneous, meaning that the probability of changing states depends only on the states, and not on the time points [97]. Thus "the initial distribution, followed by the probabilities of transitions from one step to the next, completely define the probabilistic motion of the chain [97]."

The proposed model modifies DTMC by adding some logic to the transitions, thereby muddying the waters somewhat in terms of what sort of model it truly is. In its initial implementation, there are four different types of offensive (friendly) assets based on their function (air, land, sea, and strike). These assets each contain a set of states that govern how they interact, from "stored" and "launched" to "attacking" and "destroyed". They progress through these states with various probabilities: 1 in the case of some logic that tells them when to launch or when they are within range, or $P_k ill$ if they are being attacked by a given asset.

In Figure 28, after a certain launch start time, the strike asset proceeds to the launch phase with $P_{launchrate})$. Once it is launched, it may proceed to either the Perished states or Attacking states with probabilities $P_{failurerate}$ and $1 - P_{failurerate}$, although it only proceeds to the attacking phase once it has covered a certain distance, mainly $D_t otal - D_{effectiveradius}$, with its average speed. Once it attacks, it proceeds to the Perished state with a probability of 1, since a strike asset cannot be reused. It should be noted that every asset has its own probability to kill matrix, which reflects the probability that it will kill a given asset that it attacks. When an asset is in the Attacking state, it will act on other assets, causing them to enter the Perished state with its given probability to kill.

A key element of this combat model is the concept of probability of kill, referred to in the model as lethality. Offensive assets have lethalities against each defensive asset, and vice versa for defensive assets. These lethalities are in essence the products of kill-chain probabilities, shown by the following equation:

$$P_K = P_A P_{D|A} P_{L|D} P_{I|L} P_{H|I} P_{K|H}$$

Where $P_K$ is the probability of kill or lethality, $P_A$ is probability of actively searching

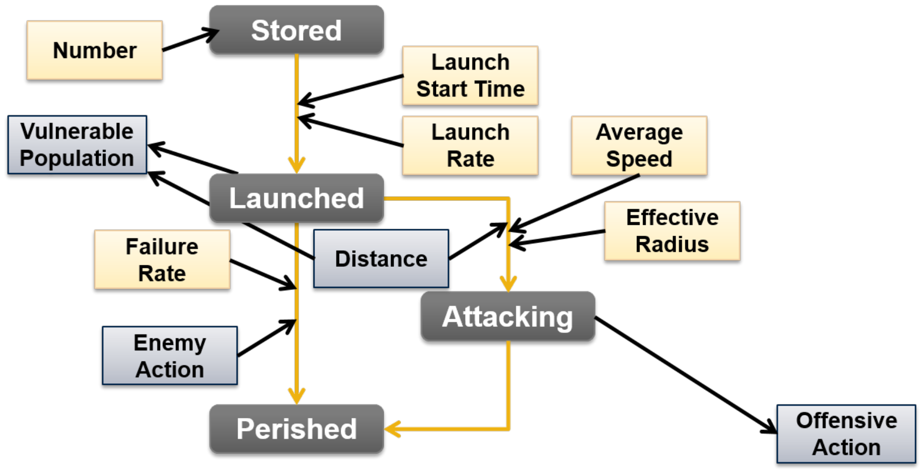



Figure 28: Example Block for a Strike Asset in Sample Modeling Approach

for target, $P_{D|A}$ is the probability of detecting the target given it is being searched for, $P_{L|D}$ is the probability of launching a weapon after detection, $P_{I|L}$ is the probability of successful guidance toward the target after launch, $P_{H|I}$ is the probability of a hit on the target after guiding the weapon successfully near it, $P_{K|H}$ is the probability of killing the target after hitting it.

Targeting decisions are coded directly into the model and can get as complicated as required. The initial implementation of the model uses a simplified targeting logic: a population of attacking assets will attack that population of target assets against which it can cause the greatest damage. This damage is calculated by the equation:

$$\vec{A}_{off,i} = rn\vec{P}_k$$

Where $\vec{A}_{off,i}$ is offensive (friendly) action against all potential targets, $i$ is the asset in question, $r$ is that asset type's fire rate, and $n$ is the number of that asset type currently in the attacking state. Thus, the damage caused by asset $i$ is $A_{off,i,j} = max(\vec{A}_{off,i})$ where $j$ is now the target enemy asset, or $j = loc(max(\vec{A}_{off,i}))$. This process is identical in the defensive asset's case.

This model has been tested against historical data, namely the OMAHA beach battle during the Normandy landings of World War II. Run time was roughly 2 minutes for a simulation of tens of thousand assets (friendly and enemy) that participated in an 8-hour battle. It was shown to reproduce the friendly and enemy casualties rather well once the lethalities were calibrated, this demonstration highlighted an important issue - without access to validated kill chain probabilities (or lethalities), it is difficult to know how realistic this model truly is, and where it can be improved.

The question becomes how realistic are the lethalities, and this is a more difficult matter to address. That is because any attacking assets always attack at each time step, and (unless they have run out of non-zero-lethality targets) always cause damage against some enemy. Thus the difficulty would theoretically lie in attempting to average out realistic lethalities, multiplied by the fire rate, over the course of the entire duration of the combat simulation.

However, it is at least encouraging that given sufficient lethality calibration, the model can indeed reproduce the historical result. A more formalized method for calculating lethalities must be left to future work.

# CHAPTER III

# DEVELOPMENT

## *3.1 Summary of Research Question Findings*

The previous chapter began with an outline of the research questions of the dissertation. Some of those were discussed and answered in that chapter, and all of them are reproduced in Table 5. As the previous chapter dealt primarily with outlining the current state of the art in the literature, this section will begin with an outline of the answers to the questions outlined more briefly.

In the problem formulation, interoperability was noted as a highly relevant capability for future systems that likely has significant effects on the performance of a future fleet. It was also observed that the extent to which interoperability aids the fleet is influenced by the budgetary and mission scenarios the fleet is in, because budgetary decisions affect interoperability upgrade and system purchasing decisions, while mission scenarios affect required system performance, SoS (fleet) performance, and which interoperability linkages between assets must be in place.

Research Question 1 was introduced by first highlighting how acquisition is done in the DoD today, and discussing fleet sizing and mix planning methods, as well as fleet purchase schedule methods. It was discussed that there were multiple different ways to perform fleet mix and purchase schedule planning, and that in general they consisted of enumerating a vast array of potential fleets, evaluating their effectiveness in multiple different missions, and then tying together fleets into a plan based on some criteria such as cost, asset numbers, etc. Both parts of the research question will be addressed in this chapter as the methodology is developed.

Research Question 2 was investigated in the same section as fleet sizing and mix problems, as relevant literature was found in this field. In general, there was not a satisfactory approach to scaling a mission's SoS to a full size strategic fleet - defense fleets have characteristics, such as multi-mission assets, which make traditional civilian-fleet-centric scaling methods more difficult to modify. Thus, a simple scaling method is proposed in this section and will be investigated in the experiments.

Research Question 3 was first introduced via scenario planning and strategic decision making. The discussion branched into two fields of study: a graph-theory-based approaches that are based on the structural resemblance of fleet plans to problems in graph theory, and decision-theory-based approaches developed for aid in decision making. In the end, the Mandelbaum-Buzacott criterion was selected as sufficient for demonstrating the methodology. In this section, this approach will be fleshed out in more detail in order to enable an example problem to be solved - the approach will then be tested in the experiments. Research Question 3.2, discussing the best way to represent shifting budget and threat environments, will be answered simultaneously based on the needs of the approach.

Interoperability is a topic that has seen more study in computer science literature than in systems design. However, there are no less than 12 methods for studying interoperability, ranging from qualitative ones like LISI or SoSI to quantitative ones like the similarity- or reliability-based methods. As one of the success criteria pertains to the desired method being quantitative, only the two quantitative methods dealing with system-to-system interoperability were highlighted. Furthermore, since system-to-system interoperability can take a wide variety of forms, the matter of which type of interoperability to model was narrowed down to communications and data interoperability, since C2 interoperability modeling with graph-theory approaches tends to provide greater challenges in prediction than the other two types given the human-centric nature of C2, and since physical interoperability had less of an effect on the mission model than it did on logistics, which has an indirect effect on mission performance. In the discussion section, various criteria based on the primary success criteria were developed to determine which of the two selected modeling methods ought to be chosen, if any. The criteria determined that existing interoperability modeling methods sufficed for the purposes of this methodology and new ones need not be developed. Research question 4.3 was tentatively answered by the selection of the reliability-based interoperability method. However, this selection will be tested in experiments to determine whether it can properly replicate trends seen in literature.

Research question 5.1 was addressed via a search of all available mission and combat modeling methods. Models were identified that spanned the range of possible modeling types, including system dynamics (exemplified by Lanchester's laws), discrete events simulations, hybrid models, agent based models, discrete time Markov chains, etc. Desired characteristics were determined in the discussion section, and as such it was determined that new modeling capabilities were not needed so long as modeling speed was kept to a relatively high level. This addressed question 5.2. Question 5.3 will be addressed in the experiments chapter, as will the selection of a mission model that can perform well in a demonstration of the methodology.

Table 5: Research Questions

| |
|---|
| 1.1: Given a fleet sizing and mix method, how should the overall methodology be structured?<br>1.2: What fleet sizing and mix method is sufficient for testing this methodology? |
| 2: What method is best suited for taking a set of disparate SoS operating different missions and rapidly scaling them up or unifying them into a full force? |
| 3.1: What method is best suited for defining and calculating adaptability of a plan (not just a set point in time) or a set of plans?<br>3.2: How should shifting budgetary and threat priorities be represented to best capture uncertainty and volatility for calculation of adaptability? |

| |
|---|
| 4.1: Which types of system-to-system interoperability should be included in the model?<br>4.2: What methods are sufficient for modeling the given interoperability types?<br>4.3: Which method should be chosen for the purposes of a demonstration of the methodology? |
| 5.1: For evaluating force plans with and without interoperability, what are the necessary criteria for a mission model that evaluates force effectiveness?<br>5.2: What mission models exist that can accommodate the criteria of this methodology, and which should be chosen?<br>5.3: What missions should be modeled in order to gain confidence in the results of the methodology? |

## *3.2 Success Criteria*

Based on the summary of the research questions, the following success criteria are proposed as metrics by which to judge the eventual product of the dissertation.

1. The process outlined by the methodology should be quantitative whenever possible.
2. Methodology results should be traceable and transparent.
3. The methodology should be rigorous and repeatable, but should be flexible enough to consider a broader set of sub-problems.
4. The methodology should outline an analysis that can be conducted quickly (less than six months, after data gathering).
5. The methodology results should be amenable to decision support system-based analysis.
6. The methodology should allow a fleet's performance to be evaluated with respect to multiple missions with uncertain preference weightings.
7. The methodology should characterize the adaptability of a fleet purchasing plan to uncertain mission weighting scenarios and to uncertain budgetary scenarios.
8. The methodology should incorporate interoperability into the performance analysis.

9. The methodology should be as realistic as possible.
10. The process outlined by the methodology must be usable for requirements exploration for strategic forces.

## *3.3 Broad Framework*

In determining how the overall method should be structured, it is necessary to understand what type of problem it is, in general, and from there to understand whether there are existing structures which may be adapted or whether a new one must be developed. As the end product of the method is essentially a fleet purchasing plan, it is argued that the methodology should be structured in a manner conducive to this generating this output.

As seen in the previous chapter, fleet planning methods generally comprise the following four steps:

1. Problem formulation (input generation)
2. Alternative generation
3. Alternative modeling
4. Plan generation

The first step of the framework will necessarily involve input generation. Next, steps 2 and 3 above will be combined, as they are in fleet planning methods, into an optimizer-based solution that will balance finding good mission performance (exploitation) with finding a wide variety of mission performance (exploration). Each investigated alternative will be saved for use in the fleet plan generation. This process is very similar to Abbass [3]. An intermediate step will be added wherein the results from each SoS in each mission will be scaled up to generate full fleets by comparing SoS performance to fleet constraints and scaling until the constraints are met. In the second to last step, fleet mix plans will be generated by comparing the scaled-up fleets to the constraints to ensure that the plan meets cost and performance constraints for every point in time. Finally the adaptability of the fleet paths will be assessed.

The revised fleet acquisition schedule method would look like this:

1. Problem formulation (input generation)
2. Alternative generation and modeling
3. Alternative scale-up to full size
4. Force purchasing plan generation
5. Adaptability characterization

## *3.4 Evaluating Capability Constraints*

### 3.4.1 Mission Modeling

Mission modeling is used in order to generate measures of effectiveness for each mission in question. For the purposes of application of the methodology, each mission can have either a single overall measure of effectiveness associated with it or multiple measures of effectiveness per mission. The difference between these two modes of operation is that extra weightings must be input into the methodology to allow for some sort of linear combination of metrics into one. If the overall fleet capability is a single number (or a range) for each point in time, then some sort of combination of measures of effectiveness is required per mission. If this is not the case, then measures of effectiveness can be treated separately.

For the rest of the dissertation, mission uncertainty during the fleet plan generation is accounted for by allowing for time-variant weightings on missions. In this way, the importance of each mission can be captured via inputs from the decision maker if desired. This is equivalent to implementing various scenarios or threat environments, as we previously assumed that missions do not get abandoned during wholly new threat environments - only their priority is reduced. Because the goal of this methodology is to provide options for the decision maker, this is an improvement from previous methods which do not seem to account for the prioritization of missions. However, by setting all weightings equal to each other this method reduces to the traditional analysis.

Strictly speaking it is not desirable to commit the methodology to any specific mission model. There are many reasons for this: the defense community performs a multitude of various mission types, each of which may lend itself better to different mission models. Remaining model-agnostic would allow the methodology to take multiple disparate mission models and unite their results, minimizing workload for engineers who already have access to their preferred mission models by reducing the problem from a model construction one (from a "preferred model" to a "compatible model")to a model integration one (pre- and post-processing model inputs and outputs to achieve compatibility with the methodology). Furthermore, advancements in modeling methods would require significant rework. Thus is advisable to simply highlight certain criteria that determine whether a mission model is a candidate for use in the methodology.

Based on the success criteria highlighted above, the following factors must be considered when any combat model is a candidate for inclusion:

- The mission model must run sufficiently quickly to enable a several-month-long analysis. As all mission models will be wrapped in an optimizer and this is the most time consuming process, we adopt the the general rule of thumb is that $(\sum_{i=1}^{n} t_{model_i})N_{fcalls} \leq 6\, months - t_{buffer}$, where $t_{model_i}$ is the runtime of each model, $N_{fcalls}$ is the expected total number of "function calls" by the optimizer (where the function consists of all of the mission models), 6 months is assumed to be the desired analysis duration, and $t_{buffer}$ is the time for the rest of the analysis to occur, which should be shorter than the optimizer-guided exploration for most cases.

- The mission model must be able to account for the effects of interoperability. This may vary by mission, asset, and measure of effectiveness, therefore the task of confirming that this is the case falls on the owners of the models.

- Measures of effectiveness must be normalize-able. This is to ensure that mission or measure of effectiveness weightings can be properly applied.

- Mission models must either represent “average” missions or be probabilistic. If the latter is the case, replication studies must be run on the mission in question for each fleet, to ensure that the performance of that fleet can be statistically approximated. This creates more stringent run-time demands on the mission models.

- Mission models should be parametrized to at least some extent. That is to say they should be able to accept various SoS types from the optimizer, and be flexible enough to model different asset types and functional characteristic ranges so long as they are relevant to the mission. If this is not the case, an optimizer guided exploration has no design space to explore for that particular mission. The only situation in which it seems appropriate not to parametrize the mission is when the requirements, performance, and asset types for that mission are to be considered fixed and yet it is desirable to still model this mission and assets as part of the larger methodology. This is especially relevant when determining the amount of asset overlap for the fleet scaling step.

### 3.4.2 Interoperability

The reliability-based interoperability modeling method was be tested by incorporating it, along with the information-entropy based collaborative effects model, into the combat model. As in previous literature [49], reliability-based interoperability was assumed to eventually translate into an interoperability value for each system pair, ranging from 0 to 1. This value per system pair was used inform the collaboration effects variable, which was used to modify functional characteristics in the combat model. This particular instantiation of collaboration effect was originally developed to track the effects of interoperability on probability of detection by UAVs performing an ISR role.

#### 3.4.2.1 Collaborative Search

As stated previously, the particular process of developing a collaboration effects variable for UAVs involved:

1. Dividing search space into grid, where each grid point was sufficiently small that no two enemies were collocated.
2. Modeling a search process as a Poisson process described by an exponential distribution.
3. Combining the search variables into the equation $\lambda_i = 1 - e^{-(svT/A)}$ where $s$ is sensor sweep width, $A$ is search area, $v$ is platform search speed, and $T$ is search time. The sum of these for each platform is the effective sensor coverage.
4. Defining knowledge associated with search exponential distribution as $ln(\lambda/\lambda_{min})$ if $\lambda$ is between $\lambda_{min}$ and $\lambda_{max}$, and 0 or 1 elsewhere.
5. Defining knowledge associated with interoperability exponential distribution as $ln(\theta/\theta_{min})$ with similar conditions on $\theta$ as on $\lambda$.
6. Performing operations on the collaboration and resource processing matrices to determine the maximum eigenvalues, and calculating overall system collaboration effects, as well as effects of collaboration.
7. Adjusting these with a system complexity factor.

For the purposes of the framework, modifying this process too much would fall outside of the scope, as it is desirable to show an overall integration of these many numerous methods instead of attempting to validate that any new evolution of a method is sensible. However, the selected combat model is 1-dimensional, whereas the search grid used in [49] is 2-dimensional. The question is whether the equations used are applicable in this change of sensor model.

This is highly application dependent - in the World War II sample missions that will be used for the experiments, sensors were rather limited in ground operations. Aerial reconnaissance is assumed to be similarly limited. Furthermore, communication between assets was generally more difficult; it is assumed that there were only manpack radios available to squads of infantry. Thus, as opposed to a function of sensor effectiveness, overall sensor coverage parameter is assumed to be a function of the relative sizes of friendly forces vs. enemy forces or $\lambda = {}^{n_{offense}}/_{n_{defense}}$. Furthermore, we will assume that only those forces that are radio-enabled have a significant impact the overall probability of detection for the force. This means that the typically the number of enemy forces is greater than friendly radio-enabled forces, meaning this metric will be less than one for most of the engagement for forces of relatively equal size.

This description of sensor coverage requires a few critical assumptions, yet it makes intuitive sense. The probability of the location of an enemy asset being discovered must be some function of the number of friendly assets that are searching for the enemy, as well as the number of assets that can transmit its location. However, since any non-radio-enabled asset must find a radio-enabled asset anyways, the radio-enabled assets dominate the search. Furthermore, the more friendly assets there are, the greater the effective coverage of the battlespace since the rate of enemy discovery increases. The more enemies there are relative to friendlies, the lower the relative rate of discovery is. It is still possible to assume that this search parameter takes the exponential distribution - discovering one enemy asset in a field, as opposed to inside the house next to the field, does not mean that the rest of them are in the field nor that the rest of them are in the house.

With this assumptions made, the same general approach can be taken as in [49] with the exception of the different definition of $\lambda$. At each time step of the simulation, a new effective sensor coverage parameter is calculated based on the number of friendly and enemy assets in the "Attacking" state, except that in the case of friendly assets this total asset number consists solely of number of transmitting assets per unit type. This is an asset variable defined in the inputs for each asset population (e.g. a radio can be found in 1 out of every 4 or 5 infantry troops, since that is the squad radioman, etc.). Once the effective sensor coverage parameter is calculated, the calculation of the overall probability of detection can proceed in the same manner as in [49]:

A resource processing matrix is created by taking the product of the interoperability reliability criteria (per resource) for each friendly asset with each other friendly asset, with the diagonal being zero. Since computing the eigenvalues for large matrices can be quite computationally expensive and we only need the maximum eigenvalue, an estimate for the largest eigenvalue is computed with Von Mises (power) iteration. This method converges slowly when there are eigenvalues similar in magnitude to the largest eigenvalue [118], but from testing for this problem set the algorithm converged much quicker than exact the default 'eig' method for MATLAB, which uses Cholesky factorization or the generalized Schur decomposition. The CK matrix is produced according to the conditions specified in [49] for $\theta$, and its maximum eigenvalue is estimated in the same way as for the RP matrix. Once all of these factors are calculated, the overall probability of detection $k_{cc}$ is calculated. $k_{cc}$ is used as a multiplier for system-level metrics. Perry[108] modifies estimates of missile arrival rates using this value. Domerçant[49] modifies Perry's approach to create the probability of detection for UAVs in that test case. In both cases, $k_{cc}$ is essentially a probability modifier related to the knowledge about certain variables. Thus, one can think of it as a modification of kill-chain variables already used in the selected combat model, specifically a modification of "find", "track", and "target". In the combat model, the lethalities defined in the inputs are implicitly the products of kill chain probabilities:

$$P_K = P_A P_{D|A} P_{L|D} P_{I|L} P_{H|I} P_{K|H}$$

Where $P_K$ is the probability of kill, $P_A$ is probability of actively searching for target, $P_{D|A}$ is the probability of detecting the target given it is being searched for, $P_{L|D}$ is the probability of launching a weapon after detection, $P_{I|L}$ is the probability of successful guidance toward the target after launch, $P_{H|I}$ is the probability of a hit on the target after guiding the weapon successfully near it, $P_{K|H}$ is the probability of killing the target after hitting it. Our aim is to modify the total probability of kill by multiplying it by the collaborative-based probability of detection. Thus we must first divide out the original probability of detection, $P_{D|A}$.

$$P_{K,new} = \frac{P_K}{P_{D|A}} k_{cc} = P_A k_{cc} P_{L|D} P_{I|L} P_{H|I} P_{K|H}$$

When calibrating any given mission, the "lethalities" or probabilities of kill are generally varied in order to provide reasonable results. Since the model does not account for missing the target, and has no "search" state, this is equivalent to setting all of the constituent probabilities to 1 except for $P_{K|H}$. Thus it is not necessary to know the initial value of $P_{D|A}$ - it is set to 1 anyways. Thus the interoperability-modified lethality is simply the old lethality multiplied by the collaborative probability of detection.

In terms of implementation, friendly damage on enemy assets is calculated by the following equation:

$$\vec{A}_{off,i} = rn\vec{P}_k$$

Where $vecA_{off,i}$ is offensive (friendly) action against all potential targets, $i$ is the asset in question, $r$ is that asset type's fire rate, and $n$ is the number of that asset type currently in the attacking state. It should be noted that both fire rate and lethality (probability of kill) act on the same equation, and solely in this equation. As such, it is equivalent to modify either fire rate or lethality.

As a reminder, because the dissertation discusses a proposed methodology and not a definitive method for solving this class of problem, the development of this linkage between this interoperability method and the combat model is purely for demonstrative purposes. Regardless, a hypothesis is developed to determine whether the development is successful, and will be examined in the experiments.

> **Hypothesis 2:** If reliability-based interoperability modeling is combined with information entropy-based collaborative effects that model complexity, the selected combat model will show an increase in the rate of enemy casualties.

#### 3.4.2.2 Discussion of Other Interoperability Effects

While the model will only be demonstrated with interoperability in collaboration in a search, and the resulting effects on probability of detection, it may be instructive to discuss at a high-level how another type of interoperability could be incorporated into the chosen combat model. A candidate for this is Naval Integrated Fire Control - Counter Air (NIFCCA), mentioned in the previous chapter. NIFCCA essentially aims to extend the range of at-sea assets by having closer, stealthy intelligence, surveillance, and reconnaissance (ISR) assets provide the targeting information once the missile gets close enough to the target.

Within the context of the combat model, this is effectively an extension of the effective attack/targeting range of a given asset. This sort of framework would work for any asset type except for strike assets, which are currently treated separately from the assets that launch them. As an example, a Tomahawk missile can be a strike asset with the effective range being its blast radius, but the guided missile destroyer that launches it is not modeled - it is currently implicit within the model. On the other hand, air, land, and water assets (assets currently used for deployment during amphibious landings) all have effective range variables as well, but these variables are the effective targeting range, not the blast radius.

Assets transition to the attacking phase based on the relationship:

$$\frac{(V \times 3600)}{D - R} \tag{6}$$

Where $D$ is the distance from the takeoff/launch location to the target, and $V$ is the asset's speed.

As such, modifying the effective radius would change the rate at which assets enter the attacking phase. This makes some intuitive sense. If increased interoperability allows an asset to fire a missile and hand off control of it to an asset closer to the target, it may never need to approach closer to the target and can simply fire from afar.

The difficulty comes from determining how exactly to modify the effective range. One potential solution is to utilize the same formulation of collaboration as in [49] for search of a grid, and allow that collaboration to work in much the same way as it does in the current implementation. Another possible option is to augment the effective range of the launching platform by the effective range of the guiding platform. That is, if the effective range of the launching platform is $R_L$ and the effective range of the guiding platform is $R_G$ then the new rate for the launching platform would be related to:

$$\frac{(V \times 3600)}{D - f \times (R_L + R_G)} \tag{7}$$

Where $f$ is some scaling factor based on the interoperability. Because assets are treated as populations and not individual assets, the ability of an asset to extend its range could be related to the sizes of the respective populations. Depending on how the NIFC-CA collaboration is structured, multiple assets of different types could contribute to the collaboration as well. This could result in a need to incorporate multiple different ranges to the equation, possibly based on the strength of the collaboration between each asset type.

$$\frac{(V \times 3600)}{D - mean(f_1 \times (R_L + R_{G_1}), f_2 \times (R_L + R_{G_2}), ..., f_n \times (R_L + R_{G_n}))} \tag{8}$$

Of course this is not a fully developed method but instead an example of another insertion point for interoperability into the combat model, as well as the variables and equations available and required for such an insertion.

A benefit of the interoperability model selected is the ability to model multiple separate resources that are exchanged. For example, targeting data and communications could be considered two separate resources, with asset self-status as a viable third. Interoperability reliabilities are then created for all N of these resources, and the design space is similarly expanded. It is thus possible to compare different types of interoperability against each other by comparing the resultant combat effectiveness of the resources exchanged. Similarly, the effects of interoperability on adaptability can be broken down into multiple different types of resources and compared - perhaps NIFC-CA has a greater effect on some mission types than others, and therefore its effect on adaptability is relatively small compared to general situational awareness, or vice versa.

### 3.4.3 Fleet Scaling

Prior to this point, the discussion has centered mostly on how to model the missions performed by a fleet, how to ensure that the fleet is planned with robustness to budget and missions in mind, and how interoperability can be integrated into these analyses. However, the discussion regarding how to link an individual mission to the performance of the fleet, especially given that the definition used for "fleet" in this dissertation is essentially "a SoS that is large enough so as to affect the *strategic* decisions of stakeholders", determined that there was not an available method sufficient for this purposes. It must be noted that unless fleets participate in war games or researchers conduct war simulations of massive scale and duration, rarely would a mission in a model utilize enough systems so as to comprise a strategically-significant fleet. Thus, it is asked, how can a link be made between the total fleet and the subset of that fleet that operates in a single, model-able mission. This section aims to address that by answering this research question:

> **Research Question 2.1:** What method is best suited for taking a set of disparate SoS operating different missions and rapidly scaling them up or unifying them into a full force?

To create such a link, the ideas seen in the fields of combustion, circuit design, etc., will be used as inspiration to create the logic for the fleet scaling portion of the methodology. Although there are many other ways to achieve fleet scaling, including direct modeling, it is believed that the following method will present the best compromise between speed and accuracy.

In both combustion (with networks of chemical reactors) and circuit design (with networks of circuit elements), the idea of connecting smaller elements with known behaviors in order to create a larger novel system is not new. In [104], for example, a more complex combustor

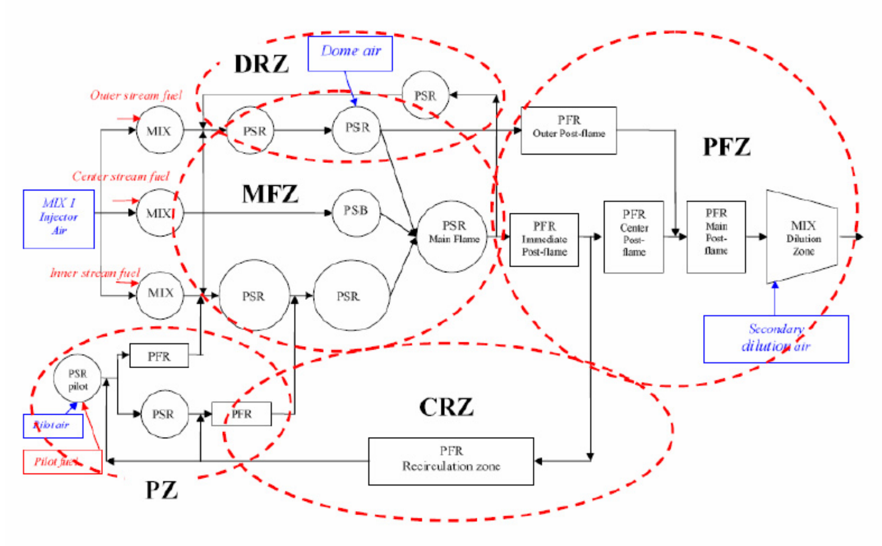



**Figure 6-3. 31-elememnt CRN for the single-injector, can-type, GT combustor.**

Figure 29: Combustion Reactor Network Shown in [104]

is modeled as a series of smaller reactors show in Figure 29 meant to recreate the overall behavior. Elements such as ”Mix”, ”Plug Flow Reactor” (PFR), ”Partially Stirred Reactor” (PSR) share inputs and outputs, combine to create a reactor network whose purpose is to approximate a specific combustor’s behaviors.

The benefit of these types of ‘building block’-style methods is that they break down complexity into a network of well-understood sub-problems. As Novosselov states in the case of chemical reactor networks (CRN), “the turnaround time is typically several orders of magnitude less than the simplest [computational flow dynamics] simulation” [104]. Similarly with fleet scaling, it is hoped that by breaking down the performance of the fleet into multiple sub-problems whose computation, however complex and time-consuming, is nevertheless simpler than computing performance for the entire fleet, computation time would be reduced without a dramatic reduction in accuracy.

To borrow from these ‘building block’-style methods, it is necessary to identify which parts of fleet design can be treated as fundamental in the same way as resistors or PFRs are. To do this, analogies will be drawn between mission modeling and SoS design and chemistry. Firstly, it seems apparent that systems share many properties with molecules - they can either interact to create new molecules (such as two opposing systems interacting to produce destroyed systems, or an aircraft carrier hosting many smaller systems) or they can work together but not react with each other in the case of catalysts, much as systems can aid each other in achieving an outcome. Distance between systems is an important component in mission modeling, much as in chemistry, and various systems have a greater or lesser speed much as molecules have various diffusion rates. Furthermore, systems have a propensity to 'react' based on characteristics such as armor, weaponry, avionics, etc.

What then in this analogy is a reactor? In chemistry, it is a 'container' about which, and about the molecules in which, the chemist makes specific assumptions. Different reactors produce different reactions because the conditions inside them vary in a manner that impacts the behavior of molecules in those reactors. In some reactors, such as the PFR, molecules flow in one dimension (downstream) without diffusing axially. These types of assumptions bear some resemblance to mission concepts of operation, in which the systems are the reacting molecules and the type of reactor is the type of mission. By analogy, then, perhaps missions can be treated as a fundamental building block of a fleet in much the same way as resistors or reactors are a building block of much more complex networks.

However, this conclusion is not necessarily intuitive because a fleet is by definition the collection of systems it is composed of, not the collection of missions it can perform. However, it is asserted that there functionally is no difference between the capabilities that a fleet possesses and the assets it contains.

Therefore, the following assertion will be made:

> **Assertion 3:** A fleet can be defined either in terms of which missions it can perform or in terms of its assets, given that each is defined with sufficient detail.

How then are missions, the asserted building blocks of the fleet, to be combined such that they represent the totality of the fleet? Going back to the analogy of chemical reactors and as denoted in Figure 29 by the blue rectangles, one can note that every reactor model has

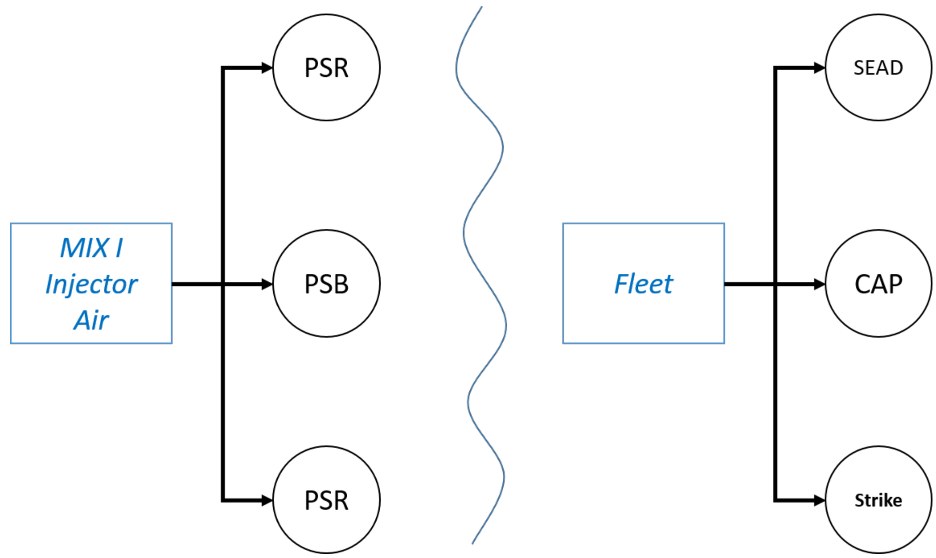



Figure 30: Comparison of reactor network and mission network

Left: An inlet provides molecules for reactions occurring simultaneously inside the parallel partially-stirred reactors (reproduced from [104]). Right: By analogy, the fleet provides sufficient unique systems for parallel missions being performed simultaneously

an inlet and outlet through which the chemical species enter and leave. If missions are modeled as reactors by analogy, then what supplies the missions with systems? Surely it is the fleet.

Thus, the fleet inputs 'species' into the 'reactor' to get a certain result, and if there are multiple reactors connected in parallel then the fleet must have enough assets to supply each reactor. Similar to when parallel reactors perform their reactions simultaneously, so too would parallel missions perform their operations simultaneously, as shown in Figure 30. With this "parallel mission" observation we can make our critical assumption.

> **Assumption 1:** The assets used in the full set of missions a fleet can perform, including simultaneous missions and missions that have overlap of assets, represent the totality of the fleet in question.

In simpler terms, this assumption states that if a user *a priori* generates the total number of missions (and the required systems per mission) a fleet can perform simultaneously, then in practical terms the user has defined the fleet. For this dissertation we will also make the following simplifying assumption, keeping in mind that it could be relaxed in future work:

> **Assumption 2:** A mission that is of the same type as another mission is performed with exactly the same performance.

That is, if the mission is set up in the same way (the same assets, enemies, concept of operations) then it will be performed in the same way with the same effectiveness. Although in reality this is not true since a more complex combat model could define stochasticity, variations in soldier experience, etc.

Going back to our reactor analogy, the effect of our first assumption is to effectively drain the input's supply of molecules, meaning that if there is some finite amount of reactants in our fleet, and we can simply add reactors (or missions) in parallel until the fleet has supplied all of its assets. If we know the number of reactors we need to add in parallel, and we know how many molecules would go in each one, then we know what size fleet we started with. As a reminder, adding a new mission type one would like the fleet to perform is akin to adding another a new type of reactor X in parallel, and specifying the number n of simultaneous operations of this new mission type one would like the fleet to perform is simply adding n-1 more instances of reactor X in parallel.

Because we have assumed for the moment that simultaneous operation of the same mission type produces the same mission results, the results of one mission can be extrapolated to all simultaneous operations of the same type. Furthermore, borrowing from the concept of mass from chemistry, if the total number of assets operating in a single operation of a mission is $m_{j,k}$, then the number of assets operating in simultaneous operations $k$ of mission type $j$ are simply $m_j = k m_{j,q}$, where $q$ is an individual simultaneous operation, since that number is equal for all missions. Furthermore, to borrow from chemistry the concept of species fraction $Y_i$, the asset fraction of an asset type operating in a single operation (out of a set of simultaneous operations) for a given mission type can be stated as $Y_{i,j,q} = m_{i,j,q}/m_{j,q}$, and the number of that asset would be calculated as $m_{i,j,q} = Y_{i,j,q} m_{j,q} = \frac{Y_{i,j} m_j}{k}$ since for missions that are exactly the same, $Y_{i,j,q} = Y_{i,j}$.

All that is left for now is to determine what occurs when operations have assets that overlap. In this case, the most important thing is to keep track of the overlapping assets across the summation and ensure that they are summed only once so that the number of required assets is not overestimated.

Given asset $i$ in operations $j_1,\ k_1$ and $j_2,\ k_2$ such that $Y_{j_1,k_1} \cap Y_{j_2,k_2} = \{Y_{i,j_{1+2},k_{1+2}}\}$

$$Y_{j_1,k_1} m_{j_1,k_1} = Y_{j_2,k_2} m_{j_2,k_2} = \left( \frac{1}{\frac{1}{Y_{j_1,k_1}} + \frac{1}{Y_{j_2,k_2}}} \right) (m_{j_1,k_1} + m_{j_2,k_2}) = Y_{i,j_{1+2},k_{1+2}} m_{j_{1+2},k_{1+2}} \tag{9}$$

and

$$Y_{j_1,k_1} m_{j_1,k_1} = ... = Y_{j_n,k_n} m_{j_n,k_n} = \left( \frac{1}{\frac{1}{Y_{j_1,k_1}} + ... + \frac{1}{Y_{j_n,k_n}}} \right) (m_{j_1,k_1} + ... + m_{j_n,k_n})$$

For scaling up the performance of the fleet, the following assumptions are made:

> **Assumption 3:** If two fleets of unrestricted size but equal asset types can perform a set of missions with equal performance, the fleet that can perform some of these missions simultaneously is the better fleet.
>
> **Assumption 4:** Mission capability is expressed as a normalized, non-dimensional variable.

In simple terms, it is assumed that a fleet that can do more at once is a better fleet than one that cannot. This assumption may not necessarily be true, e.g. holding the number of missions constant, the fleet with less assets will require those assets to repeat missions they have performed previously. The more a pilot performs the same mission, higher the chance they will perform it better. However, this problem has been addressed with Assumption 2, and while worthwhile, is outside the scope of this dissertation.

Assumption 3 also implies that a fleet that does not share assets to perform missions simultaneously ought to have a higher performance value than one that does. Although intuitively one might argue that the latter fleet is more capable, the former fleet is also more redundant. Holding the types of systems (and all other system numbers) constant, a fleet with two aircraft carriers each coordinating one mission is likely more powerful than a fleet with a single aircraft carrier coordinating two missions, although perhaps not by much (since the carriers must share the same number of aircraft). Thus we develop the following equations for missions without shared assets:

$$\sum_{j,k} q_{j,k} = Q \tag{10}$$

And the following equation for missions with system overlap:

$$\left(1 - \frac{1}{\frac{1}{Y_{j_1,k_1}} + ... + \frac{1}{Y_{j_n,k_n}}}\right)(q_{j_1,k_1} + ... + q_{j_n,k_n}) = Y_{i,j_{1+2},k_{1+2}} q_{i,j_{1+2},k_{1+2}} \tag{11}$$

Where $q_{j,k}$ is the performance of a subset of the fleet in the operation, $k$ is a single mission of type $j$, and the performance of the whole fleet is $Q$.

This method is summed up in the following hypothesis:

> **Hypothesis 3:** If a force is defined as the number of average missions of any and all types that can be performed simultaneously, it is possible to recreate a full force based on modeling only the archetypical mission types and multiplying those results and mission forces by a scaling factor.

Similarities with Somboonwiwat's method are as follows [126]: While the method is also a grouping of systems, Somboonwiwat groups like function with like function. This creates difficulties in mission modeling, as the groupings immediately become less relevant when there is a need to convert them to mission groupings of systems. In Somboonwiwat's case, a systems' function and its mission are relatively synonymous (one transport vehicle performs one transport mission) and there is little need to group by any other metric, while this is not the case in general. Thus, the proposed method can be viewed as a more general case of Somboonwiwat's, which simplifies into that case when there is one system operating only a single mission.

## *3.5 Evaluating Costs and Limitations*

Unfortunately, at present there are few ways to assess costs of highly abstract or conceptual systems without a great deal of assumptions. If one knows what sort of system one is designing, it is possible to create surrogate models of physics-based analyses and approximate the cost for a type of system, such as a transport aircraft or car. One may also use historical data regression if one assumes that the systems in question will be similar enough to the data points used in the regression. Finally, one can poll subject matter experts and get estimates on costs in this manner. [92, 115]

Regardless of the method one chooses to evaluate costs, the sensitivity to cost of the analysis should be kept in mind. It is not unreasonable to assume this sensitivity will be significant, given that cost is one of the value functions proposed. However, by putting a range on the cost, one can at the very least evaluate multiple different cost options for a given system and therefore have fleet plans for many different system-cost situations.

It is outside the scope of this dissertation to create new cost-modeling methods: it will be assumed that some have already been chosen and that they are compatible with the types of functional characteristics required by the mission models.

As an important reminder, frequently requirements definition methods at the low-fidelity, earliest design stage are aimed at determining the minimum feasible requirements. An example of this is the energy-based sizing and synthesis method found in Mattingly [92], where after plotting the mission constraints on a thrust-to-weight vs. wing loading graph, the lowest feasible point is selected. This is because no costs are accounted for in improving any one parameter above another, and engineering experience and intuition have shown that more permissive requirements are easier to achieve, i.e. have lower costs (of some sort) associated with them. Selecting an arbitrarily better design over the minimum feasible one means that one may be committing to unforeseen costs, penalties, difficulties, or complexities further down in the design cycle. Of course to ensure that the selected design is desired, higher fidelity modeling of point designs is always the next step. This will be the case for this methodology as well.

For this dissertation, cost values will be assumed for the various assets modeled in the mission, as well any $\Delta$ in a given asset functional characteristic. This will, of course, skew some fleets to the higher end of the spectrum in perhaps unrealistic ways when once considers historical data for each functional characteristic and asset. However, given that the scope of the methodology is to provide the capability to perform this type of analysis, the goal is not to provide an answer to any question but to show that for a given data set it is possible to arrive at this answer. Thus, for developing the methodology, it is more important that the methodology can account for these factors in a logical manner that is consistent with experience.

One other important matter is that of interoperability and how it factors into the cost equation, both in terms of dollar amount and in terms of the consequences of too much interoperability [57]. Interoperability can be naturally limited by factors mentioned in the previous section [6], including increased latency, diminished bandwidth, increased signal interference, and increased complexity stemming from an overwhelming amount of information to process. This last cause has been somewhat addressed in the collaboration metric utilized for the demonstration of this methodology. However, it is all too clear that there are many other factors which diminish the marginal benefits of interoperability as it increases. This is currently a limitation of low-fidelity approaches and there was no literature available to deal with this limitation [84]. It is important to consider this factor when a decision maker evaluates a fleet in a fleet plan - too much interoperability can increase the unreliability of the network. Until lower-fidelity ways to account for these issues are developed, it is assumed that any candidate fleet plans will be analyzed in higher-fidelity models in order to estimate the strength of these detrimental effects and confirm or refute a particular fleet plan's desirability.

## 3.6 Fleet Mix Planning (Scheduling)

### 3.6.1 Fleet Plan Generation

As mentioned in the previous section, there are multiple different ways to create fleet evolution plans given a set number of time steps. In general, no one method is more preferable than another as they each have advantages and disadvantages. However, a few methods have some more problematic issues.

For instance, for this methodology it is generally not desirable to perform fleet mix scheduling as done in the method by Abbass et al. [4]. In this method, as mentioned previously, robust fleets are composed of the initial set of non-dominated fleets by taking the ceiling of each asset type, for all fleets within a certain cost distance of each other. This process is repeated for all new fleets until the algorithm stabilizes and no new fleets can be created. The fleet path is then created based on the resulting hierarchy, with each fleet on the path necessarily becoming bigger and more expensive.

This is problematic because it builds in cost increases into the fleet plan, where none may be required due to constraint conditions. For example, if budgets decrease, this method does not present good options for how to change the fleet to better reflect the new budgetary environment, short of backtracking to one or more of a few connected sub-fleets.

In general, it is best for a method to not assume that cost or capability requirements will always increase. Thus, the selected method for demonstrating this methodology is simply to enumerate the "city block distance" between every fleet based on the cost of each asset in the fleet, with each asset functioning as another distance dimension. Once this distance matrix is constructed, fleet paths are created based on a selected threshold value. This threshold value is used to create an adjacency matrix of all fleets within that distance to each other, and an algorithm is selected to traverse the adjacency matrix in order to enumerate all paths.

For this case, it was considered undesirable for a path to be self-intersecting. Thus all enumerated paths are in actually "simple paths", to borrow the graph theory term. The algorithm for traversing the adjacency matrix was then selected based off of the need to find all of the simple paths in the matrix, otherwise known as the "all simple paths" problem. Algorithm selection was done by finding recommended algorithms that do well with this type of problem, such as the depth-first and breadth-first searches [14]. Due to the relatively limited number of time steps being considered, it was determined that a depth-first search would suffice.

### 3.6.2 Quantifying Flexibility

#### *3.6.2.1 Mandelbaum-Buzacott Adaptability*

As mentioned in the previous chapter, the Mandelbaum-Buzacott criterion is a reasonable starting-point for assessing the adaptability of a fleet plan. The criterion assumes that there is some function that represents the true losses incurred by making a decision, but that this function is hidden from the decision-maker (because it constitutes total knowledge of future probabilities). There is additionally a second function - the decision maker's model, that outputs some imperfect estimate of the losses of any decision. Thus the goal in creation of the criterion was to bring the imperfect estimate as close as possible to the perfect estimate, and it was found that (at least under uniformly distributed loss uncertainties) flexibility decreased the error in estimating the true losses. This can be seen in Equation 2:

$$\mathcal{L}(a \mid I) = L^*(a) - \frac{\beta - \alpha}{2} + \frac{\beta - \alpha}{n(a) + 1} \tag{12}$$

Where the $n(a)$ term represents the number of options at decision point $a$.

When a fleet purchasing decision is made, the decision-maker is committed to certain costs and is provided certain capabilities. These factors carry with them disutility, or losses in utility, because they are likely not the best-performing decisions that could have been made. For example, a fleet could be selected with a cost as high as 90% of the permissible range, and 99% of expected feasible capability. Thus, its losses in terms of capability are rather small, but it carries with it 90% losses in terms of its budget - a lower-priced fleet would have been more advisable. This is what Mandelbaum and Buzacott mean by losses. Furthermore, it should be noted that their uncertainty distribution is for the decision maker's model, not for the true model. Thus we are not violating assumptions by assuming that the decision maker's forecasts can be used as loss of utility distributions in Mandelbaum and Buzacott's criterion.

> **Assumption 5:** The uncertainty distrubtions associated with capability and budget forecasts are the loss of utility distributions.

From 2, it is clear that as the number of options at a decision increases, the third term goes to 0 for large enough numbers. This uniform distribution assumption will also be carried forward for the demonstration of the methodology, although this is not a requirement because Mandelbaum and Buzacott provide a general equation. However, it is asserted that polling decision-makers about complex probability distributions is not advisable; instead, simplicity in questionnaires is generally better.

> **Assumption 6:** The uncertainty distrubtions associated with capability and budget forecasts are uniformly distributed.

With the finding that 2 is applicable to the problem without modification or re-derivation, a brief outline of how this equation will be used in the demonstration follows:

It is assumed that all fleet paths have already been enumerated. Thus each decision point, as well as the number of choices associated with that decision, are both known. Because the fleet capabilities and costs are also calculated at this point, as part of the fleet design space exploration step, the losses associated with each decision at each decision point are known. For each decision at $a$, $L^*(a)$ is calculated as the difference from the upper bound of each capability, mission, or cost. For each mission, the measures of effectiveness are weighted by the MoE weightings, and the the sum of this is weighted by the mission weighting for that mission. The cost is similarly weighted. The sum of these is then considered the loss for that particular decision. The adaptability of the fleet plan is taken to be the sum of the criteria of each fleet in the plan. This can then be averaged, or not, since it is assumed that the length of the paths does not change for any given analysis.

This implementation of adaptability will be tested in the experiments in order to ascertain wither the Mandelbaum Buzacott criterion is applicable. However, given its treatment of the uncertainty forecasts, this implementation addresses the following research question:

> **Research Question 3.2:** How should shifting budgetary and threat priorities be represented to best capture uncertainty and volatility for calculation of adaptability and robustness?

As a result, the following hypothesis is proposed. This, as well as the remaining research question pertaining to adaptability, will be resolved in the experiments.

> **Hypothesis 3:** If a force is defined as the number of average missions of any and all types that can be performed simultaneously, it is possible to recreate a full force based on modeling only the archetypical mission types and multiplying those results and mission forces by a scaling factor.

#### *3.6.2.2 Unsuccessful Approach*

Another method of quantifying adaptability was attempted unsuccessfully. The goal was to develop an equation somewhat inspired by Kadano's work with robustness in graph theory [80]. The general idea was to capture another tradeoff of flexibility that is not addressed in the Mandelbaum-Buzacott method, namely the uniqueness and quality of the options at each decision point and not just their quantity.

The inspiration from Kadano's work is simply that the "robustness" of the path would be based on the robustness of the links, which is defined by their distance among other things.

Distance in our case would not be physical but rather a similarity or difference in performance and cost. At each step, the performance and cost for each option at that particular decision step is multiplied by the cost weighting, and measure of effectiveness weightings and mission weightings, to arrive at a vector of weighted performance characteristics for each fleet mix in the decision space. The Euclidean distance between each other fleet mix's vector and the vector of the chosen fleet mix in the path are then calculated. They can then be averaged or summed together in order to arrive at a measure of the overall variety of options at each step in the path.

This uniqueness or variety measure would then be multiplied against the number of options, as well as the quality of the actual decision of the path, to arrive at a measure of the adaptability of the node. The adaptability of each node could then be summed or averaged to get the adaptability of the path, or the maximum of the adaptabilities of all the nodes in the path could be taken in a manner similar to Kadano.

The primary problem with the attempt was that, given the lack of a theory upon which to base the equation and the lack of a case study to test it on, there is no reason to believe that this formulation would be the right one. Thus the equation, while containing many useful metrics, is rather arbitrary. However, further development of this idea, grounded by more solid theory and justification, may be worth investigating.

# CHAPTER IV

# METHODOLOGY DESCRIPTION

The methodology outlined below is the culmination of an investigation prompted by the research objective:

**Primary Research Objective:** Develop a methodology to perform system requirements development based on strategic force-level adaptability analysis. Account for purchasing budget, multiple uncertain scenarios, interoperability, and SoS. Provide meaningful, realistic solutions in a reasonable amount of time.

The methodology is approached as a modified fleet purchasing plan problem, where the plan is analyzed for flexibility to budgetary and mission uncertainty. Interoperability is assessed at the fleet capability assessment level, where mission modeling is used to determine the fitness of each fleet. To bypass the issue where fleets can be larger than the number of systems operating in a given mission, a fleet scaling method is implemented to scale up the fitness of a fleet based on its size.

The next figure shows a broad overview of the methodology.

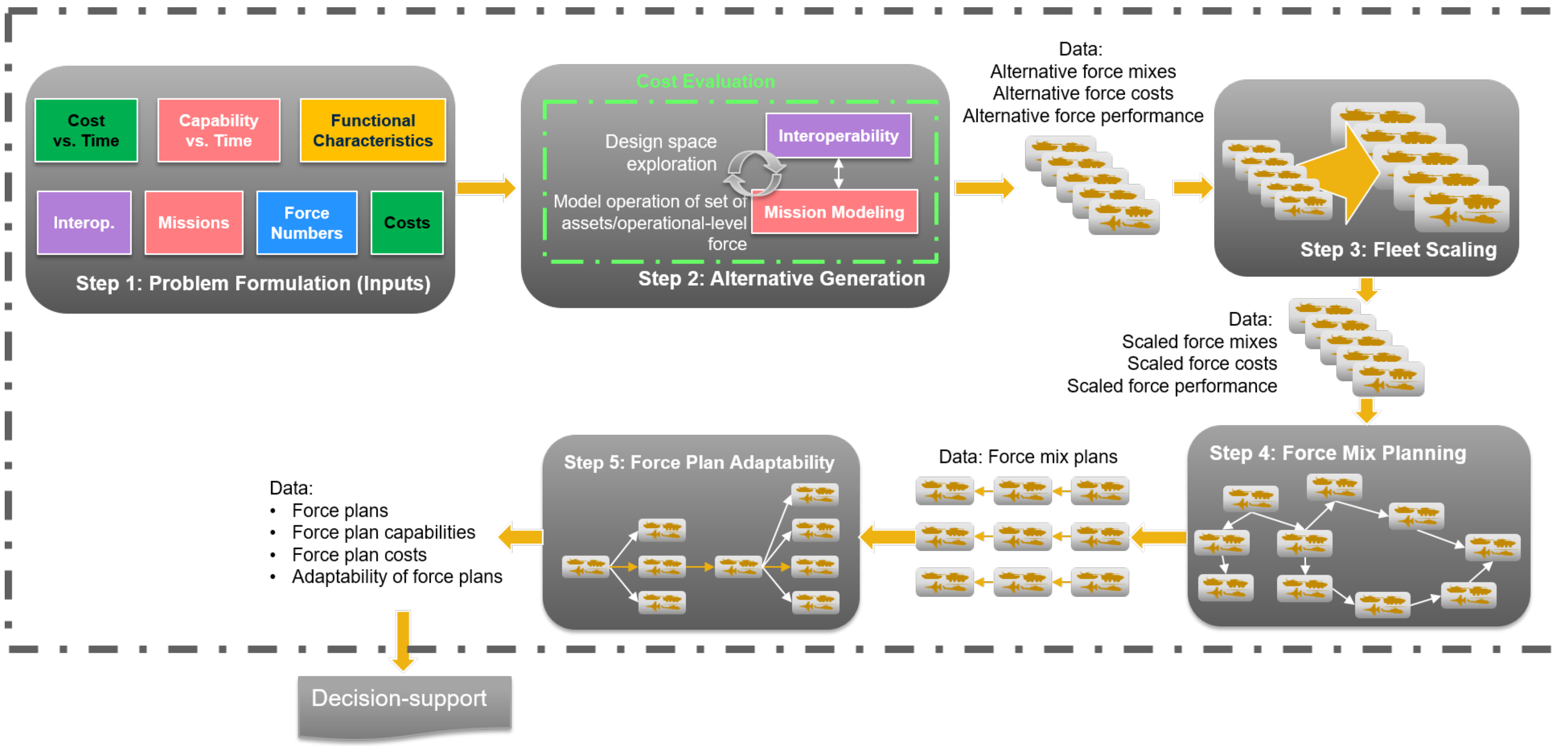



Figure 31: Depiction of full fleet mix planning methodology, with modified steps.

## 4.1 Phase One: Problem Definition

Defining the problem means defining at least these parameters (unless otherwise noted):

1. Initial Fleet Conditions:
   (a) Scenarios: List of all possible mission scenarios.
      i. List of required tasks for each mission.
      ii. Measures of effectiveness (MoE) of each mission.
      iii. Friendly order of battle for each mission (type and number of systems/troops).
      iv. Enemy order of battle for each mission (type and number of systems/troops).
   (b) Candidate system(s): Range of functional characteristics for any system whose requirements are being developed.
   (c) Fleet systems: Functional characteristics for all other systems in the fleet being considered, as well as starting numbers.
   (d) Budget and Time Period: How much money is available to be spent and over what period of time is the fleet being examined.
2. Costs and Benefits:
   (a) (Optional) Interoperability: Estimated cost for increasing interoperability, as well as cost function for increase in complexity as a result of increased interoperability.
   (b) (Optional) Functional characteristics: Models or estimates of the benefits and costs of improving the functional characteristics of the candidate system. Preferably with a sizing and synthesis component.
   (c) Fleet size: The cost of each individual system.
3. Constraints:
   (a) Objective Constraints:
      i. Min, max, desired capabilities of the entire fleet, per mission and mission MoE, over time. The starting point of each of these distributions should include the current fleet's baseline capability.

ii. Min, max, likely total available budget over time. The starting point at time 0 should be the current budget and should equal the total cost of each system in the current fleet, as well as any additional costs included in the analysis such as operating costs.

(b) Variable Constraints:

i. Min and max interoperability values for candidate systems and for fleet systems.

ii. Min and max candidate and fleet system functional characteristics.

iii. Min and max candidate and fleet system total numbers.

It should be noted that many of the costs and benefits can be addressed by combining a sufficiently high-fidelity combat model or simulation, a physics-based aircraft conceptual design utility, and a monetary cost estimation model.

As a notional example, Table 6 is presented.

| Aspect | Cost Modeling | Benefit Modeling |
|---|---|---|
| Interoperability | Monetary cost penalty function for improving interoperability; physics-based conceptual design surrogate | SoS combat model that can account for interoperability |
| Candidate system functional characteristics | Physics-based conceptual design utility for assessing trade-offs and monetary costs | SoS combat model[1] |
| Fleet size | Monetary cost estimation model (list of system acquisition and operation costs) | SoS combat model |

Table 6: Example cost and penalty methods

To establish value, it is necessary to set some sort of target to optimize against. This target, or value function, should reflect the desires of the stakeholders and can take multiple forms, as shown in Table 7.

[1] A SoS combat model can also be used to assess costs (or diminishing returns).

| Capability Value Function | Physical meaning |
|---|---|
| $f(t = t_{final}) = C = aC_{baseline}$ | Define a target capability for the fleet at the end of the time period, which can be a percentage of the original capability. |
| $f(t) \geq C_{baseline} \quad for\ 0 \leq t \leq t_{final}$ | Mandate that the fleet capability must not decrease over the time period. |
| $f(t) \quad for\ 0 \leq t \leq t_{final}$ | Mandate some other function for fleet capability over time. |

Table 7: Notional capability value functions

The function can also be defined as a percentage of the initial capability, as in the following equation for mandating a 10% capability increase over time:

$$f(t) = (0.1\left(\frac{t}{t_{final}}\right) + 1)f(0) \quad for\ 0 \leq t \leq t_{final} \tag{13}$$

If this function is not defined with the help of subject matter experts, it can lead to arbitrary capability goals. It is also important to note that the capability value function should preferably be a range of acceptable capabilities at any point in time, since otherwise meeting the constraint could be quite difficult. It is recommended that at least a min-max approach be used and that separate capability value functions are adopted for each of the metrics. This creates a uniform distribution of decision-maker capability desires. If the decision-maker desires a non-uniform capability distribution at a point in time, then more complex distributions with time-variant parameters can be adopted.

This same approach is prescribed for inputting the estimated budget over time. Two capability functions for missions are shown below in Figure 32, as well as a function for budget over time.

(note - need to fix plot for capability so that it narrows towards a single point on the left)

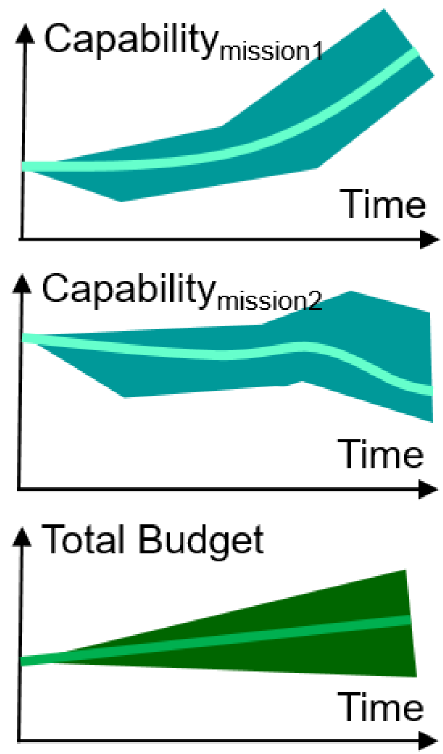



Figure 32: Notional value functions for capability and budget.

## *4.2 Phase Two: Alternative Generation*

Once the inputs and starting point have been defined, the next phase is alternative generation, shown in Figure 33. This is the most time-consuming phase, as it involves investigating the alternative space and making many calls to the mission model.

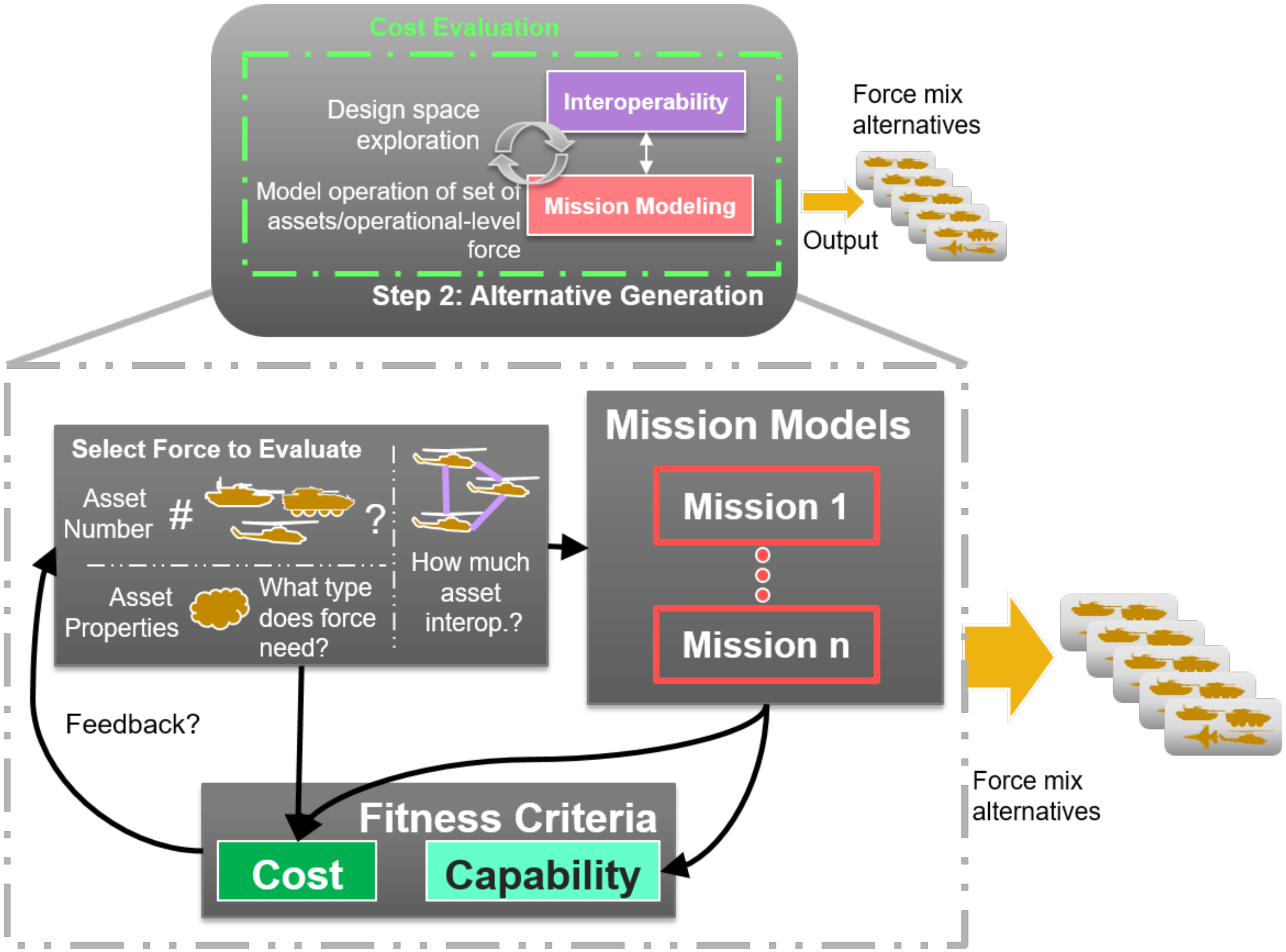



Figure 33: Phase two: Alternative generation.

### 4.2.1 Fleet Design Space Exploration

Once system variants are chosen for all candidate systems to be investigated, the methodology proceeds as an optimization problem, defined as below:

$$
\begin{aligned}
& maximize \quad P_{tot} = \sum_k P_{mission_k} \\
\text{s.t.} \quad & Cost \le C_{max}(t), && \text{for at least one} \quad t,\ 0 \le t \le t_{max} \\
& N_{i_{min}} \le n_i \le N_{i_{max}}, && i = 1, ..., m \\
& x_{i,q,min} \le x_{i,q} \le x_{i,q,max} && i = 1, ..., m,\ q = 1, ..., z \\
& \vec{L}_{i,j,min} \le \vec{L}_{i,j} \le \vec{L}_{i,j,max} && i = 1, ..., m,\ j = 1, ..., m \\
\text{where} \quad & Cost = \sum c_i n_i \\
& c_i = c_s + c_L + c_O, && i = 1, ..., m \\
& c_L = fn(\vec{L}_i), && i = 1, ..., m,\ j = 1, ..., m \\
& c_s = fn(\vec{X}_i), && i = 1, ..., m \\
& \vec{X}_i = [x_{i,1}, ..., x_{i,z}] && i = 1, ..., m \\
& n_i, \quad \text{integer} && i = 1, ..., m \\
& \text{some} \quad x_{i,q} \quad \text{integer} && i = 1, ..., m,\ q = 1, ..., z
\end{aligned}
\tag{14}
$$

Where $c_i$, $c_s$, $c_O$, and $c_L$ are the total system cost, the system cost from functional characteristics $x_i$, the operating cost if used, and the system cost from interoperability respectively. $n_i$ is the number of system $i$, and $N_{i_{min}}$ and $N_{i_{max}}$ are the minimum and maximum constraints for the number of that system. $L_i$ is the interoperability vector for that system, consisting of the interoperability of that system with every system type including itself. Finally, although it is described in the general optimization problem as a variable that affects the system cost, in reality each $x_{i,q}$ is selected together with a set of other variables values out of the variants generated by the DOE.

This optimization problem is modeled on the multi-mission fleet sizing and mix (FSM) methods, where pre-defined systems are created and their numbers are optimized for with respect to multiple missions, given cost and performance constraints. Some FSM methods add risk as well, however this is currently outside the scope of this work.

Selecting an advantageous starting point for interoperability exploration will likely depend on a few heuristics drawn either from subject matter experts, historical data, or other literature. A proposed starting point is to break systems down into how forward-deployed they are (forward echelon, mid, and rear) and give systems that share an echelon higher interoperability, systems in an adjacent echelon mid-level interoperability, and systems two echelons apart the worst interoperability. This type of schematic would be based on the likelihood that systems would have to interact with each other, with the idea being that systems that interact with each other frequently need greater interoperability, and systems in like echelons interact with each other the most frequently while systems in adjacent echelons interact with medium frequency.

Secondly, and most importantly - the performance of each point of the design space, including all associated calculations such as cost, asset interoperability, and mission performance, ***must be stored***. This is highly important for the last phase of the methodology, as all investigated fleets, regardless of optimality, are treated as potential candidates for the fleet purchasing plan. An alternative method is to store only the final, population of fleets after the optimization has proceeded to its conclusion.

### 4.2.2 Combat and Mission Models

Criteria for models to be included in evaluation of fleet performance are that:

1. The mission list is thorough; that it represents the full range of possible missions the fleet will perform, regardless of whether a candidate asset is expected to be needed for a particular mission. This can be achieved through some combination of parametrization of the missions or wholly different model configurations.
2. The missions in question can be modeled.

3. These models have sufficient fidelity to ascertain performance of the SoS via measures of effectiveness for the missions in question.
4. Models have fast run-times. This is necessary as the alternative generation step will make numerous calls to multiple combat models - for $y$ missions, there will be $y$ calls per potential fleet.
5. Models have sufficient fidelity to enable interoperability modeling to occur.
6. Models have sufficient fidelity to enable granular differentiation between system types; e.g. differentiate an F-15 fighter vs. an F-22 fighter vs. a B-2 bomber, as opposed to 'air system' vs. 'land system' or 'blue' vs. 'red' force.
7. Models must be parametric with regards to different system types and different numbers of systems.
8. Models must be baselined, calibrated, or validated in some way.

As this dissertation deals with creation of a methodology, there will not be a prescription of a specific mission model that works best for all applications. However, it is believed that the above criteria present adequate restrictions on the types of models employed, such that these models will guarantee compatibility with the rest of the methodology. Specifically, issues of speed, interoperability capability, fidelity, scalability, and thoroughness are all highly relevant in order to ensure that the resulting methodology is realistic, rapid, can include interoperability in the analysis, is scalable to many different fleet architectures, and decision-makers can be confident of the results they receive.

## *4.3 Phase Three: Fleet Scaling*

Fleet scaling operates on the following assumptions:

> **Assumption 1:** The assets used in the full set of missions a fleet can perform, including simultaneous missions and missions that have overlap of assets, represent the totality of the fleet in question.

> **Assumption 2:** A mission that is of the same type as another mission is

performed with exactly the same performance.

**Assumption 3:** If two fleets of unrestricted size but equal asset types can perform a set of missions with equal performance, the fleet that can perform some of these missions simultaneously is the better fleet.

**Assumption 4:** Mission capability is expressed as a normalized, non-dimensional variable.

These two assumptions are the foundation of the fleet scaling method outlined in this dissertation. First, the user begins by defining each mission type that the fleet can perform. Each mission can then be performed $k_j$ number of times, where $j$ is the mission type and $k$ is the number of simultaneous operations of that mission type. If each simultaneous operation is identical to each other and there is no overlap in assets across operations or missions, than the number of assets in a given mission type across all simultaneous operations of that mission is simply:

$$Y_{i,j} = \frac{\sum_k Y_{i,j,k} m_{j,k}}{\sum_k m_{j,k}}$$

Where $m_{j,k}$ is the total number of assets in a mission operation $j,\ k$ and $Y_{i,j,k}$ is the 'asset fraction' of system $i$, i.e. out of all of the systems involved in mission type $j$, operation $k$, $Y_{i,j,k} \times 100$ percent of them are of type $i$.

In such a way, the summing of total assets across all mission types can proceed up from summing across operations to summing across missions:

$$Y_i = \frac{\sum_j Y_{i,j} m_j}{\sum_j m_j} \quad \text{where} \quad m_j = \sum_k m_{j,k} = k m_{j,k}$$

This equation gives the asset fraction of system $i$ across all missions $j$ and operations $k$. Thus, to find the total number of assets in the fleet of each type, one must simply multiply the total asset fraction of $i$ by the total number of assets $m$, as below:

$$m_i = Y_i m$$

For operations where there is overlap, the most important thing is to keep track of the overlapping assets across the summation and simply sum them up only once.

Given asset $i$ in operations $j_1,\ k_1$ and $j_2,\ k_2$ such that $Y_{j_1,k_1} \cap Y_{j_2,k_2} = \{Y_{i,j_{1+2},k_{1+2}}\}$

$$Y_{j_1,k_1} m_{j_1,k_1} = Y_{j_2,k_2} m_{j_2,k_2} = \left(\frac{1}{\frac{1}{Y_{j_1,k_1}} + \frac{1}{Y_{j_2,k_2}}}\right)(m_{j_1,k_1} + m_{j_2,k_2}) =$$

$$Y_{i,j_{1+2},k_{1+2}} m_{j_{1+2},k_{1+2}}$$

and

$$Y_{j_1,k_1} m_{j_1,k_1} = ... = Y_{j_n,k_n} m_{j_n,k_n} = \left(\frac{1}{\frac{1}{Y_{j_1,k_1}} + ... + \frac{1}{Y_{j_n,k_n}}}\right)(m_{j_1,k_1} + ... + m_{j_n,k_n}) \tag{15}$$

Finally, perhaps the most important aspect of fleet scaling is scaling the performance of the fleet. This is where the second given assumption becomes important, as it outlines what sort of behavior ought to be expected from a scaled fleet. The rationale of the method is as such: if a fleet can perform an additional mission simultaneously, its performance increases linearly with its performance in the operation of that mission, which is identical to its performance in all previous operations of that mission. In other words, independent missions (those without overlap of assets) act as 'building blocks' of a sort when calculating the full, scaled performance of the fleet. However, under overlap of assets, a fleet will suffer a slight penalty to its performance due to a loss of asset redundancy. However, it is contended that the penalty will be outweighed by the cost of fielding a second identical system when the first can already operate in more than one mission simultaneously. Thus, fleet performance scaling is as follows:

Given $q_{j,k}$, the performance of a subset of the fleet in the operation $k$ of a single mission of type $j$, the performance of the whole fleet $Q$ is merely the sum of the individual performances, over the entirety of the operation and mission set, $\sum_{j,k} q_{j,k} = Q$. However, in the case of overlap of assets as described in previous equations, two separate mission operations have their performance summed as:

$$\left(1 - \frac{1}{\frac{1}{Y_{j_1,k_1}} + ... + \frac{1}{Y_{j_n,k_n}}}\right)(q_{j_1,k_1} + ... + q_{j_n,k_n}) = Y_{i,j_{1+2},k_{1+2}} q_{i,j_{1+2},k_{1+2}} \tag{16}$$

## *4.4 Phase Four: Fleet Mix Scheduling*

After the fleet, asset, and interoperability spaces have been explored and alternatives with their corresponding cost and performance values enumerated, the third phase of the methodology involves generating fleet plans. This can be done in several ways, as highlighted in the discussion on fleet mix planning. The most important thing is that all fleets have performance values for all missions, that all of the fleets' cost estimates have been calculated, and that there are well-defined budget and capability constraints based on expectations either from decision makers or forecasting.

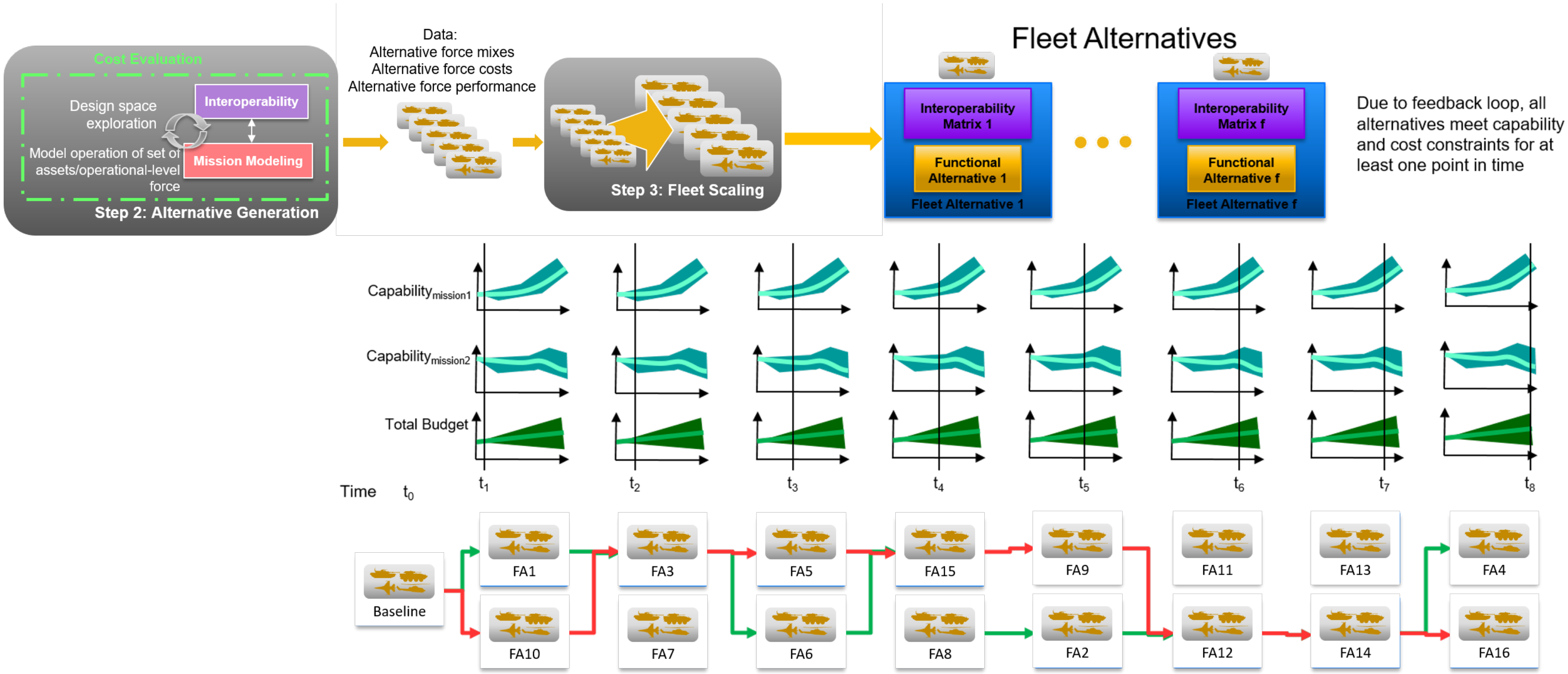



Figure 34: Phase three: Fleet mix planning.

### 4.4.1 Generating Fleet Plans

Inputs into this section are the fleets, their performances for all relevant missions, and their cost, as well as the decision-maker's cost and performance constraints. Once these have been input, there are multiple avenues to take to generate fleet plans. It is necessary to ensure that successive fleets in the fleet plan do not by change too many systems at once, and do not change by too much cost at once. For example, [140] multiplies the cost of each system by the number of that system and calculates the difference of each fleet from each other fleet as the Euclidean distance of the cost vectors of the fleets. The available fleet plans therefore increase by a set amount of cost each time period.

A sample example method is provided below:

First, the cost for each fleet is separated into per-asset costs as per the following table. The Minkowski distance (Minkowski parameter, $p = 1$) between each fleet is calculated using Equation 17.

$$D = \left( \sum_{i=1}^{n} |x_i - y_i|^p \right)^{1/p} \tag{17}$$

| Asset Type | Total Cost (Notional) |
|---|---|
| Tank | $1000 \times \$1.5e^7$ |
| Personnel Carrier | $2000 \times \$5e^6$ |
| Fighter | $1500 \times \$1.5e^7$ |
| Bomber | $300 \times \$3e^8$ |
| Destroyer | $20 \times \$1e^9$ |

This creates an symmetric matrix of the distances between each fleet, as shown below:

$$\begin{bmatrix} 0 & D_{12} & \dots & D_{1n} \\ D_{21} & \ddots & & \vdots \\ \vdots & & \ddots & D_{(n-1)n} \\ D_{n1} & \dots & D_{n(n-1)} & 0 \end{bmatrix}$$

Each non-zero element in the matrix then passes a boolean check regarding whether $D_{ij} \leq D_{thresh}$, where $D_{thresh}$ is the step change in money available - effectively this serves as a bound on the amount of change a fleet can undergo in any time period, whether in terms of reduction of assets or increase of assets. The result of each can be inserted into a Boolean matrix of 1's and 0's, which then serves as the adjacency matrix.

Following this, a depth-first search is performed, treating the adjacency matrix as an undirected graph. Any nodes that have already been discovered are added to a list, and following the conclusion of the depth first search algorithm these edges are removed from the graph. The result is a directed graph of all simple paths. The paths are once more discovered using a depth-first search, where the search is set to always begin at the baseline fleet and only proceed for the desired number of planning periods or time steps. These paths are the fleet mix plans that are used for the next step.

## *4.5 Phase Five: Calculating Fleet Plan Adaptability*

After the network of fleet plans is created, the flexibility of the fleet paths is calculated. This can be done via a modified depth-first search, where the adjacency matrix is explored for paths, and at each step in the path, the Mandelbaum-Buzacott Flexibility Criterion is calculated and recorded for that step, along with what fleet was chosen for that path. An example recursive algorithm is shown here:

1. Given p = 1, starting fleet = #1, adjacency matrix, flexibility criterion matrix L
2. For each time step starting with p
    (a) Determine which decisions, based on the starting fleet $i$, available at this time step

(b) For each of those decisions $j$

  i. If the element $L_{i,j,p}$ is zero

    A. Then for each performance metric in each mission, as well as the cost, for that fleet: normalize them by the uncertainty bounds at that time step

    B. Calculate the losses by adding $1 - Perf$ for all mission performance metrics, and $1-(1-Cost)$ for the cost, ensuring that each performance metric, mission, and cost are weighted appropriately.

    C. Apply the Mandelbaum-Buzacott equation by taking $\mathcal{L} = L - 0.5 + 1/n$ where $n$ is the number of decisions.

    D. Set $L_{i,j,p}$ equal to this value, where $i$ is the starting point, $j$ is the decision, and $p$ is the time step.

(c) Once the flexibility of each decision is calculated, then for each decision $j$:

  i. Repeat from step 2, with $p = p+1$, starting fleet = #$i$, the adjacency matrix, and the updated L

The most adaptable fleet paths, according to the Mandelbaum-Buzacott criterion, can then be determined either by summing or averaging the criteria for each fleet path. It should be noted that use of this criterion is not required for the methodology and that it is presented as an example and a starting point for assessing future work. Other criteria for adaptability may be used so long as they capture the tradeoffs of interest.

### 4.5.1 Decision Support

The generated fleet paths, their performance and cost values changing with time against the constraints, and their flexibility are all useful inputs into a decision support system that decision-makers can take advantage of. Utilizing data visualization of the path flexibility versus path performance, a decision-maker can now assess which of a set of possible fleet plans to pursue further analysis on.

# CHAPTER V

# EXPERIMENTS AND RESULTS

The experimental plan will consist of multiple phases. The first phase will involve testing, verification, benchmarking and attempts at validation of an implementation of the methodology to a particular case study. The second phase will consist of a demonstration where a new asset is inserted into an existing strategic fleet, and fleet evolution plans are developed and analyzed.

## *5.1 Step 1: Testing Constituent Models*

The methodology assumes that constituent parts are valid and apply to the assets being modeled. To test the methodology, a mission model was selected that, it was asserted, could accommodate interoperability and show its effects. This assertion will now be tested, piece by piece.

### 5.1.1 Experiment 1: Mission Model Interoperability Testing

The combat model selected for use with the proposed methodology is not uniquely suited for showcasing the strength of the methodology. Indeed, only a few requirements are placed on any mission models to be used with this methodology. However, it must be shown that the selected model does indeed meet these requirements. In the development section, it was shown that the mission model can take into account functional characteristics and use this to output the mission effectiveness of the force. It was also shown that the runtimes for the model are relatively quick. Chief among the remaining requirements is that the model is of sufficient fidelity to be realistic. Second, the combat model must be able to account for the interoperability model used.

To test these two requirements, the experiment will first ensure that the results provided

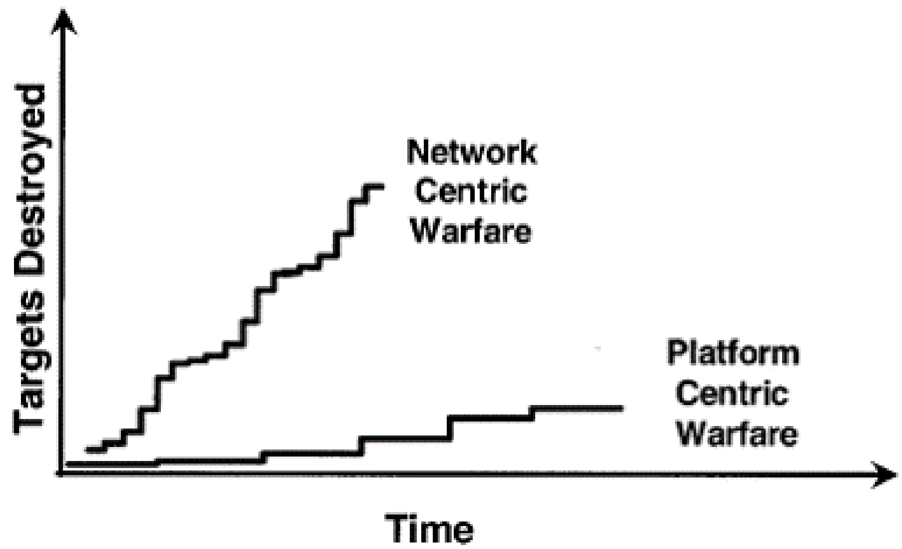



Figure 35: Fleet Battle Experiment Delta results [7]

are realistic as compared to historical data. Although this is not a validation of the combat model, it will provide a useful grounding of the result to ensure that they do not detract from the conclusions. Next, the interoperability must be tested. It is difficult to ascertain whether interoperability is truly being accurately modeled unless one performs validation studies of the model. As such, the only feasible course of action is to attempt to replicate trends seen in the literature. A good candidate for this is Fleet Battle Experiment Delta, which showed an increase in targets destroyed as interoperability increased. Figure 25 is reproduced again here in Figure 35.

Due to the depth of available data, the Normandy beach landings of World War II were selected as a suitable operation to model. However, due to the vast number of assets landing on June 6th, 1944, only OMAHA beach, most often regarded as the most dangerous of the five sectors, was chosen.

This beach was the landing spot for tens of thousands of American soldiers and was defended by only several thousand German troops [82]. However, due to a confluence of circumstances there were severe difficulties with assaulting the defenses, ranging from the tide and weather, to missed Allied bombings earlier that morning, to mechanical failure with the amphibious equipment. The results were casualties much higher than the other landing zones, estimated to be in the low to mid thousand range.

#### *5.1.1.1 Experiment 1a: Reproducing Historical Data*

Historical data about combat operations can be hard to find in any detail. As such, the mission models developed here will be used throughout the experiments. Data was gathered [86] and estimated where required in order to give a reasonable approximation of the order of battle for the Normandy operation. Broadly, the United States is assumed to land 18 waves of landing boats, landing craft, amphibious tanks, and assault craft. Roughly in between these waves, 10 Navy ships fire upon the defenses with guns. The landing assets all had varying failure rates, with the amphibious tanks (modified M4 tanks dubbed DD Tanks) having the largest failure rates as documented. The interoperability level between the allies was assumed to be 0.6, although it could be varied and recalibrate to be any other number. Furthermore, they are assumed to have two resources that can be used to interoperate.

German defenses were compiled from a map of German defenses and summed to create the final populations [74]. German defenses consisted of numerous positions containing mortars, machine guns, and anti-aircraft, anti-tank, and artillery guns. Furthermore, German defenses consisted of infantrymen and flamethrowers.

These data are all provided in an appendix. Only 8 hours of the combat will be modeled, even though the landings continued throughout the next month. This highlights a difficulty in when a battle is declared over - for this case, it is declared over at the 8 hour mark because the beaches had been largely secured and the Allies had begun moving inland. Of course, the combat model does not take into account morale and retreats, and thus it is unrealistic to assume that it would replicate historical results with 100% accuracy. However, given the numbers of assets being modeled, the scale, and the quality of the historical data in the first place, this combat model provides at least an initial approximation and thus serves as a point of comparison across multiple different assets and fleets.

The table below shows the results of this model.

Table 8: Comparison of simulated Omaha beach results to historical results

| Metric | Historical (Estimated) | Simulated |
|---|---|---|
| Allied Casualties | ~2000-4000 | 2908.576 |
| Enemy Casualties | ~1200 | 1263.5 |

With the ability to tune the lethalities of the assets to modify final measures of effectiveness, it is somewhat unsurprising that the model was able to replicate historical data so closely. However, so long as the lethalities are not set to unreasonable values, this is an acceptable result for now. This is especially true since this is not a validation study.

*5.1.1.2 Experiment 1b: Interoperability Testing*

**Hypothesis 2:** If reliability-based interoperability modeling is combined with information entropy-based collaborative effects that model complexity, the selected combat model will show an increase in the rate of enemy casualties.

After the linkage between interoperability and the combat model was implemented, this linkage was tested in the OMAHA beach mission in order to test the following hypothesis.

**Hypothesis 2.1:** In the implemented combat model, interoperable systems will score a greater number of kills in the combat model over ones that are not interoperable.

To test Hypothesis 2.1, the interoperability $\theta$ for all assets was varied from 0.1 to 1.0 while all other factors were held constant. This means that all assets were increasingly more interoperable with all other assets. This is of course an extreme case, as there is currently no such uniformity in interoperability. However, this allows us to not needlessly complicate the matter. The question of which asset-pairs' interoperability causes the largest change in the variability of the performance is a different though still important one. The aim of increasing the interoperability was to effectively reproduce a trend similar to those seen in other experiments performed, such as in [121] [102].

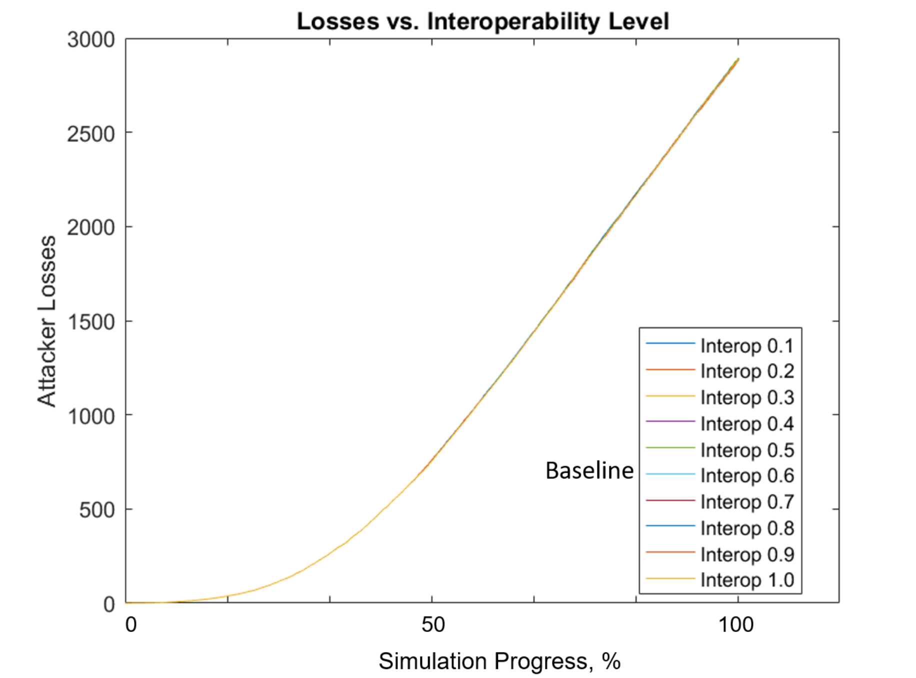



Figure 36: Friendly (attacker) casualties versus force-wide interoperability level

The results of this text are shown in figures 36 and 37. As seen in Figure 37, the effects on enemy casualties are pronounced. Past a certain point, the integration of interoperability into the combat model does produce an increase in casualty rates. This is expected from the way the integration was performed, yet is an important result to achieve in order to be able to model the effects of interoperability on fleet planning as the methodology requires.

Figure 36 shows that interoperability did not have any significant effect on the number of friendly casualties. Potentially, this is a result of targeting decisions in the combat model coupled with the population size of enemy assets. Targeting decisions in the combat model are currently made by each asset determining which target they can do the most damage on, and selecting that target. It is thus conceivable that if friendly assets are targeting an enemy asset that is not primarily responsible for their casualties, and there is enough of that enemy asset that they cannot neutralize it completely in the time allotted, there will be only

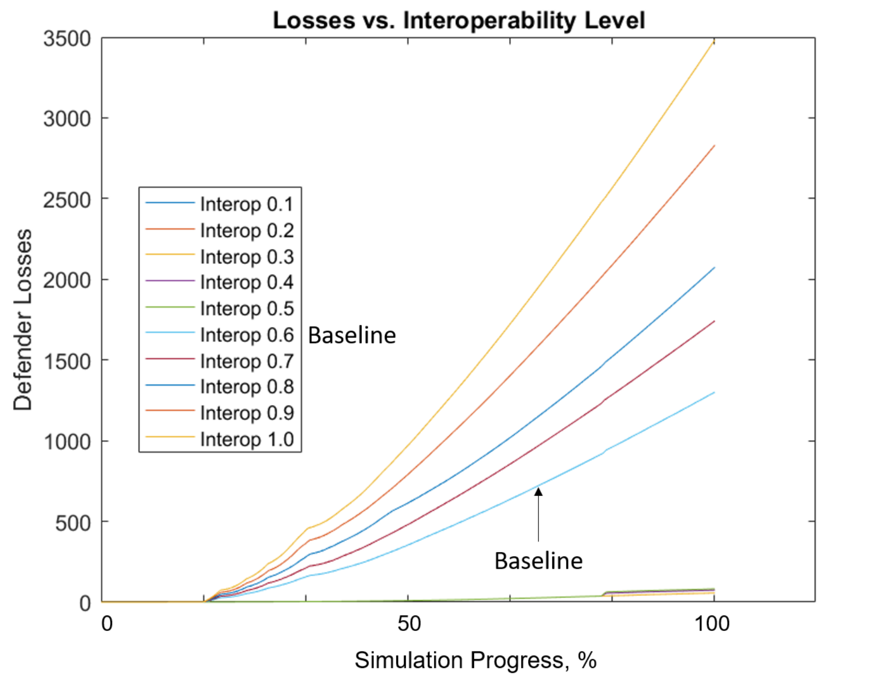



Figure 37: Enemy (defender) casualties versus force-wide interoperability level

a small effect on friendly casualties casualties.

To test this, the population of the Axis Infantry asset type was reduced from 7800 to 1500. Because this new number is within the range of numbers seen in Figure 37, it is feasible for friendly assets to neutralize this number of Axis Infantry asset before moving on to a potentially more harmful asset type. The results of the test confirm this. Shown in Figure 38 are the friendly casualties with a reduced number of attackers. Although the effect is slight, it is clear when compared to Figure 36. Figure 39 shows that all high-interoperability forces reach a number slightly at or above 1500 before the rate changes significantly. This implies that a certain population of the attackers is consistently targeting Axis Infantry, and once that population is down to 0 the attackers in question switch to the next targets.

Looking closer at the friendly losses in Figure 40, we can see that the same expected trends show themselves. The highest interoperability level has the least casualties, and casualties increase as interoperability decreases - an effect of the reduced enemy number.

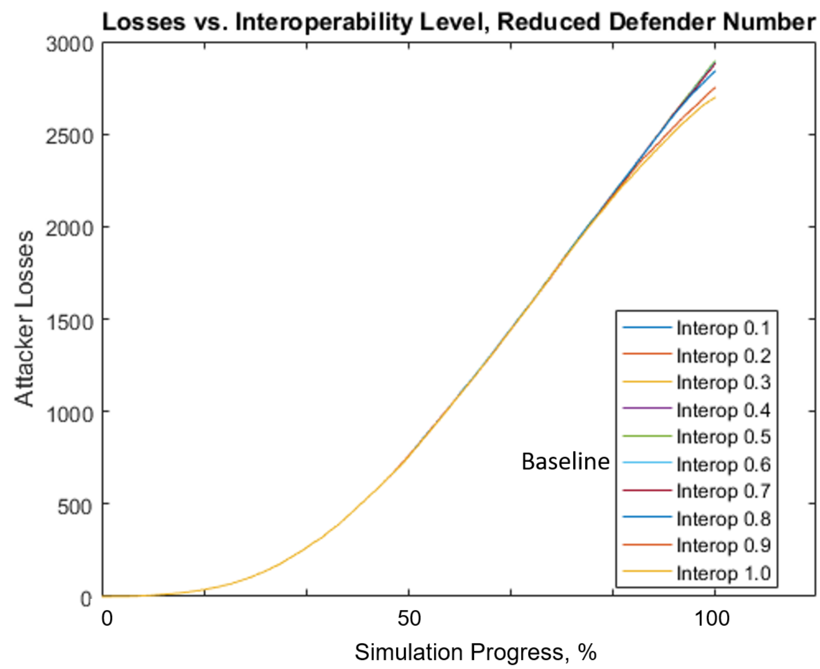



Figure 38: Friendly (attacker) casualties versus force-wide interoperability level, reduced defender numbers

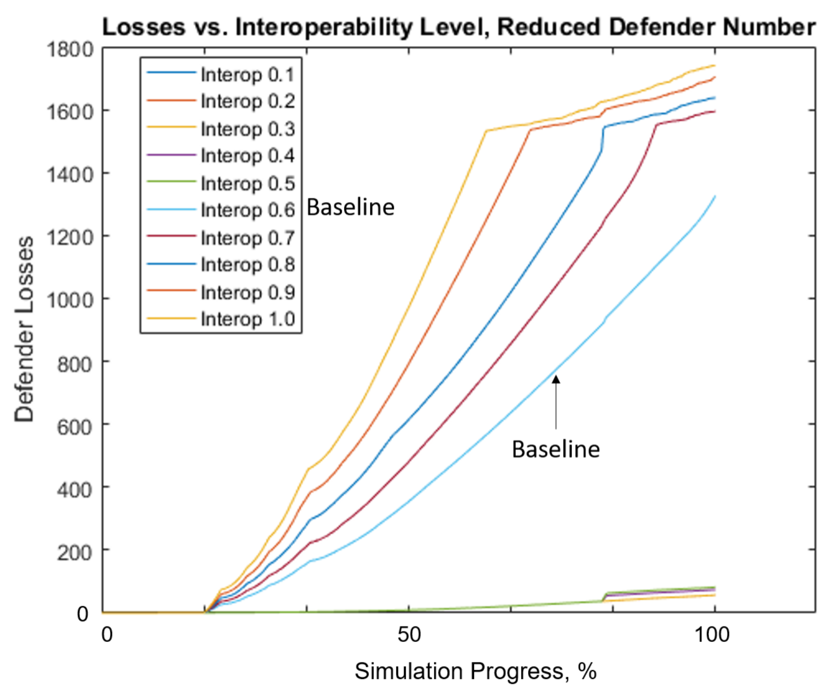



Figure 39: Enemy (defender) casualties versus force-wide interoperability level, reduced defender numbers

The reason for the relatively high casualties is that Axis Infantry are calibrated to not be the primary source of casualties for the attackers - that is the many defense emplacements outfitted with artillery, mortars, and machine guns.

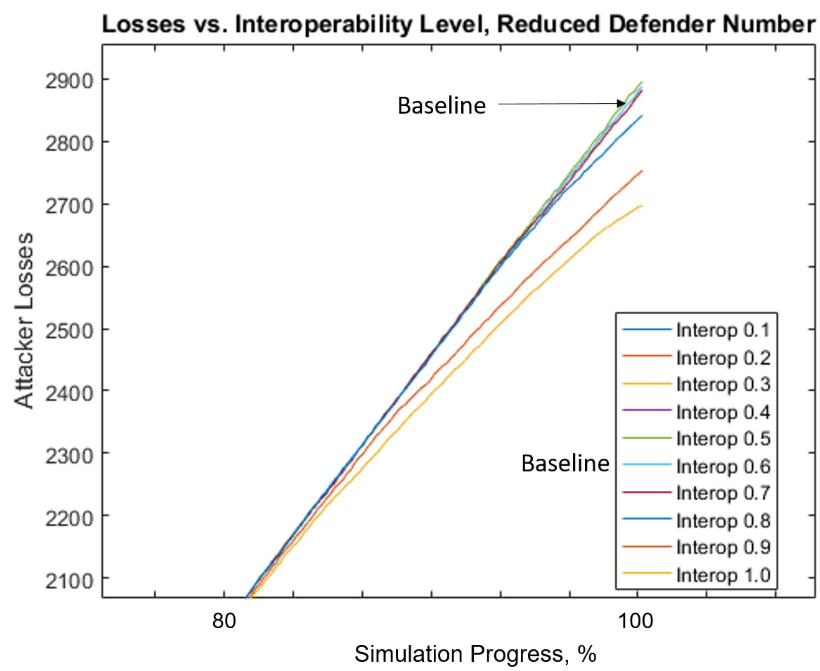



Figure 40: Figure 38, Zoomed

This experiment has demonstrated that the integration of interoperability with the selected combat model was sufficient to reproduce trends seen in the literature. Thus, the following research questions are assumed to be addressed:

**Research Question 4.3:** Which method should be chosen for the purposes of a demonstration of the methodology?

**Research Question 5.3:** What missions should be modeled in order to gain confidence in the results of the methodology?

### 5.1.2 Experiment 2: Fleet Scaling

> **Hypothesis 3:** If a force is defined as the number of average missions of any and all types that can be performed simultaneously, it is possible to recreate a full force based on modeling only the archetypical mission types and multiplying those results and mission forces by a scaling factor.

The fleet scaling method developed in this dissertation essentially consists of a set of observations and assumptions used to justify scaling all force values (both assets and performance) values by a multiplier. This multiplier is simply the minimum factor required to make the mission model results meet the global requirements for that mission type. In essence, this means we are determining the number of missions that could be performed simultaneously by a force that has a given performance in that mission type, such that the total performance for all simultaneous operations of the mission do not exceed the global desired values for that mission type. Although the method is quite simple, the assumptions required to derive it are not wildly unreasonable, especially for a high-level requirements development approach and given the lack of other good options at the time of writing.

The justification for the design of this experiment begins with the observation that the OMAHA beach landing was one of five simultaneous beach landings in Operation Overlord. Furthermore, since the method is not logically complex, its results can be predicted rather simply. Thus, if one assumes that the overall strategic force is only the force involved in all five amphibious landing missions, then the developed method used on one mission ought to replicate the results of the overall strategic force, assuming the mission modeled is an average mission.

The goal of experiment is more-so to demonstrate the strengths and weaknesses of the scaling method than to determine whether it is accurate, although of course if the method cannot recreate any performance whatsoever it is of little use - thus this is a secondary goal fo the experiment. This experiment involves scaling up the OMAHA beach SoS based on multiple simultaneous missions. This was done by first assessing the 'degree of averageness' of the OMAHA mission compared to the other four beaches. From this, an estimate was developed regarding what values the scaling would produce. This estimate was then tested by inputting the 'desired' scaled up performance (i.e. the summed historical casualties for all 5 beaches), along with the simulated OMAHA performance and order of battle, into a fleet scaling code. The scaled up performance, and the resulting scaled up fleet, were then compared to their actual values.

As a reminder, the measures of effectiveness(MoE) statistics used for the OMAHA beach model were as follows:

| MoE | Allied Losses | Axis Losses |
|---|---|---|
| Value | ~2000-4000 | 1200 |

The simplified order of battle on OMAHA beach was as follows:

| Force | Allied Troops | Axis Troops |
|---|---|---|
| Value | 34,250 | 7800 |

However, of the companies involved in the landings, only roughly 12,000 were involved in the assault [82] and this is the number that will be used for scaling.

As mentioned previously, the OMAHA mission model adequately reproduces these results. Looking at the overall landing (summed for the five beaches) statistics, the numbers become even less certain. However, there are estimates that the following figures are reasonable:

| Force | Allied Losses | Axis Losses |
|---|---|---|
| Value | 7769 | 6200 |

| Beach | Allied Troops | Allied Losses |
|---|---|---|
| UTAH | 21000 | 3396 |
| OMAHA | 34250 | 3000 |
| GOLD | 38750 | 350 |
| JUNO | 22000 | 340 |
| SWORD | 28845 | 683 |

In an attempt to estimate the results of the fleet scaling method, it is clear that these data will immediately present challenges for the simple scaling algorithm developed. The missions to be scaled are assumed to be "average" missions, meaning that a mission will output the same result if performed by the same force. For all intents and purposes, the five beaches of Normandy are assumed to be the same mission. However this is, of course, not true - some beaches, such as UTAH and OMAHA, posed significantly greater challenges to their respective assault forces due to either ineffective bombardment, the effects of tides, or difficulties in getting tanks ashore. For this reason, casualties are quite high in UTAH and OMAHA but relatively low in the other three beaches. In terms of relative contribution to the total allied losses statistic, OMAHA beach contributes nearly half, with another near half coming from UTAH. However, in terms of Axis Losses, OMAHA beach contributes a roughly proportional percent (~1200 out of ~6000). Since the scaling multiplier is applied to all measures of effectiveness equally, scaling OMAHA beach statistics to the full landings will cause the scaling to reach the expected friendly casualty performance before it reaches the expected enemy casualty performance.

However, the goal of finding historical data was meant to aid in the construction of a mission simulation whose outputs were not unreasonable, and to aid in construction of a fleet scaling method whose outputs were similarly not unreasonable. The well-researched but not classified OMAHA beach and Normandy landings provided easily-accessible data, yet they are imperfect because, as demonstrated, any of the five missions would violate the "average mission" assumption made for fleet scaling. In fact, it is questionable whether any

World War II mission (or even any mission at all) would ever truly be “average” enough to suffice, and yet present sufficient “simultaneous” performances of that mission that good test of the scaling method could be performed. The properties of the Normandy landings - that five missions were performed simultaneously, that they are well researched and thus any data at all is available regarding measures of effectiveness, and that sufficient information is available regarding the exact order of battle - mean that they are perhaps uniquely suited to this analysis, as imperfect as the data set is.

With this expectation that the scaling will likely estimate the friendly casualties well and underestimate the enemy casualties, we proceed with the scaling to test this claim.

A simple MATLAB script was written to determine the proper multiplier for all performance criteria that does not cause any of the criteria to exceed the expected values - this script is provided in an appendix. This script determined that the proper multiplier was nearly 3, meaning that the scaled performance is as below:

| Scaling Factor | Scaled Allied Losses | Scaled Axis Losses | Allied Losses | Axis Losses |
|---|---|---|---|---|
| 2.9952 | 7753.7 | 3777 | 7769 | 6200 |

As discussed above, this result was expected. Had friendly casualties been somewhat close to 1500 as opposed to something between 2000 to 4000 for OMAHA beach, the modeled mission’s friendly casualties would not have driven the scaling factor to the extent that it did. However, as per the stated goals of the experiment, the scaling method is deemed sufficient to at least demonstrate that such scaling can give reasonable (if not always accurate) estimates of total performance for simultaneously-operated missions. As a final note, because the combat model utilized by way of demonstration uses population pools and real numbers for rates of change, populations can take non-integer values. This fact is allowed to propagate to the fleet scaling method. However, it is relatively trivial to programmatically determine what value within a certain range causes all performance metrics (and asset numbers) to take whole numbers. Or one can make the simplifying assumption that a change in $\pm 0.5$ units does not impact the rest of the analysis too greatly.

Thus, the following research question is addressed:

> **Research Question 2.1:** What method is best suited for taking a set of disparate SoS operating different missions and rapidly scaling them up or unifying them into a full force?

### 5.1.3 Experiment 3: Flexibility Criterion

In this experiment, the flexibility criterion is examined to determine whether it reflects force plans that can adapt to changes in budget and capability requirements over time. The goal of this experiment is to answer Research Question 3.1 by posing Hypothesis 4:

> **Research Question 3.1:** What method is best suited for defining and calculating adaptability of a plan (not just a set point in time) or a set of plans?

> **Hypothesis 4:** If adaptability is calculated by accounting for the losses caused by a force purchasing decision as well as the number of other available options at that decision point via a decision-theoretic approach, this adaptability criterion will adequately reflect the adaptability decision-making tradeoff.

To perform this experiment, there needed to be a common point of comparison. As a universally accepted and accurate definition of adaptability is difficult to reach, and because there was no case study available to compare results, it was determined that hand-crafted examples of adaptable versus non-adaptable paths would be a good starting point to help further research.

Thus, the key goal of hand-crafting fleets was to create a scenario where one branch of the fleet paths possessed superior performance but limited choice and the opposite would be true for the other branch. 15 fleets were created with varying performance and cost characteristics, mirroring the data set derived from the historical battle examples of Omaha

Beach and Operation Cobra. The same performance metrics were used, and the same performance uncertainty ranges as well. However, for the sake of simplicity in hand-crafting the fleets, they did not possess the breadth of assets and asset types that the original data set possessed.

In Figure 41, the lower branch can be seen to have limited choice: The first choice along this branch (time step 2) provides two options, and the next choice for these two paths provides either only one option or two options. The upper branch provides four options at the outset, yet is similarly limited after the fact, with only one choice providing more than one option. However, the lower branch is better-performing than the upper branch. The final feature of this fleet path graph is both branches have paths that converge onto one fleet - fleet 12.

The fleet paths created from these fleets are also shown below:

| Time Step | | | |
|---|---|---|---|
| 1 | 2 | 3 | 4 |
| 1 | 2 | 4 | 10 |
| 1 | 2 | 4 | 11 |
| 1 | 2 | 5 | 12 |
| 1 | 3 | 6 | 12 |
| 1 | 3 | 7 | 12 |
| 1 | 3 | 7 | 13 |
| 1 | 3 | 8 | 14 |
| 1 | 3 | 9 | 15 |

With the fleet path options described as above, we could imagine that the choice for a human may only be slightly difficult to make. The upper branch has slightly more options at the outset, and each of those options is not markedly different in terms of choices from the paths on the lower branch besides performing more poorly across the board. The goal of experiment 3 is to compare the flexibility criterion's rankings to see whether it reflects

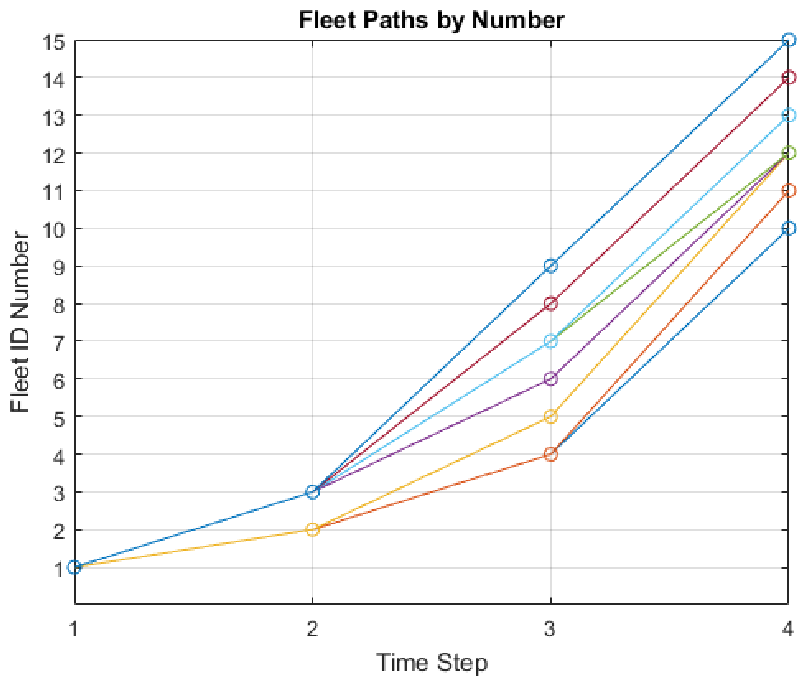



Figure 41: Fleet paths shown by fleet ID No.

the trade-off here.

With these fleet paths created, the Mandeulbaum-Buzacott criterion was applied to each decision at each decision point as described in previous sections. Then, these values were summed for each fleet path to enable a comparison across fleet paths as opposed to across decision points. Figure 42 may be misleading initially, but the convention is that "warmer is higher" or better - since a lower criterion is a more adaptable path, Figure 42 can be thought of as coloring results by higher adaptability, not higher criterion values.

In Figure 42, the lower branch has a warmer set of colors in general, especially when compared to the upper-most fleet paths of the top branch. However, we see that path number 5, [1 3 7 12], is shown as being nearly as good as path 1, [1 2 4 10], (criterion values of 3.8318 versus 3.7709). To help elucidate why this is, we turn to Figure 43.

The colors in Figure 43 match up to those in Figure 42 as both are colored by increasing adaptability. However, in Figure 43, the performance metrics have been normalized by where they fall on the uncertainty range and then averaged together (non-weighted average,

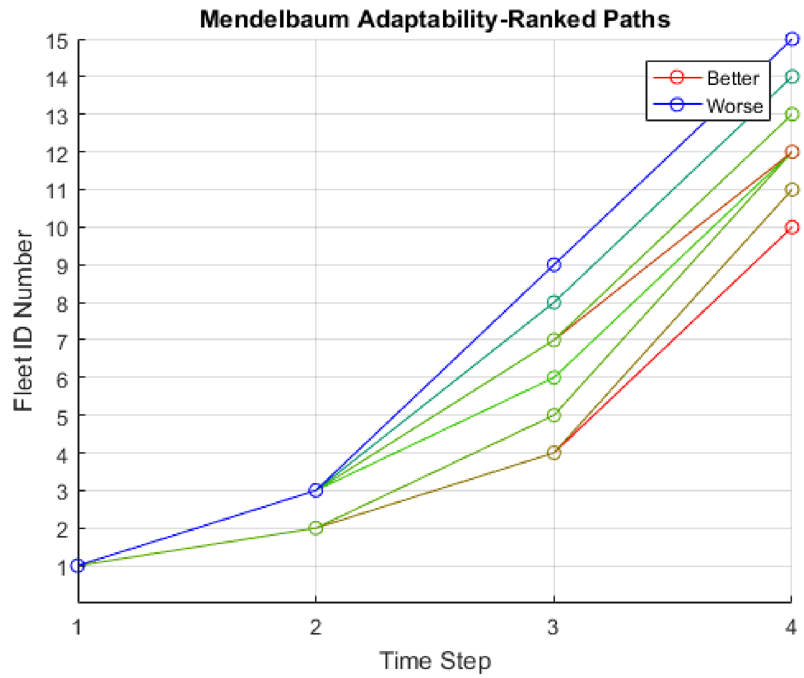



Figure 42: Fleet paths shown by fleet ID no., colored by criterion ranking

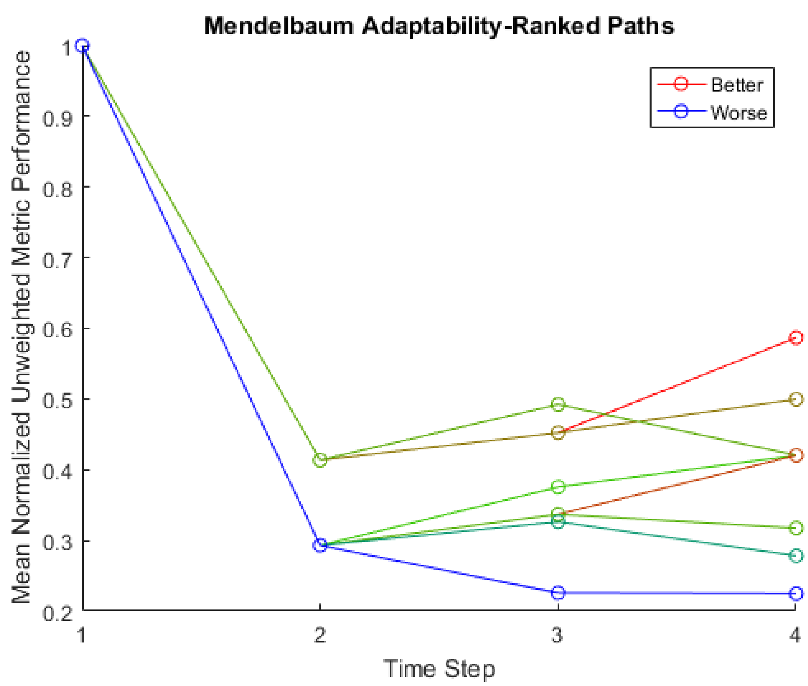



Figure 43: Normalized fleet performance, colored by criterion ranking

because the weightings were set to be equal for all performance criteria). This gives us an overall fleet performance (and cost) metric to use in comparisons. Now, of course, the two primary branches have switched - the lower branch in Figure 42 is now the upper branch in Figure 43 since it was better-performing overall.

We can see the three paths converge on fleet 12 as before. And we see that the highest performing path overall, path 1, also happens to posses the highest or 2nd highest performance at each time step. We further see that plan 5, the second most adaptable according to the criterion, actually performs worse overall compared to plan 4 ([1 3 6 12]). This is despite both fleets sharing all but one fleet (fleet 6 vs 7 in time step 3). The difference can of course be explained by the fact that plan 5 has 4 and then 2 options available to it (in step 2 and 3 respectively), while plan 4 has 4 and then only 1 option available to it. The single additional option in the better plan outweighs the marginal increase in performance from the less adaptable path.

> **Research Question 3.2:** How should shifting budgetary and threat priorities be represented to best capture uncertainty and volatility for calculation of adaptability and robustness?

To address Research Question 3.2, when applying the Mandelbaum-Buzacott criterion it was determined that the weightings for the various missions, as well as the cost, would be incorporated into the loss function. This means that the loss function is not independent of the weighting, which implies that a different weighting preference could create different fleets. This potential problem was tested during 5.2.1. However, the results will be included here to retain consistency of topic. In the experiment, 3 top-level metrics were used to create the Mandelbaum-Buzacott criterion - the equally-weighted measures of effectiveness for Omaha Beach, the equally-weighted measures of effectiveness for Operation Cobra, and the total cost. These values were normalized by the maximum value of the uncertainty prior to use. Furthermore, the values were weighted by 3 weightings - a weighting for Omaha, a weighting for Cobra, and one for cost. These weightings were varied in order to investigate their effect on the stability of the Mandelbaum-Buzacott criterion results.

To generate the next four figures, the weightings were varied and the top 20 fleet paths under each weighting scenario were recorded. If the adaptability criterion was mostly arbitrary, one would expect that the most adaptable fleet paths would change with each scenario, meaning that for $N$ weighting scenarios, $20 \times N$ unique fleet paths would be recorded. In a bar chart of frequency against unique fleet path ID number, one would then expect that most fleet paths would occur roughly once. If the criterion does indeed indicate some measure of adaptability, then one would expect that there would be repetitions of fleet paths under various scenarios. This would mean it would be possible to pick a fleet path and have that fleet path remain adaptable despite various changes in the strategic environment. Finally, it should be noted that it would be highly unlikely to arrive at the result that any top fleet path is adaptable under any arbitrary weighting scenario. This is because it is possible to set various weightings to 0.

For the first test, we use just 5 weighting scenarios that indicate specific desirements, ranging from equal importance on all three weights, to cost being the most important. These are highlighted in the following table:

| Omaha | Op. Cobra | Cost |
|---|---|---|
| 1/3 | 1/3 | 1/3 |
| 1/2 | 1/2 | 0 |
| 4/5 | 1/10 | 1/10 |
| 1/10 | 4/5 | 1/10 |
| 1/10 | 1/10 | 4/5 |

The use of 5 scenarios suggests that in the worst case, we may have 100 ($20\, fleetpaths \times 5\, weighting\ scenarios$) fleet paths each occurring once. However, in Figure 44 we can see that the frequency is roughly as expected. Out of a set of more than 200,000 fleet paths only

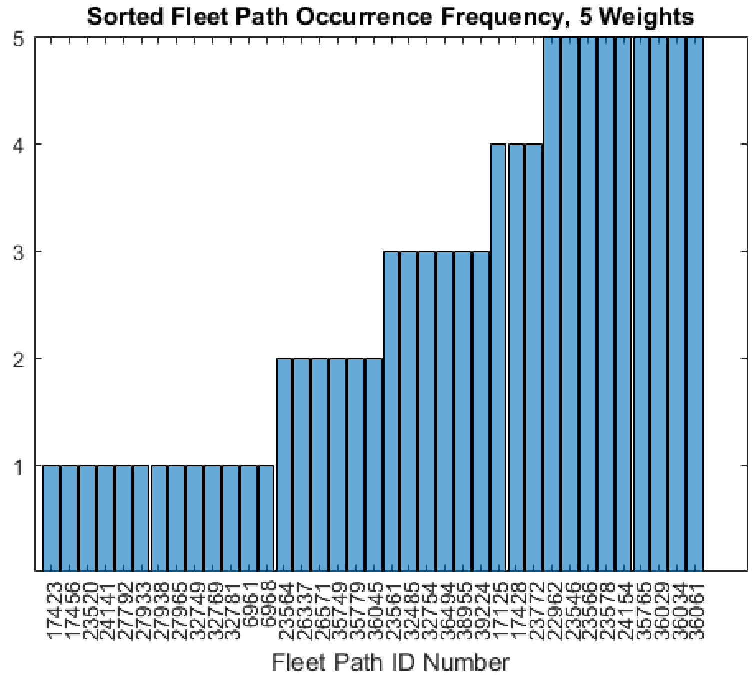



Figure 44: Total occurrence of various paths in the top 20 most adaptable paths, under each of 5 different weighting scenarios.

a very small subset of the total fleet paths remain viable despite changes in weightings. Instead, the actual number of fleet paths is 37. This result may be somewhat disappointing, but one must remember that fleet mixes must also be investigated in addition to the fleet mix plans that utilize them. In Figure 45, we can see that there are only 13 unique fleet mixes appearing, meaning that each path in Figure 44 utilizes roughly the same area of the decision space - the only thing that changes is which decision is made from the set. This is an encouraging result, as the number of potential fleet mixes could have approached 300, since each path is composed of a baseline fleet plus 3 time steps and there could have been 100 possible paths plotted.

This implies that adaptable fleets do remain somewhat stable across weighting scenarios, though of course more stability is always desired in order to attain 100% certainty when investigating fleet paths and fleet mixes. To test this stability a little bit more, a much larger set of 100 weighting scenarios is used. This set is constructed with a random number generator - 3 random numbers from 0 to 1 are chosen and then normalized by their sum,

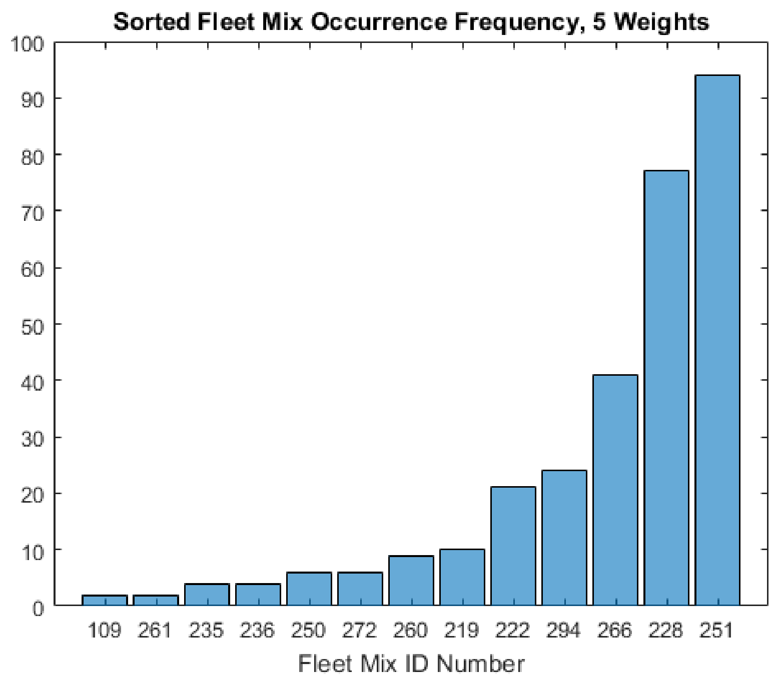



Figure 45: Total occurrence of fleet mixes associated with top the 20 fleet paths under each of 5 different weighting scenarios.

such that they add to 1. This process is repeated 100 times. The result of this is shown in Figures 46 and 47.

Much like in the last test, the results are rather good. In Figure 46 we can see that only 42 total fleet paths appear out of a possible 2,000 ($20 most adaptable fleets \times 100 weighting scenarios$). This is an increase of only 5 fleet paths resulting from 20 times the scenarios considered. In Figure 47 we can see that only 14 fleet mixes are used for the most adaptable paths. Again, out of a possible 6,000 fleet mixes to investigate this result is quite promising, as it means there is less high-fidelity analysis that must be performed.

To summarize the experiments, it was first shown that the adaptability does seem to capture the type of tradeoff desired. This tradeoff is one between the number of options and the quality of those options. Furthermore, because we are dealing with a situation where weightings may change rather frequently due to a volatile strategic environment, it is important to investigate whether fleet paths do remain adaptable despite a change in the strategic environment, whether due to budgets or the threat scenario (i.e. weighting

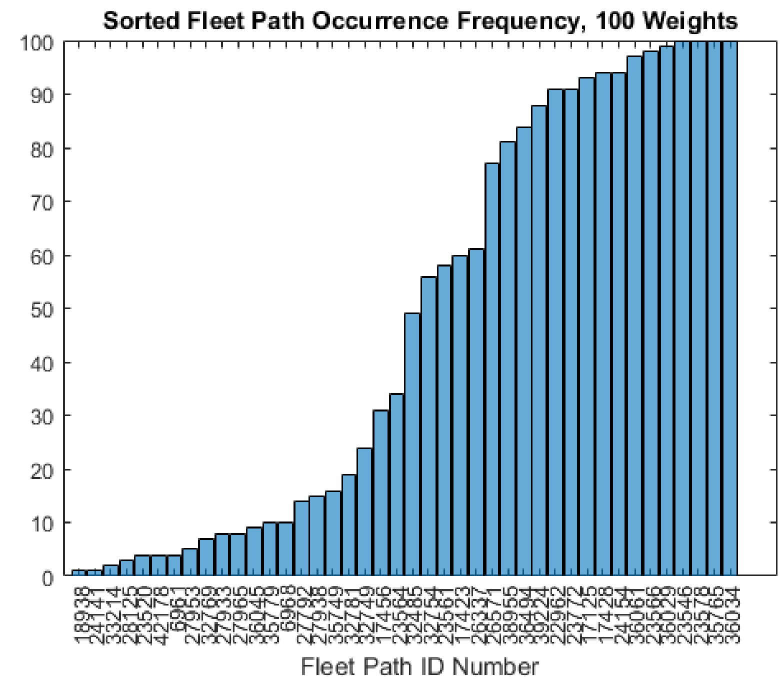



Figure 46: Total occurrence of various paths in the top 20 most adaptable paths, under each of 100 randomized weighting scenarios.

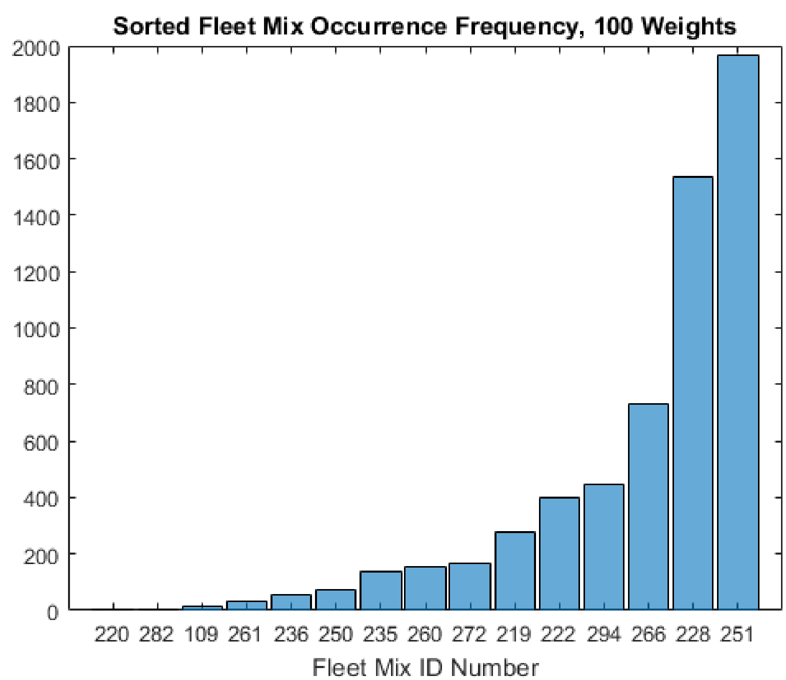



Figure 47: Total occurrence of fleet mixes associated with top the 20 fleet paths under each of 100 randomized weighting scenarios.

on missions). This second investigation showed that although there is some degree of instability in the solution, there is still a marked decrease in the number of options that must be investigated under shifting weightings. Furthermore, the increase in fleet plan options under these weightings is not very large. By answering Research Questions 3.1 and 3.2, Hypothesis 4 can be tentatively accepted with the understanding that the results can be improved in the future with a more tailor-made method.

## *5.2 Step 2: Testing the Thesis*

### 5.2.1 Experiment 4: Demonstration of the Methodology With and Without Interoperability

#### *5.2.1.1 Introduction and Experimental Setup*

The final experiment will investigate the primary hypothesis of the paper: That an interoperability-enabled fleet mix plan would create significantly more adaptable fleet plans that one that does not incorporate interoperability. To evaluate this thesis, a methodology had to be created to address multiple gaps in the literature: that interoperability had not been modeled in fleet mix planning problems, that adaptability had not been defined with respect to fleet mix plans, and that for defense applications there had to be a link between those SoS operating in missions and the strategic force they belonged to.

It is important to first note that there are many more expansions of this methodology that can and should be added to enhance its benefits to the decision-making process. Thus the methodology represents a framework of sorts that functions as a guideline for how to study this type of problem. The fleet scaling method developed, the adaptability definition used, and perhaps expansions such as modularity and costing can all be modified or added to further strengthen this methodology.

The claim in Hypothesis 1 will be investigated by proceeding through the methodology twice: Once with fixed interoperability values (effectively stripping out the interoperability analysis) and once with variable interoperability. In effect, this is a demonstration of interoperability as a potential technology infusion into the fleet mix. The goal is to enable the investigation of whether inserting an asset with fixed interoperability will improve or worsen adaptability. Simultaneously, an investigation can take place regarding whether interoperability has more or less effect on adaptability than any other asset design variable. It is hypothesized that more of the fleet mix plans generated with the first iteration will be more adaptable than those generated with the second.

The experimental setup consisted of creating another combat mission, this one modeled on Operation Cobra, which was a more tank and aircraft heavy battle than was OMAHA beach, where a majority of the bombers missed their targets and a large number of the tanks failed to land. The input data for this mission are provided in an appendix. However, due to insufficient historical data regarding the results, only the general trend of the combat mission was modeled.

OMAHA beach and Operation Cobra thus served as the two missions of the “multi-mission’ methodology. They had sufficient similarities in terms of assets that some assets could overlap, and sufficient differences so as to provide variety. The capabilities of the respective SoS in these missions were explored in an optimizer - in both cases, an additional asset was inserted into the SoS in order to determine whether adding this asset was beneficial or not to the MoEs for each mission. The asset could take the form of a soldier, vehicle, or aircraft asset type, and had varying inputs depending on which of these forms it took in the optimizer. Each asset type was explored an equal number of times (population of 100 for each asset type) in the NSGA-II implementation in MATLAB for a final population of 300. Although this could bias the results towards one or more assets, the goal of this experiment was not to design an asset - the asset simply served as a foil for the exploration of interoperability that also took place.

The combat model requires two lethality matrices as inputs. One matrix describes each offensive asset population’s lethality against each defensive asset population’s lethality. The second describes the opposite - lethality of defensive populations against offensive ones. The new asset would require lethality values for and from each enemy asset population, which would imply many more design variables for the optimizer to vary. To reduce the number of variables required, the asset's row (and column) matrices were simplified by grouping enemy assets into similar types. The resulting seven enemy types are in the following list, and lethality by the new asset as well as weakness of the new asset were both based on only these seven types instead of the much longer original list.

1. Soldier
2. Morter and Machine Gun Emplacements
3. Artillery
4. Anti-Air
5. Double Embrasure Pillboxes
6. Tank
7. Tank Destroyer

The fixed-interoperability trial set the interoperability value at 0.6 as was done in the baseline case. This was done to prevent the optimizer-guided exploration from treating this value as an input. After the optimizer guided exploration created 300 non-dominated fleets and the baseline was added to the set (for a total of 301 fleets), the fleets and MoEs were scaled up according to the historical data for asset numbers, and combined to form single "strategic-level" fleets (in this case, a strategic fleet that can only perform two mission types). These strategic level fleets were used to create a set of fleet paths, created via the "all simple paths" algorithm described in a previous section. The fleets were ranked based on the adaptability criterion. The same process was repeated for the second variable-interoperability case, except that in this set interoperability was allowed to vary from 0.4 to 1.

The number of fleet plans created depended on the threshold value used for fleet plan generation - in other words, the maximum allowable distance between the fleets. This number is a function of the number of different assets as well as the price per asset. Notional values were created for price per asset - for the purposes of demonstrating the point, the actual values did not matter as much as the distance between the fleets. The following table shows notional per-asset costs used for this experiment:

Table 9: Notional asset costs

| Inf. | Eng. | Chem. | LCVP | LCT | LCA | LCM | LCI |
|---|---|---|---|---|---|---|---|
| $\$1 * 10^4$ | $\$2 * 10^4$ | $\$2 * 10^4$ | $\$3 * 10^6$ | $\$4 * 10^6$ | $\$2 * 10^6$ | $\$8 * 10^6$ | $\$1 * 10^6$ |
| DUKW A | DD A | DUKW | DD | Ship | Bazooka | L. Mort. | M. Mort |
| $\$1 * 10^4$ | $\$2 * 10^4$ | $\$3 * 10^4$ | $\$3 * 10^6$ | $\$4 * 10^6$ | $\$2 * 10^6$ | $\$8 * 10^6$ | $\$1 * 10^6$ |
| LMG | MG | M18 | M4 | M5 | L. Art. | Art. | Bomb. |
| $\$1 * 10^4$ | $\$2 * 10^4$ | $\$3 * 10^4$ | $\$3 * 10^6$ | $\$4 * 10^6$ | $\$2 * 10^6$ | $\$8 * 10^6$ | $\$15 * 10^6$ |
| New Sldr | New Veh. | New A/C | | | | | |
| NewPrice | NewPrice | NewPrice | | | | | |

Figure 10 shows the notional costs per each functional characteristic level for the new asset. Because each variable was normalized prior to being priced, each variable's cost would only vary within a predictable range. Furthermore, some variables were treated differently because the measure of goodness was reversed, e.g. a high failure rate was worse and less costly to achieve than a low failure rate. The effect of the cost of interoperability was tested in a separate analysis and was not shown to significantly affect the conclusion. Of course, having a far higher fidelity cost model would be an important next step in showing the benefits of the methodology.

Table 10: New asset notional functional characteristic costing

| Variable | Price $c$ | Equation, where $v$ is variable level |
|---|---|---|
| Interoperability | $\$1 * 10^4$ | $c \times 10v$ |
| Effective Radius | $\$1 * 10^4$ | $c \times v$ |
| Average Speed | $\$1 * 10^3$ | $c \times v$ |
| Failure Rate | $\$1 * 10^4$ | $c \div v$ |
| Fire Rate | $\$1 * 10^4$ | $c \times v$ |
| Launch Rate | $\$1 * 10^2$ | $c \times v$ |
| Endurance | $\$1 * 10^3$ | $c \times v$ |
| Lethality | $\$1 * 10^4$ | $c \times 10v$ |
| Survivability | $\$1 * 10^4$ | $c \div 10v$ |

As each asset is an orthogonal vector when determining fleet costs, the cost threshold has a significant effect on the number of fleet paths created. The following three figures illustrate this point, as well as show which threshold was chosen and why. As seen in Figure 48, the number of fleet paths created with a threshold of $\$1 \times 10^8$ is relatively small (1,020 paths), while in the case of Figure 49 the number was 152,104. In the case of variable interoperability shown in Figure 50, the number of paths is 443 with the lower threshold and 47,264 with the higher one. To provide the method with adequate fleet paths to work with and utilize a greater range of the design space exploration outputs (with 443 paths, it is unlikely that each fleet was used at least once), the $\$5 \times 10^8$ threshold was chosen.

It is reasonable to wonder whether the use of a simple summation across the fleets within each plan is sufficient to compare adaptability across plans. In figures 52 and 53, we see that although there is indeed variation in the adaptability values within each plan, the variation in the best-adaptability plans can be rather small so long as at least one decision set in each time step is adaptable and feasible given the cost threshold. Because the plans were enumerated via an all simple paths solution, so long as the depth-first search concludes, it will have enumerated all possible paths and therefore the best-ranked paths will always tend toward having the smallest available adaptability criteria per time step.

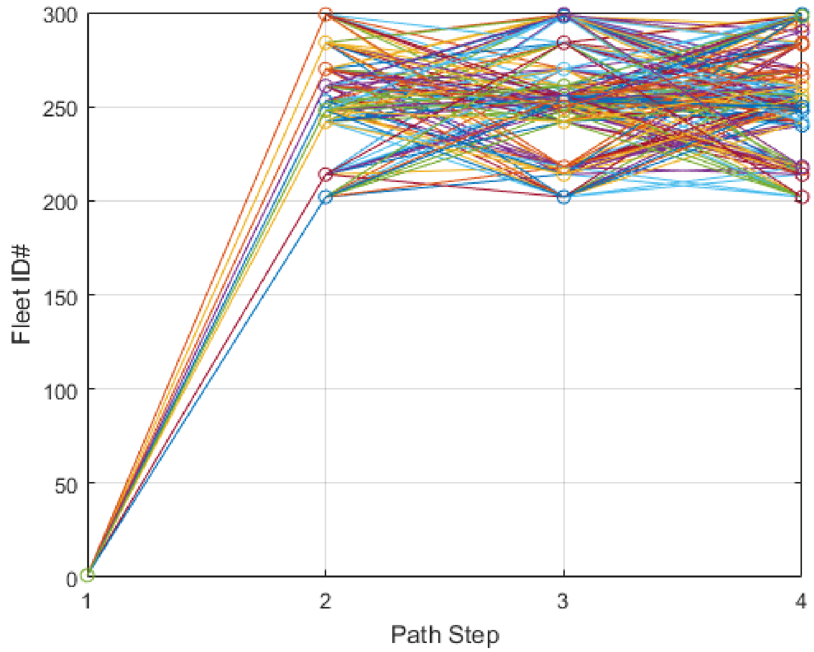



Figure 48: Fixed-interoperability case with distance threshold of $\$1 \times 10^8$, all paths plotted

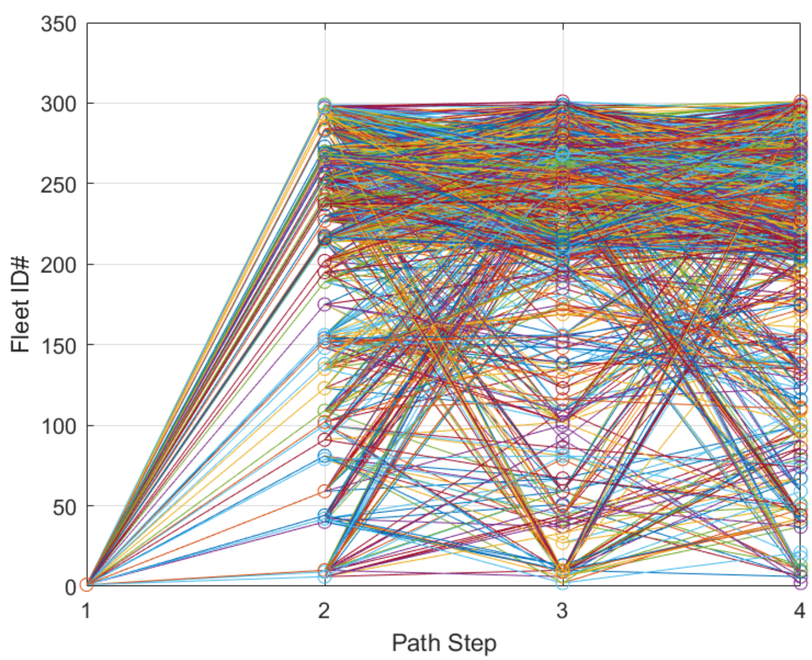



Figure 49: Fixed-interoperability case with distance threshold of $\$5 \times 10^8$, only 1 in 100 paths plotted

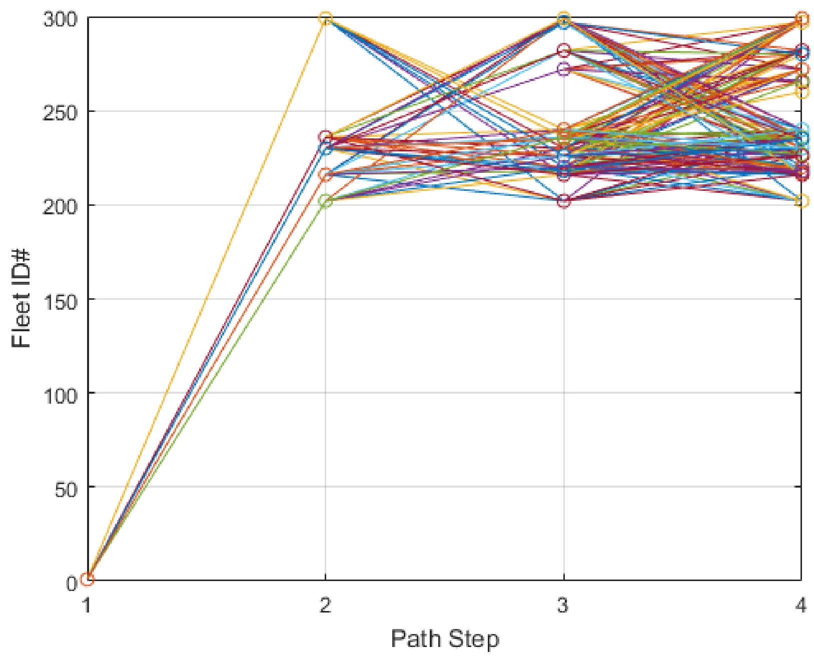



Figure 50: Variable-interoperability case with distance threshold of $\$1 \times 10^8$, all paths plotted

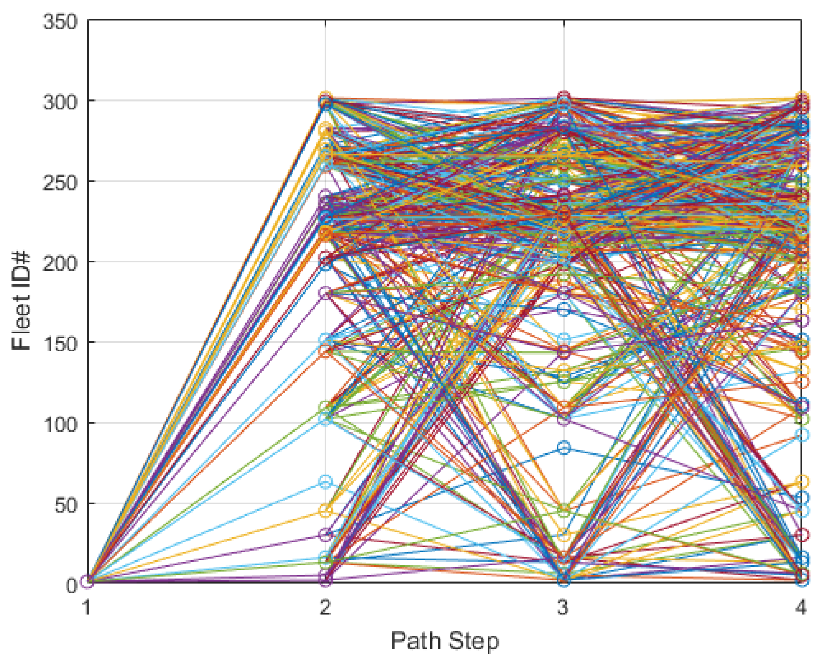



Figure 51: Variable-interoperability case with distance threshold of $\$5 \times 10^8$, only 1 in 100 paths plotted

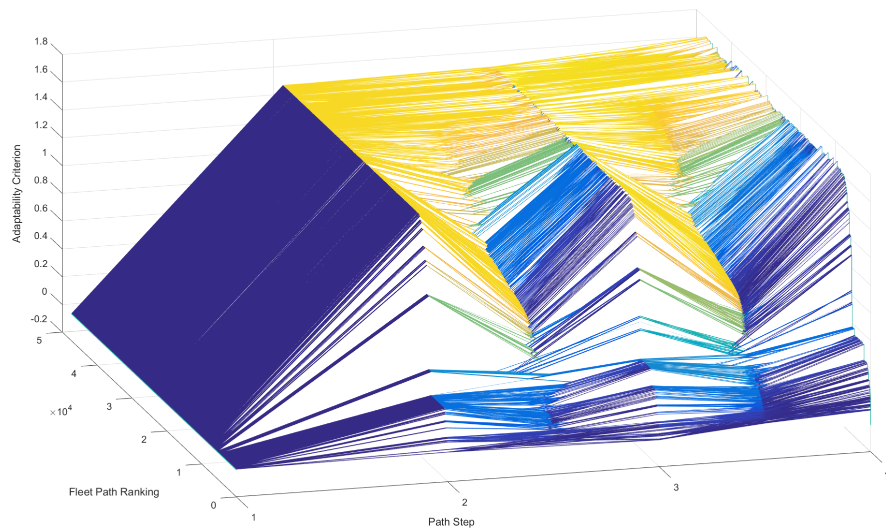



Figure 52: Variation of adaptability in the variable-interoperability case, plotted against path step and ranking. Colored by adaptability criterion value.

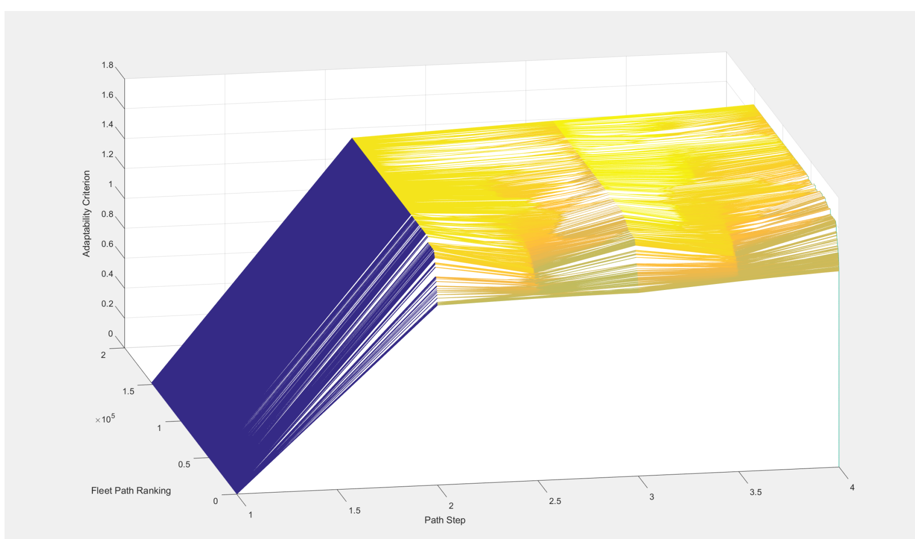



Figure 53: Variation of adaptability in the fixed-interoperability case, plotted against path step and ranking. Colored by adaptability criterion value.

Once the analyst begins to look at the middle range of options, however, the decision set becomes more complicated and less easier to understand with a simple summation. Whereas in the best and worst adaptability cases, variation within the path is relatively small, the middle range consists of both middle-of-the-road adaptability decision sets as well as fleet paths that mix very high and very low adaptability fleet mixes.

To summarize, the following list describes the overall experimental setup:

1. Optimizer-guided exploration - Separate run for each of 3 asset types, NSGA-II with 50 generations, population of 100
   (a) For each mission
      i. Mission scenario inputs and participant forces are loaded
      ii. Selection of design variables for asset and asset insertion into attacking force - only one asset type at a time
      iii. Hybrid discrete-events model performs combat
      iv. Post-processing step to calculate mission effectiveness to feed up to optimizer-guided exploration
   (b) Save final population in preparation for fleet scaling - each member of population has one unique new asset inserted in addition to the baseline fleet
2. Fleet scaling
   (a) Nominal costing for each asset type
   (b) For new asset - each design variable assumed to have simple linear relationship with cost, with nominal linear terms
   (c) Fleet scaling factor calculated based on "global" performance variables for each of two missions
   (d) Missions are assumed to have no overlap
3. Fleet planning wrapper
   (a) Each asset type is considered as a separate dimension in cost-space
   (b) Each scaled fleet's city block cost distance to each other fleet is calculated via

MATLAB pdist2.m

(c) Distance matrix converted to adjacency matrix by imposing logical condition: distance should not equal 0 and should be less than cost threshold

(d) Graph created from adjacency matrix, converted into directed graph with all self-intersecting nodes converted to non-intersecting direction

(e) Recursive depth-first search performed to salve all simple paths problem

(f) Save all path and fleet information

4. Fleet path adaptability calculator

    (a) Fix uncertainty bounds to be permissive of all fleets, set all mission and cost weights to be equal

    (b) Recursive search through each row of adjacency matrix - at each decision, calculate adaptability criterion and insert into matrix

    (c) For each fleet mix in each path, pull its adaptability criterion from the matrix

    (d) For each fleet path, sum the adaptabilities of the mixes to get the adaptability of the path

The following figure puts this summary into more visual terms. The squares with a solid gray fill and a colored outline are ones which have some sort of defaulting or nominal values. This includes the use of nominal costs, the defaulting of the capability and budget uncertainties to be highly permissive, and the use of the scaling method without asset overlap.

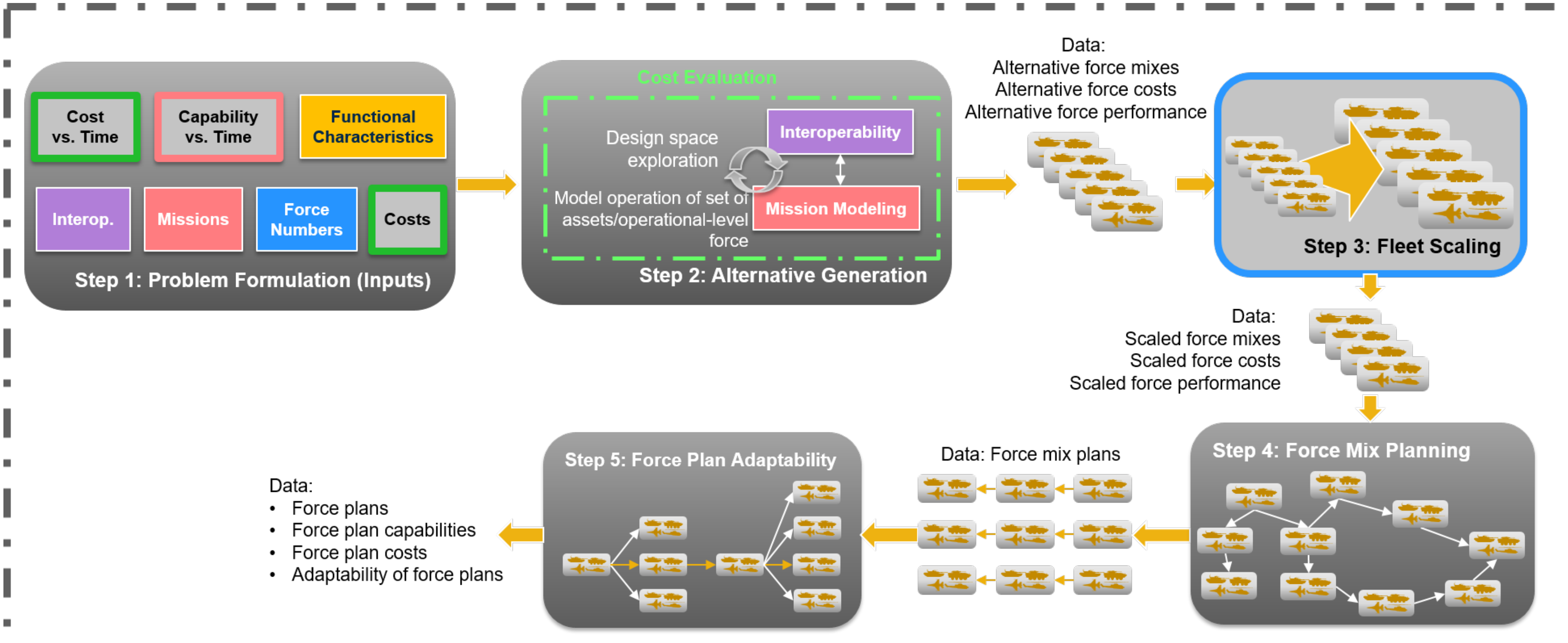



Figure 54: Simplified instantiation of methodology for purposes of demonstration

This figure shows the full methodology, as used for this demonstration. The squares with a solid gray fill and a colored outline are ones which have some sort of defaulting or nominal values. This includes the use of nominal costs, the defaulting of the capability and budget uncertainties to be highly permissive, and the use of the scaling method without asset overlap.

### 5.2.1.2 Demonstration Results

The first step is to investigate some fleet mix plans to provide a reminder of what the results actually describe. In Chapter 1, Figures 4, 7, and 8 were shown. They are reproduced here. The goal of the demonstration is to show that it is possible to begin to make tradeoffs regarding asset design and acquisition in order to improve the adaptability of fleet plans. Furthermore, a goal is to show that interoperability's effect on adaptability of fleet plans can be investigated. Thus, each figure in this section will show the effects of asset variables on fleet *plans* and on fleet plan adaptability. Not the effect on individual fleet *mix* adaptability.

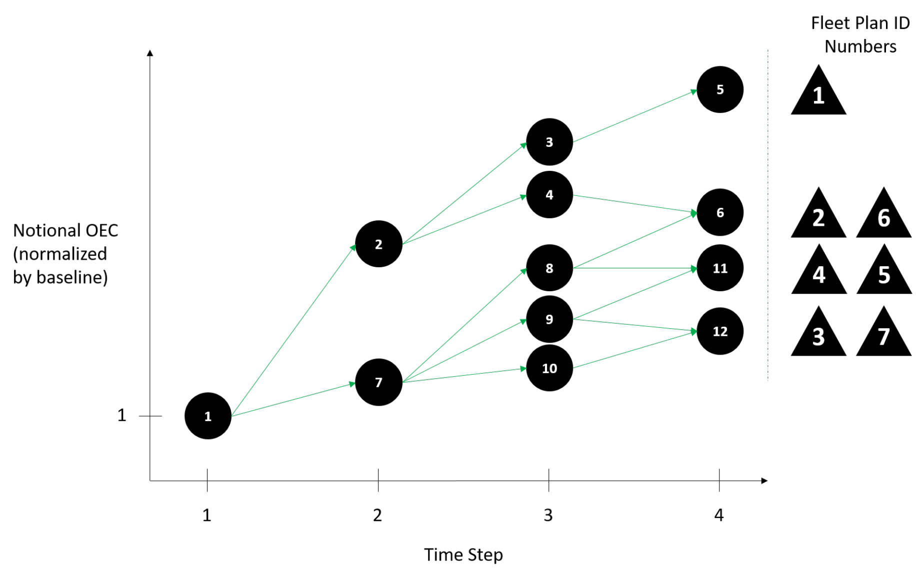



Figure 55: Notional chart of fleet mixes ranked by some OEC and connected via lines of cost sufficiency, i.e. is the cost difference smaller than some incremental budget increase.

Within each plan, each fleet mix consists of the baseline fleet (the assets involved in the historical missions) plus one additional new asset (in varying numbers). Each fleet mix may thus vary from each other fleet mix by the functional characteristics of the new asset, in which case it is assumed to either be a different design entirely or an upgraded version of a previous design. Or, a fleet mix may vary from another fleet mix by simply the quantity of the new asset included in the fleet. In almost all cases, fleet mixes will vary from each other in *both* of these ways.

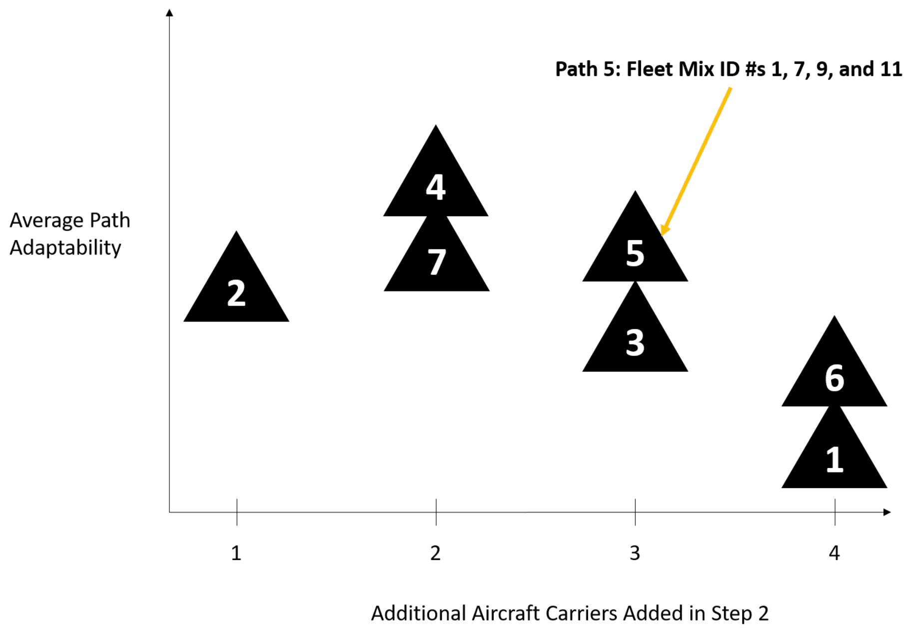



Figure 56: Potential way to investigate the effects of acquisition decisions on fleet mix adaptability.

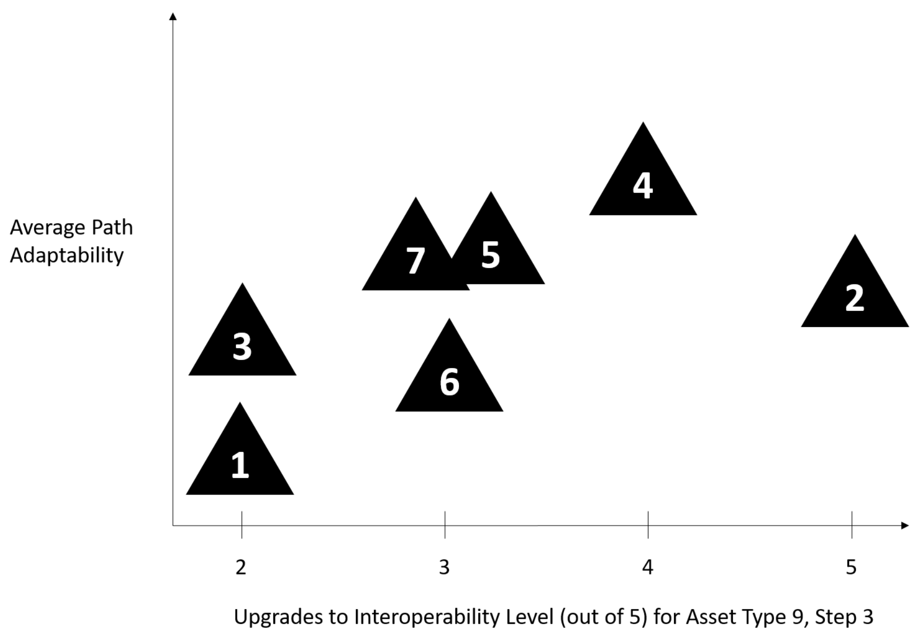



Figure 57: Potential way to investigate the effects of increasing interoperability in one system on fleet mix adaptability.

An example is provided in Tables 11 through 13. In these tables we can see how the asset evolves from the time step in which it is added, to the final time step. In the most adaptable case, we have a vehicle with relatively better interoperability with assets in the fleet than they do with each other. Its quantities are constant for the first two time steps but increase modestly in the last. Finally, it appears to be a somewhat lightly-armored asset with a high anti-armor capability. The second most adaptable fleet is identical to the first in the first two time steps, differing only in the third time step. In this step, the vehicle retains its previous interoperability (as opposed to a small increase previously) and has a smaller increase in quantity of just 15 added to the fleet, as opposed to 69 in the most adaptable case. The strengths and weaknesses of the asset do not change significantly - tanks, tank-destroyers, artillery, and double embrasure pillboxes (DEPs) are featured prominently, though this time the vehicle omits tank-destroyers from both its strengths and its weaknesses.

When compared against the least adaptable fleet plan, it is interesting to note a few differences. The first is how much larger the quantity of assets becomes at each step. Another difference is the continually-decreasing interoperability, which decreases by roughly .3 at each step. Furthermore, it should be noted that the lethalities (both by and against the asset) seem to fluctuate relatively greatly between time steps. This could mean that they are less important drivers of adaptability than are other variables, such as the quantity.

Table 11: Most Adaptable Fleet Plan - New Asset Evolution

| Step | Fleet ID | Asset | Interop. | Quantity | Strongest Against | Weakest To | Friendly Cas. | Enemy Cas. | Cost |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 228 | Vehicle | .75 | 357 | Tank Destr. (.033) | Tank Destr. (.036) | 1.0232, 0.4517 | 2.1913, 11.4488 | 1.0080 |
| 2 | 251 | Vehicle | .69 | 357 | Tank Destr. (.031) | Artillery (.025) | 1.0356, 0.4502 | 2.2293, 11.4488 | 1.0097 |
| 3 | 222 | Vehicle | .70 | 426 | Tank (.032) | Tank Destr. (.035) | 1.0245, 0.5246 | 2.0661, 11.4488 | 1.0152 |

The evolution of the new asset in the most adaptable fleet plan, across time steps. For Tables 11, 12, and 13, the interoperability column is the new asset's interoperability with other assets, not a fleet-wide interoperability. Friendly casualties, enemy casualties, and cost are all normalized by the baseline fleet. Friendly and enemy casualties list Omaha Beach, then Operation Cobra numbers.

Table 12: Second Most Adaptable Fleet Plan - New Asset Evolution

| Step | Fleet ID | Asset | Interop. | Quantity | Strongest Against | Weakest To | Friendly Cas. | Enemy Cas. | Cost |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 228 | Vehicle | .75 | 357 | Tank Destr. (.033) | Tank Destr. (.036) | 1.0232, 0.4517 | 2.1913, 11.4488 | 1.0080 |
| 2 | 251 | Vehicle | .69 | 357 | Tank Destr. (.031) | Artillery (.025) | 1.0356, 0.4502 | 2.2293, 11.4488 | 1.0097 |
| 3 | 294 | Vehicle | .69 | 372 | Tank Destr. (.025) | Artillery (.028) | 1.0390, 0.3323 | 2.1819, 11.4488 | 1.0128 |

The evolution of the new asset in the 2nd most adaptable fleet plan, across time steps.

Table 13: Least Adaptable Fleet Plan - New Asset Evolution

| Step | Fleet ID | Asset | Interop. | Quantity | Strongest Against | Weakest To | Friendly Cas. | Enemy Cas. | Cost |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 301 | Vehicle | .53 | 249 | Tank Destr. (.023) | Tank (.021) | 1.0155, 1.5809 | 1.0228, 1.2689 | 1.0085 |
| 2 | 206 | Vehicle | .50 | 411 | Tank Destr. (.034) | Tank (.043) | 1.0309, 1.1094 | 1.0306, 1.5031 | 1.0152 |
| 3 | 209 | Vehicle | .46 | 537 | Tank Destr. (.028) | Tank Destr. (.044) | 1.0196, 1.1165 | 0.9314, 1.4513 | 1.0233 |

The evolution of the new asset in the least adaptable fleet plan, across time steps.

Comparing the performance characteristics, we see that both of the adaptable fleet plans have much better results in the Operation Cobra model, compared to the worst-adaptable fleet plan. Interestingly, the least-adaptable plan performs better in friendly casualties in Omaha Beach (fewer casualties). However, because the two MoEs and the two missions are all given equal weightings, the far superior Operation Cobra enemy casualty results overwhelm everything else. Furthermore, the least adaptable fleet plan is also more expensive at every time step. Comparing the two most adaptable plans, the 2nd most adaptable plan actually performs better than the first in half of the MoEs (Operation Cobra friendly casualties and Omaha Beach enemy casualties), and matches the results for the Operation Cobra enemy casualties. Additionally, it is cheaper. This shows the potentially unintuitive nature of adaptability as developed here - because the loss function was taken to be an OEC that is modified by the number of options at each time step, the OEC values do not tell the whole story of which fleet is “better”.

Another perhaps unexpected development is the decrease in interoperability in some of the fleets. There are two answers to this question, a low-level and high-level answer. The lower-level answer is threefold: in this instantiation, there was no forcing function used to dictate that fleet mixes may not get worse in a given functional characteristic. Implementing such a forcing function would lower the number of possible fleet plans. Second, and relatedly, only the final population of the optimizer was kept for the fleet planning process, whereas potentially one could keep every population produced by the optimizer. This means that the fleets produced are relatively non-dominated (depending on whether the optimizer was allowed to converge) - non-dominated fleets will defy any forcing function that attempts to apply this constraint to all functional characteristics (or numbers of assets) in the fleet. Finally, fleet plans are calculated via the solving of an all simple paths problem. All simple paths are defined as those paths which do not self-intersect at any point along the path, meaning the path cannot repeat a fleet. Taken together, this means that in this instantiation the combination of using a non-dominated fleet population precluded the use of a forcing function to force fleets to stay the same or improve, thus no fleet can strictly improve over any other fleet and no fleet plan could repeat a fleet to satisfy this forcing function.

A higher-level answer to this question bypasses all of the limitations of this demonstration. If this result were to occur in a real implementation, what would that mean? It could mean one of two things - first, that the time steps in this implementation are so large that this is in fact a completely separate vehicle that performs worse in one metric than its precursor. Since these functional characteristic values can serve as minimum values for any given variable, one can interpret this result as implying that the next version of the vehicle need not be as interoperable as its predecessor and yet must interoperate with a reliability of at least 0.69, with the same costs and performance as in the combat model, for the fleet plan adaptability prediction to hold. If the vehicle exceeds this interoperability requirement without sacrificing in any other metric, that is acceptable. A similar interpretation is that this vehicle is an upgrade to the previous vehicle, and that to make room for certain components that guarantee other functional characteristic levels, certain interoperability components had to be removed, and that furthermore this removal is acceptable in terms of fleet plan adaptability.

The discussion of the specific fleet mixes is meant to provide some context for what exactly will be evaluated in this section. In the following analyses, the tables discussed above will not be referenced again. Much as in Figure 57, each data point in the following analyses will contain an fleet plan consisting of 4 fleet mixes (3 + a baseline). This means that, e.g., 11 will be condensed into a single data point, as will all the others. When specific design variables are discussed in the context of fleet mix plans, such as interoperability or lethality, they will be the average design variable values of the assets within each plan.

The adaptability criteria for both sets of fleet plans are plotted against each other. In Figure 58, fixed and variable interoperability cases are shown. It can be seen that the adaptability of the paths is more variable in the case of variable interoperability, as can be

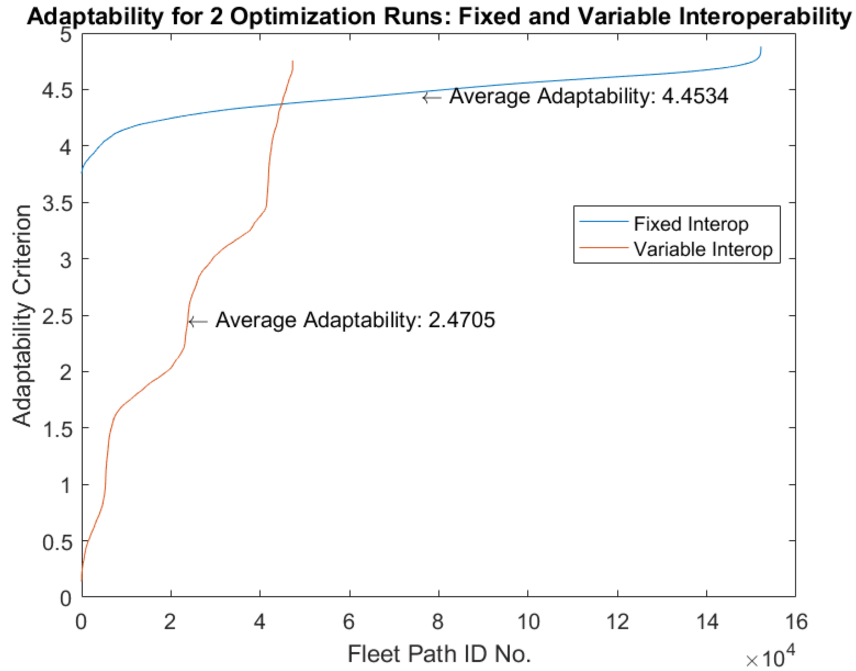



Figure 58: Adaptability of fixed- and variable-interoperability fleet paths, Y-axis starts at 3.8

seen by the tips of the variable line. This is reasonable to expect, since both poor and good interoperability were included. The poor-interoperability cases do not do worse than the fixed-interoperability cases because interoperability does not have a favorable effect until a certain threshold value is reached, as per the discussion regarding collaboration effects. As highlighted, the average adaptability was indeed lower in the variable case, although not by much, because of the poor-interoperability tip. This is illustrated in the next figure.

The average interoperability setting across each fleet plan was used as the metric by which to color the two lines, with warmer colors reflecting higher interoperability in the fleet plan overall. The colors were normalized from 0 to 1 for both datasets, meaning the colors are absolute and can be compared to each other. The results are shown in Figure 59. It can be seen that on the whole, fleet plans with a higher average interoperability setting produced higher adaptability (a lower criterion), whereas low-adaptability paths produced worse results. It should be noted, however, that there are some bands of higher or lower interoperability cases (this will be referred to as “banding”).

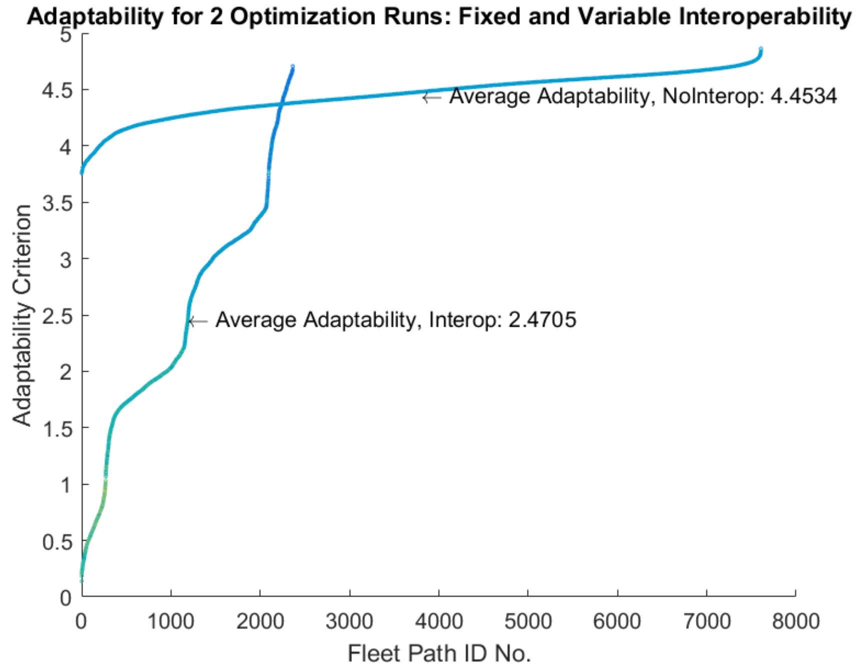



Figure 59: Adaptability of fixed- and variable-interoperability fleet paths, colored by interoperability, Y-axis starts at 3.8

To determine whether this effect was unique to interoperability, or was true for other variables as well, the same plot was produced for all design variables of the asset being added into the fleet. This plot is shown in Figure 60. It should be noted that “leth1”-“leth7” and “def1”-“def7” are lethality variables against different asset types, and launch start and launch rate were not varied throughout the model as they are not asset design variables but ConOps variables. Interoperability is in the top left plot, and it can be seen that it is the only variable with a constant, nearly banding-free change from lower to higher values of interoperability. This point is better illustrated in Figure 61.

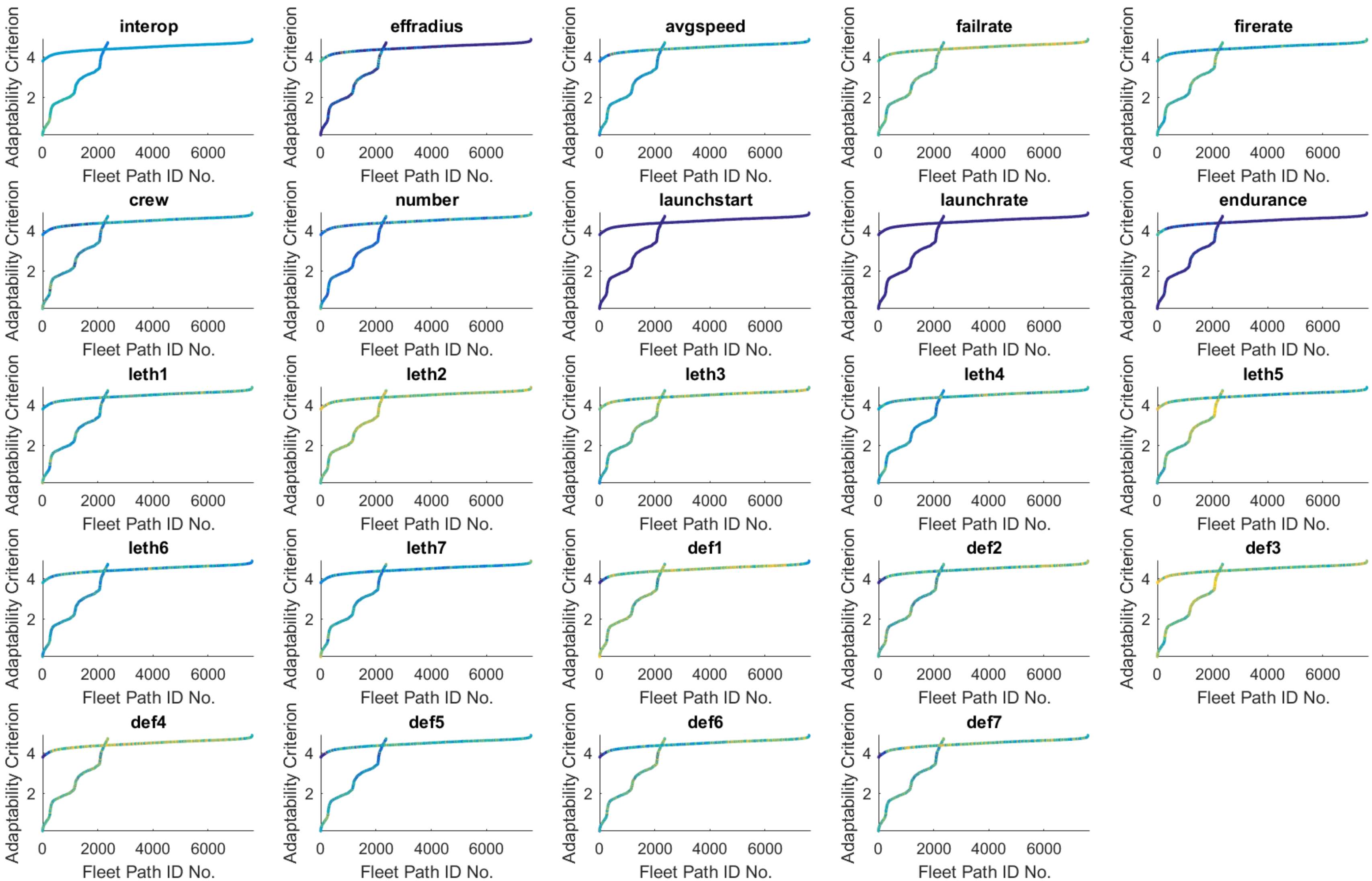



Figure 60: Adaptability of fixed- and variable-interoperability fleet paths, colored by various design variables

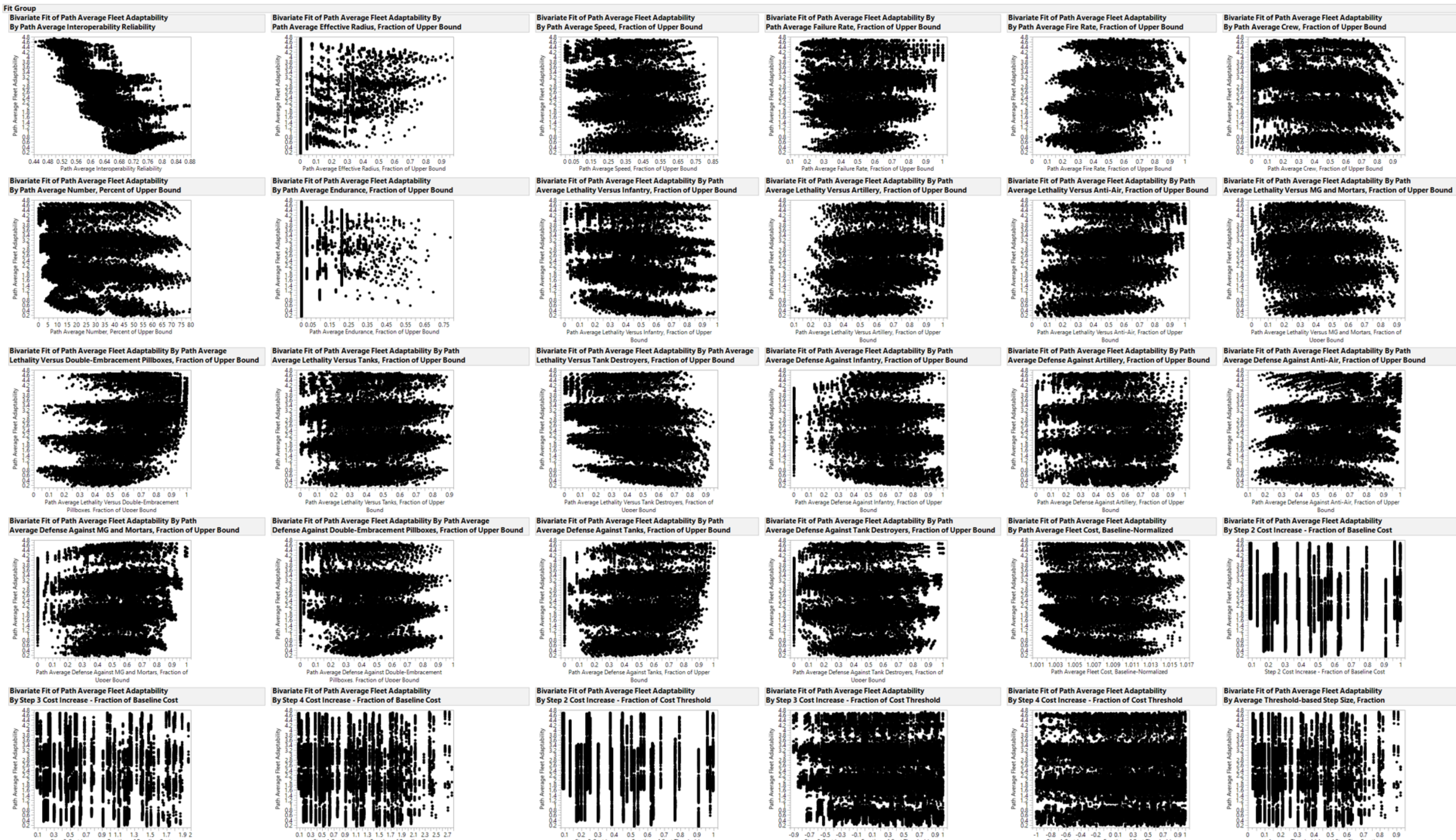



Figure 61: All variables plotted against adaptability, for variable-interoperability case

In Figure 61, it can be seen that only interoperability has any resemblance of an effect on adaptability. In some cases, lethality or other variables do have a slight effect, but on the whole there is little correlation. This is in contrast to the result of any specific run of the combat model, where the most important variables are the lethalities, the fire rate, and the number of (and crew inside) assets. As both combat models are currently deterministic, these effects cannot be explained by an insufficient number of replications, either.

A perfect fit to the data is illusive, partly because a fit was attempted only with functional variables and not cost. However, even from a comparison of two admittedly rudimentary and imperfect fits, something can be gleaned. First, fits were created for the variable interoperability case. The actual by predicted plots of these fits (as well as R Square values) are shown in the next two figures.

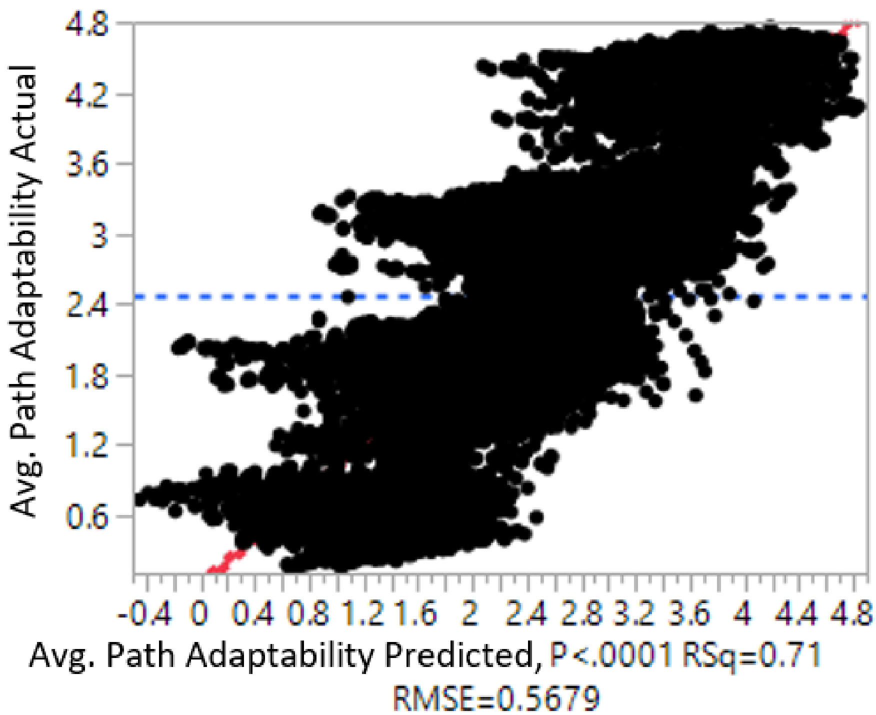



Figure 62: Actual by predicted plot for variable-interoperability case, with $R^2$ = 0.71

In general, the results in Figure 62 look better, though still not perfect, when compared to Figure 63. The $R^2$ values bear this out as well. However, these fits were not created with the same variables. The fit for the fixed-interoperability case had an advantage, in that many

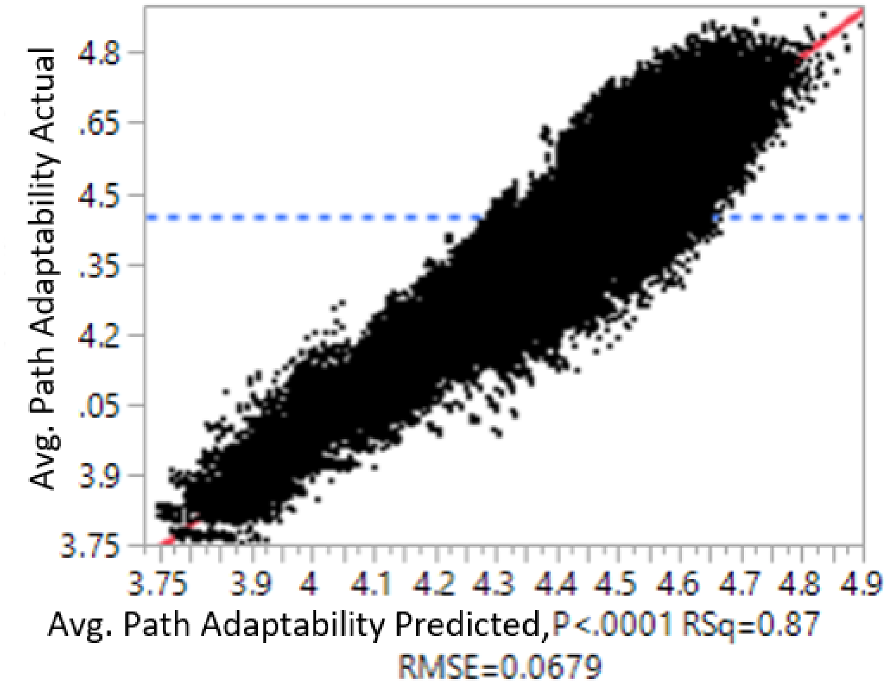
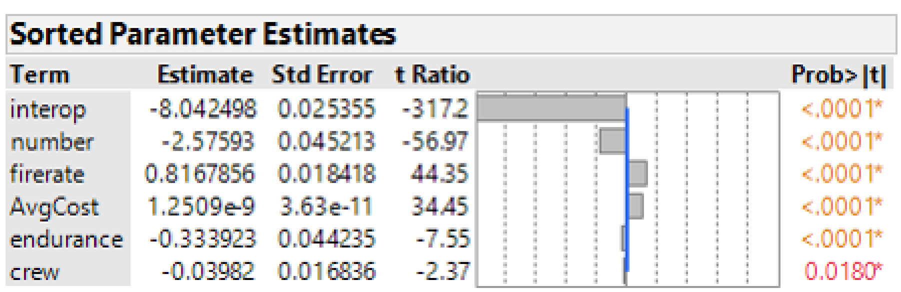



Figure 63: Actual by predicted plot for fixed-interoperability case, with $R^2 = 0.48$

more variables were used to create it. Figures 64 and 65 show which variables were used for the respective fits. As seen in Figure 64 only six variables and one interaction term are used for the variable case, with interoperability responsible for the greatest amount of variability. However, in Figure 65, almost 4 times the number of variables and no interaction terms were used to generate the worse fit. Reducing the number of variables for the fit did not improve the $R^2$.



**Sorted Parameter Estimates**

| Term | Estimate | Std Error | t Ratio | Prob>\|t\| |
|---|---|---|---|---|
| interop | -8.042498 | 0.025355 | -317.2 | <.0001* |
| number | -2.57593 | 0.045213 | -56.97 | <.0001* |
| firerate | 0.8167856 | 0.018418 | 44.35 | <.0001* |
| AvgCost | 1.2509e-9 | 3.63e-11 | 34.45 | <.0001* |
| endurance | -0.333923 | 0.044235 | -7.55 | <.0001* |
| crew | -0.03982 | 0.016836 | -2.37 | 0.0180* |

Figure 64: Effects screening for parameters in variable-interoperability case

The results of this experiment are not to be considered definitive. This is because there

**Scaled Estimates**

Nominal factors expanded to all levels

Continuous factors centered by mean, scaled by range/2

| Term | Scaled Estimate | Std Error | t Ratio | Prob>\|t\| |
|---|---|---|---|---|
| leth5 | -0.13286 | 0.00074 | -179.64 | <.0001* |
| crew | -0.169221 | 0.000969 | -174.56 | <.0001* |
| def1 | -0.084395 | 0.000887 | -95.18 | <.0001* |
| leth4 | -0.074579 | 0.000785 | -95.04 | <.0001* |
| def4 | -0.076454 | 0.00081 | -94.33 | <.0001* |
| def3 | -0.071617 | 0.000888 | -80.63 | <.0001* |
| leth2 | -0.067328 | 0.000886 | -76.03 | <.0001* |
| number | -0.134304 | 0.00187 | -71.82 | <.0001* |
| step2type[Aircraft] | -0.076824 | 0.001292 | -59.44 | <.0001* |
| avgspeed | -0.045089 | 0.000793 | -56.88 | <.0001* |
| step3type[Aircraft] | -0.075504 | 0.00138 | -54.72 | <.0001* |
| step4type[Aircraft] | -0.070105 | 0.001291 | -54.30 | <.0001* |
| step4type[Vehicle] | -0.045856 | 0.000869 | -52.78 | <.0001* |
| def5 | -0.044345 | 0.000847 | -52.37 | <.0001* |
| effradius | -0.10695 | 0.002289 | -46.72 | <.0001* |
| step2type[Vehicle] | -0.036819 | 0.000849 | -43.37 | <.0001* |
| step3type[Vehicle] | -0.040238 | 0.000938 | -42.89 | <.0001* |
| def7 | -0.031484 | 0.000813 | -38.75 | <.0001* |
| failrate | -0.033767 | 0.0009 | -37.52 | <.0001* |
| leth6 | -0.011426 | 0.000915 | -12.48 | <.0001* |
| leth3 | 0.0035691 | 0.000724 | 4.93 | <.0001* |
| endurance | 0.0235638 | 0.003707 | 6.36 | <.0001* |
| leth1 | 0.0051632 | 0.000778 | 6.63 | <.0001* |
| firerate | 0.0229127 | 0.000843 | 27.17 | <.0001* |
| leth7 | 0.0219115 | 0.000781 | 28.06 | <.0001* |
| AvgCost | 0.169867 | 0.001951 | 87.05 | <.0001* |
| step3type[Soldier] | 0.1157418 | 0.001042 | 111.05 | <.0001* |
| step2type[Soldier] | 0.113644 | 0.001004 | 113.16 | <.0001* |
| step4type[Soldier] | 0.1159614 | 0.001013 | 114.46 | <.0001* |
| def2 | 0.1018502 | 0.000698 | 146.02 | <.0001* |
| def6 | 0.2310741 | 0.000739 | 312.85 | <.0001* |
| Intercept | 4.1897424 | 0.002198 | 1905.93 | <.0001* |

Figure 65: Effects screening for parameters in variable-interoperability case

are many cases where the missions could be different, or the assets. Furthermore, costs of interoperability have not been seriously examined in this methodology due to challenges in modeling these costs. Thus, in a final implementation the result could be very different. However these results are promising and show that by including all of the aforementioned methods from literature, a methodology can be created that allows for the investigation of the problem at hand. This addresses Hypothesis 1.

**Hypothesis 1:** If a methodology is developed that incorporates interoperability modeling into a traditional fleet mix planning approach, and if the adaptability of fleet mix plans to budgetary and capability uncertainty can be quantified, then the effects of interoperability on fleet mix plan adaptability can be investigated.

### 5.2.2 Comparing the Effects of Interoperability and Other Variables on Adaptability

The results shown are not definitive proof that interoperability is beneficial for adaptability, since there are so many potentially scenario-related variables. However, a comparison of the effects of interoperability on adaptability compared to other variables, as well as the types of tradeoffs enabled by the inclusion of interoperability in this scenario, will prove beneficial as a sort of sanity check as well as serve to further illustrate the types of questions that the methodology allows one to ask.

A simple scatterplot matrix was constructed for the variable interoperability case from the previous section. However, there were many design variables included in the analysis, including lethality against 7 types of enemy assets and defense against each of those 7, 3 different asset types (soldier, vehicle, aircraft), and number and other performance characteristics. Initially we will investigate only the effects of asset number, interoperability, and average fleet plan cost (average across all the fleets of a given plan) against the average adaptability of the plan.

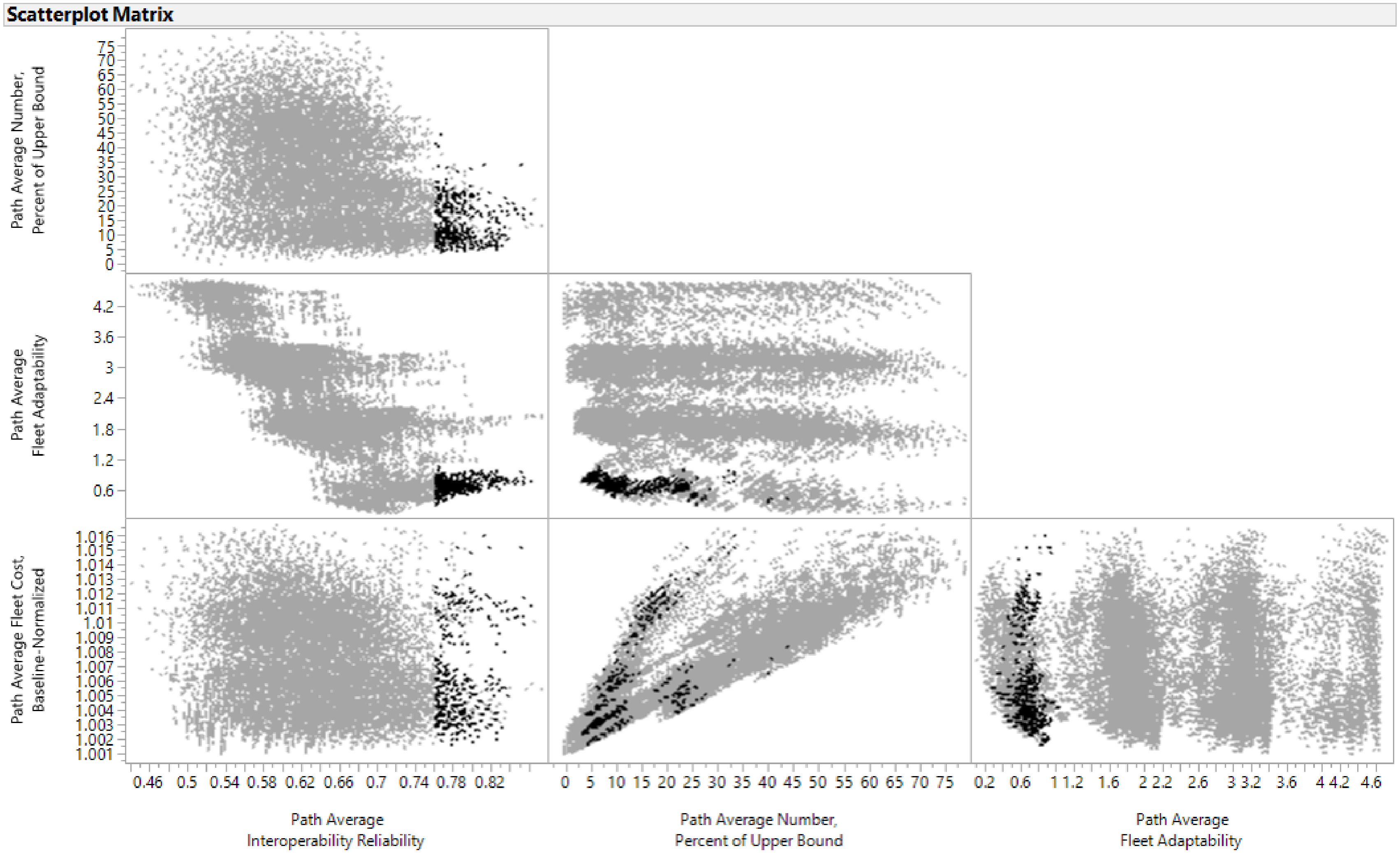



Figure 66: Any fleet paths without high interoperability and good adaptability are grayed out

In Figure 66, some paths are highlighted and the rest are grayed out. In this case, the intersection of good adaptability and high interoperability have been highlighted (in the middle-left plot). That highlighting is reflected in the rest of the plots.

A few interesting features can be seen. The first is that the number of new assets for this case is always relatively low. In fact, the scatterplot of “number” vs. “interop” shows that the fleet path calculation frequently traded number of assets for interoperability, never seeking out both at once. This is a reflection of the force-multiplying effect of interoperability versus its cost (which was notional in this example). This can be seen in the intersection of “AvgCost” and “interop”, where the high average cost seems to be skewed more towards lower-interoperability cases despite lower-interoperability cases being cheaper (all else equal, of course). In fact, the higher the interoperability, the more likely the average cost of the plan is to be cheaper (applicable within a range of roughly 0.4 to 0.84 interoperability reliability).

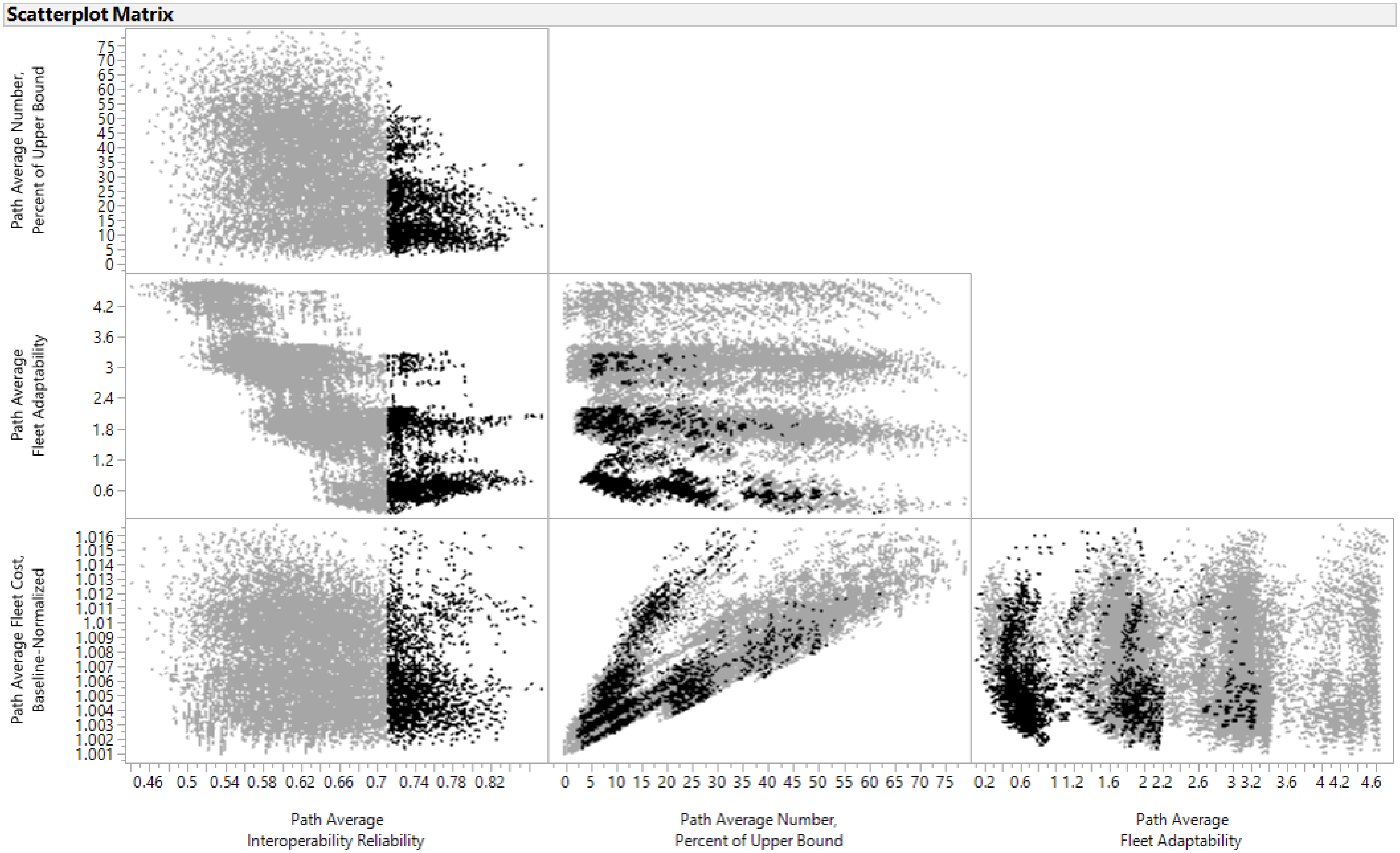



Figure 67: Any fleet paths with low interoperability are grayed out

The same is true in Figure 67, where good adaptability is removed as a criterion and only high interoperability is kept. Consistently, high-interoperability cases tend to be some of the cheapest, although they are not the only cheap cases. Conversely, low-interoperability cases tend to be some of the most expensive. This can be seen in Figure 68:

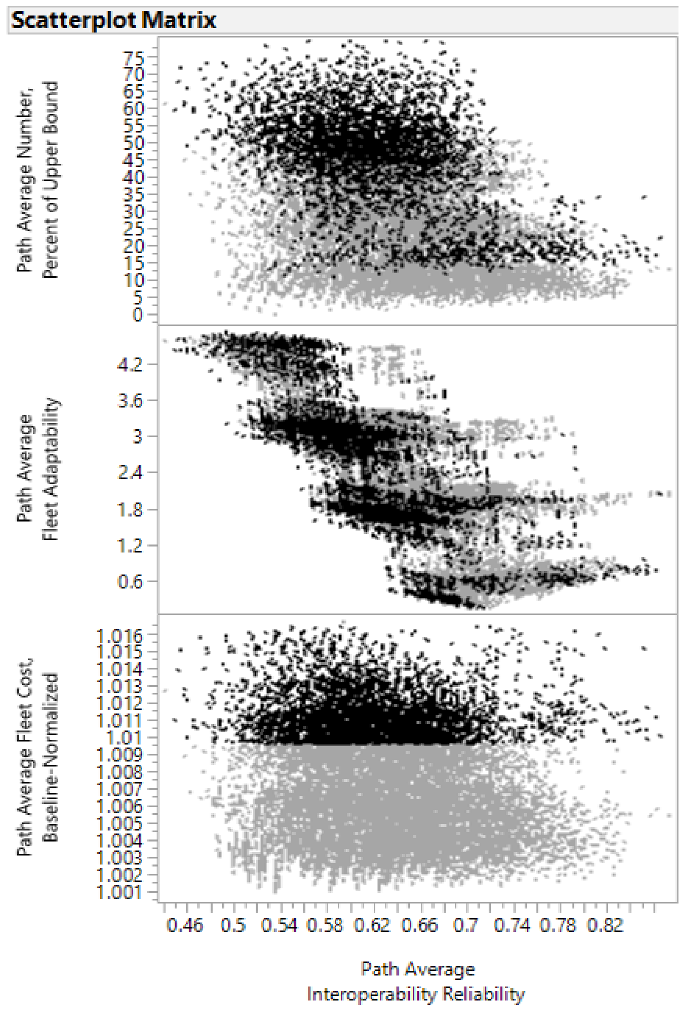



Figure 68: Any fleet paths with low average cost are grayed out

In Figure 68 only the highest-cost cases are selected. It should first be noted that the distribution of average costs is trending lower. This is because cost was one of the three performance criteria in question, along with performance at OMAHA Beach and Operation COBRA.

Second, it can be noted that all high-cost cases tend to be on the lower end of their adaptability cluster. This is especially true in the best adaptability case (lowest criterion value) and is still visible in the second best case (from “AvgAdaptability” equal to roughly 1 to 2). Only in the poor adaptability cases (“AvgAdaptability” greater than 4) can we see that a high cost begins to make the fleet paths less adaptable.

Within each cluster of adaptability, why are interoperable fleet paths generally lower-cost, but the most adaptable fleet paths are also highest cost? Part of the explanation is that interoperability is, as mentioned previously, a force multiplier which in this scenario did not result in great cost. However, to push the adaptability of the fleet paths further, more cost had to be committed (within the allowable threshold value of course). This cost manifested itself in the form of greater asset numbers or other variables. For an illustration of the first part of this idea, we can refer to Figure 69.

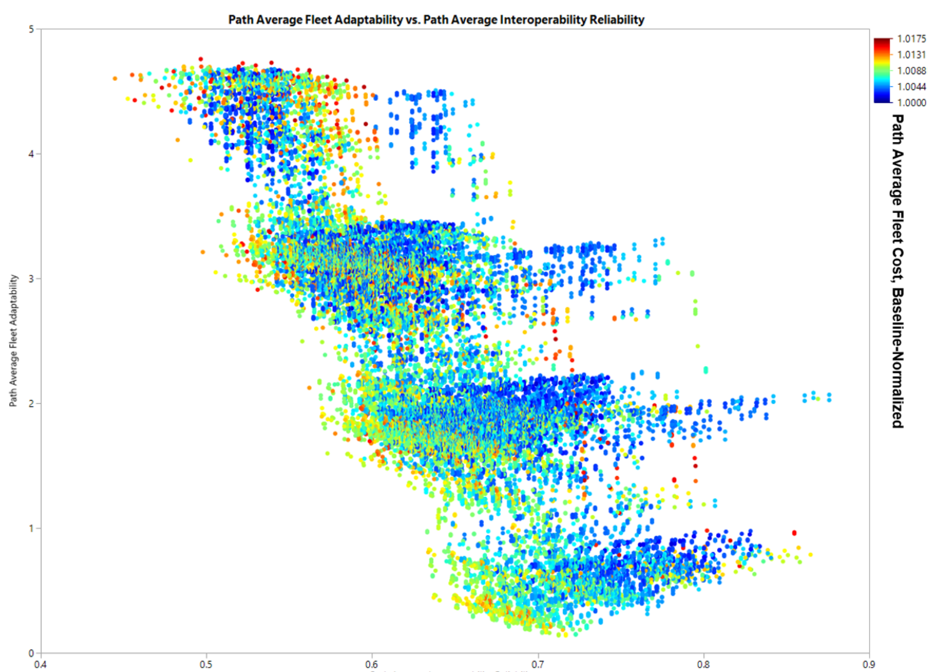



Figure 69: Average path adaptability versus average path interoperability, colored by average path cost

Here we can plainly see a sort of waterfall effect, wherein each adaptability cluster is bridged by a set of fleet paths that is high cost and relatively low adaptability for that cluster. When the fleet paths push past this barrier into the next cluster, they fall into a low cost, high interoperability region. More cost is then committed as adaptability is once more pushed to the limits possible for that cluster.

As mentioned previously, the clusters are essentially “fleet plan architectures” that reflect the type of asset used in the fleet plan, or potentially a mix of assets. This is evidenced by including asset type in the scatterplot matrix and highlighting certain cases. For instance, in Figure 70, we see that highlighting the half with medium to poor interoperability in the best adaptability cluster reveals that it is primarily composed of fleets with additional vehicles for all 3 decisions.

Conversely, from what we know regarding the tradeoffs between interoperability, cost, and asset number, this adaptability is achieved through higher relative cost due to higher number of assets. On the other hand, in Figure 71, we see that highlighting cases with good (but slightly worse) adaptability and high interoperability still shows the three-vehicle cases, but also some other combinations of soldier-soldier or vehicle-soldier. On the other hand, aircraft are almost never selected, in any time step, for this best case of adaptability.

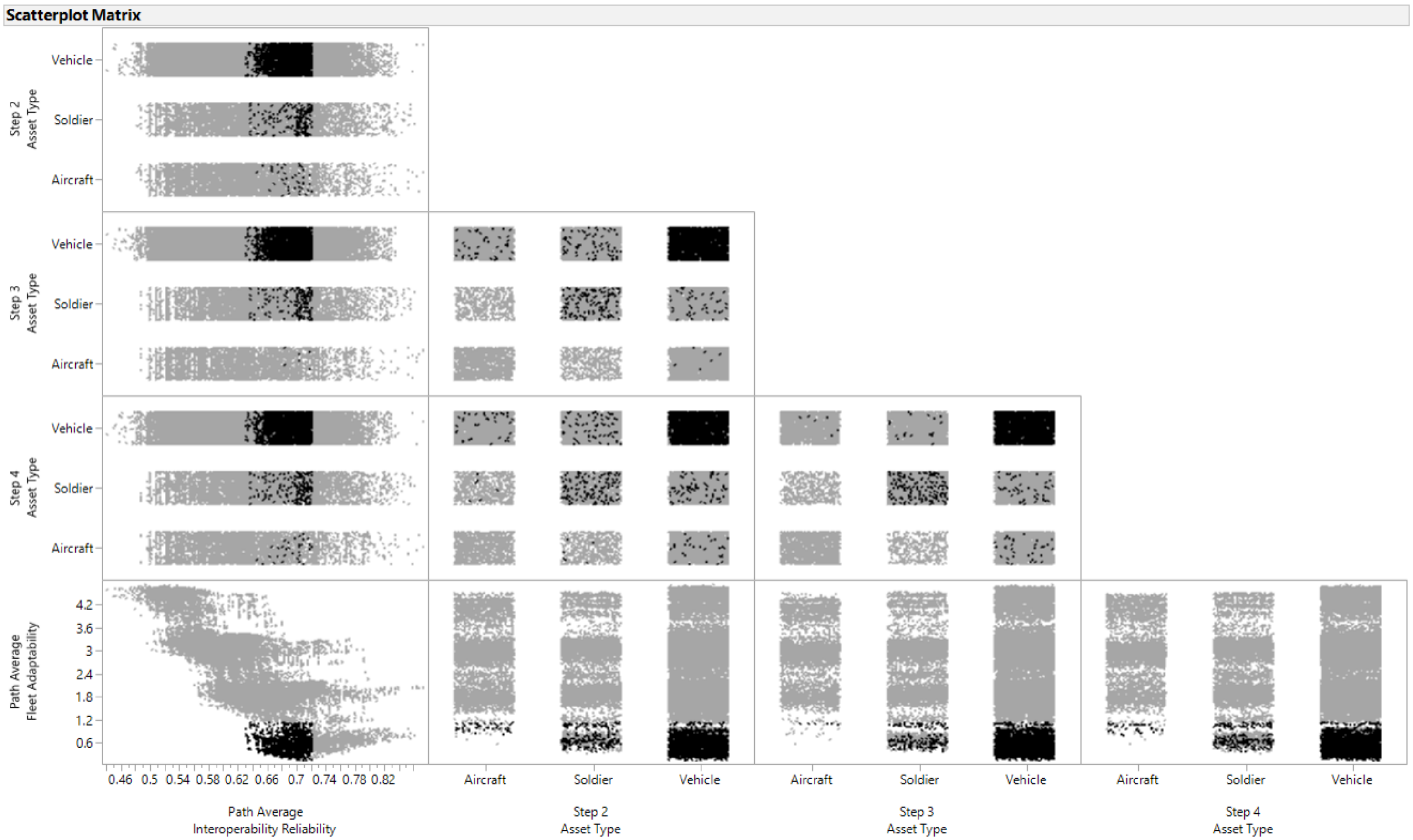



Figure 70: Variable-interoperability cases with good adaptability and bad interoperability

Scatterplot matrix of variable-interoperability case, with intersection of low interoperability but good adaptability highlighted (poor adaptability and high interoperability cases are grayed out)

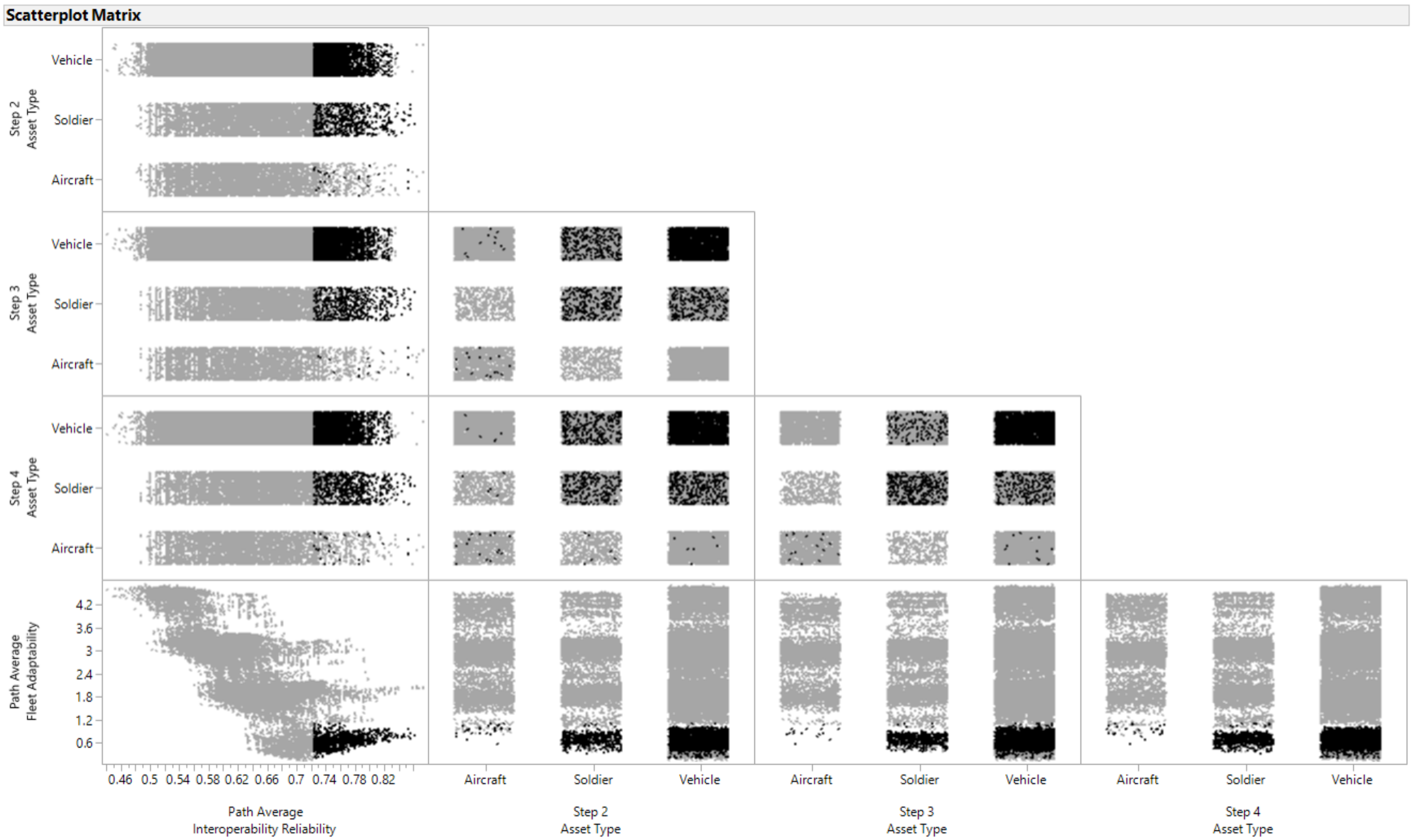



Figure 71: Variable-interoperability cases with good adaptability and high interoperability

Scatterplot matrix of variable-interoperability case, with intersection of high interoperability and good adaptability highlighted (poor adaptability and low interoperability cases are grayed out)

In conclusion, this section has demonstrated that even without any statistical analysis, it is possible to examine trends in the data en masse with simple methods such as scatterplot matrices and gain an improved understanding of the effects of various variables on adaptability. Furthermore, armed with this knowledge, it is possible to begin to down-select data points for further analysis.

For example, in the data shown in this section, the cluster with the best adaptability (lowest average adaptability criterion value) shows two cases: one case of fleet paths with higher interoperability, lower asset numbers, and lower relative fleet costs. The second case shows potential for somewhat better adaptability (the best possible) but as a result it is higher cost, trading the benefits of interoperability for a higher number of assets. Thus, decision makers can still make tradeoffs between asset number and interoperability, but they are more informed about the costs of that decision as well as being assured that the adaptability of their decisions is higher.

### 5.2.3 Effects of Increasing Asset Overlap in the Force Scaling Step

As a reminder, for this demonstration the asset overlap feature of the fleet scaling method was not used, i.e. the missions were assumed to take place completely simultaneously and therefore no assets could be shared between the missions. Of course this would be an unrealistic assumption if the method was being applied in a real analysis. However, the goal of this demonstration is to show that system-level interoperability effects can be analyzed for their effect on fleet plan adaptability. Furthermore, because the force scaling method developed is so simple, it is possible to easily predict what the effects of force overlap would be.

Force overlap, as defined in this dissertation, serves to transform the force scaling problem from that of simple multiplication to a complex scaling effect. At its core, the force scaling method uses one multiplication factor per mission to determine the number of addition missions a strategic force can complete, and therefore how many more assets are required. By changing the force overlap parameters from no overlap to some overlap (per asset type per mission), it is possible to decrease the number of assets required to "complete" the same number of missions because some assets are now "shared" between missions. In other words, some missions now use the "same" asset as other missions and so no additional assets of that type are required.

Broadly speaking, this means that whenever there is force overlap, the resulting strategic force will be smaller than if there were no force overlap. This is because the scaling method would imply that no assets can be shared for other missions, and so the addition of each simultaneous mission requires its own set of dedicated assets - ones that cannot be reused for other mission types. What then, does this mean for the overall methodology?

The effect of decreasing the size of the strategic force while maintaining largely the same capability is that the force becomes less expensive. Thus when the set of force mixes moves from the force scaling step to the force plan generation step, more force mix plans become available given a constant threshold. This will result in a greater number of options at each step, on average, and therefore the average adaptability of the paths as a whole will improve, though not necessarily evenly across all paths. Furthermore, because the force scaling step all the way through the adaptability step do not require optimization or simulation, they can be computed close to real time. This means that given a population of force mixes acquired through the fleet exploration step (in this case via an optimizer), decision makers can interact with force mix plan assumptions and relatively quickly see how the result changes. This would be of great help in a decision support system - decision makers could see how the effects of increasing multi-mission capability permeate through the decision process and affect the adaptability of all of the force plans to varying degrees.

# CHAPTER VI

# CONCLUDING REMARKS

## *6.1 Summary of Findings*

This dissertation began with a discussion of the problems with current defense acquisition processes. One of the problems identified by literature was the disconnect between the strategic decision-making at the top, which comprises such things as the National Security Strategy, the National Defense Strategy, and the National Military Strategy, and the Capability-Based Assessments that signify the beginning of any potential acquisition. This disconnect was chiefly that capabilities were determined more-so at the mission level than at the force level. Thus, not only were capabilities not necessarily multi-mission, but the resulting acquisitions may not reflect the true needs of the force. A second challenge had to do more generally with the strategic decision making process. There was no method in the literature to address the strategic environment in which decision makers act - one that is volatile and uncertain.

These two aspects of the strategic environment have significant impacts on what sorts of forces decision makers ought to plan on purchasing over time, in order to maintain their organization's ability to meet demands. Namely, uncertainty clouds what capabilities will be important in the future, and volatility clouds how long they will be important for. One need not look further than the collapse of the Soviet Union and the beginning of the Global War on Terror for an example of the change in direction that decision makers had to undertake.

Addressing the first concern was the identification of fleet evolution planning and fleet mix planning methods, a class of problem whereby fleets are investigated in a number of different missions in order to determine the proper mix of capabilities required. However, this class of problems was insufficient to fully address the gaps identified, and specifically to address the second concern. Thus, Research Question 1.1 was posed.

> **Research Question 1.1:** Given a fleet sizing and mix method, how should the overall methodology be structured?

The answer to this question was that two modifications had to be developed to traditional fleet evolution planning methodologies: a way to scale the results of mission models up to the strategic decision-making level, and a way to evaluate the adaptability of fleet plans created as a product of traditional fleet evolution planning methodologies.

Without some method that does the first, decision-makers would be choosing between unrealistically-small forces. This resulted in investigation of a way to scale up forces in Research Question 2.1:

> **Research Question 2.1:** What method is best suited for taking a set of disparate SoS operating different missions and rapidly scaling them up or unifying them into a full force?

When literature did not yield a method to address this gap, a set of assumptions and justifications was developed to allow decision makers another option. First, some analysis would yield the number of desired missions that could be operated simultaneously. This definition of a strategic-size force as one that can operate all required mission types simultaneously, with some number of simultaneous repetitions per mission type, allowed for a way to scale mission results up to the strategic force level. Nominally, this is the same as mandating something such as that "the US armed forces must be able to win two simultaneous major conflicts in different parts of the world", as was the requirement for much of the post-World War II US Armed Forces. These observations and assumptions led to the development of Hypothesis 3:

> **Hypothesis 3:** If a force is defined as the number of average missions of any and all types that can be performed simultaneously, it is possible to recreate a

full force based on modeling only the archetypical mission types and multiplying those results and mission forces by a scaling factor.

Without a way to evaluate adaptability of force plans, there would be no easy way to communicate to decision makers whether they were potentially committing their force to costly restructuring, acquisitions, and asset decommissions later on in the life-cycle. Answering this gap was the purpose of Research Question 3.1 and Research Question 3.2:

**Research Question 3.1:** What method is best suited for defining and calculating adaptability of a plan (not just a set point in time) or a set of plans?

**Research Question 3.2:** How should shifting budgetary and threat priorities be represented to best capture uncertainty and volatility for calculation of adaptability and robustness?

Although it is, of course, impossible to predict the future with certainty, a method was required to link decision-maker forecasts of future needs to the possibility that these needs, due to volatility in the strategic environment, might change rapidly. Thus, a criterion that quantified the flexibility of a certain decision was required. This criterion was found in literature and adapted for this application. The following hypothesis was proposed to assess whether this criterion would be applicable.

**Hypothesis 4:** If adaptability is calculated by accounting for the losses caused by a force purchasing decision as well as the number of other available options at that decision point via a decision-theoretic approach, this adaptability criterion will adequately reflect the adaptability decision-making tradeoff.

Finally, a useful demonstration of this methodology is the integration of interoperability into the armed forces. Its benefits have been noted previously, and yet there was no method in fleet planning literature to incorporate interoperability into fleet planning. One of the key requirements for this incorporation was to force a requirement that any missions being modeled in the method must account for interoperability in some way. A challenge to this was that interoperability modeling is frequently not quantitative. Three research questions were created to determine whether any applicable methods could be found in the literature:

> **Research Question 4.1:** Which types of system-to-system interoperability should be included in the model?

> **Research Question 4.2:** What methods are sufficient for modeling the given interoperability types?

> **Research Question 4.3:** Which method should be chosen for the purposes of a demonstration of the methodology?

It was determined that signals interoperability was sufficiently easy to model given the state of the art, as well as of sufficient scale and applicability to mission modeling, which answered Research Question 4.1. Of the two quantitative methods found, one was sufficient to demonstrate the potential benefits of integration of interoperability into fleet mix planning methods - this answered Research Question 4.2 and 4.3. It should be noted that without the need to investigate the adaptability of strategic-level fleets, the benefit of interoperability would have been only noted at the mission level. However, the mission-level effects must be modeled first. This led to the development of hypothesis two.

> **Hypothesis 2:** If reliability-based interoperability modeling is combined with information entropy-based collaborative effects that model complexity, the selected combat model will show an increase in the rate of enemy casualties.

Finally, Research Questions 5.1, 5.2, and 5.3 all dealt with the best mission models to use in order to demonstrate the methodology in action.

**Research Question 5.1:** For evaluating force plans with and without interoperability, what are the necessary criteria for a mission model that evaluates force effectiveness?

**Research Question 5.2:** What mission models exist that can accommodate the criteria of this methodology, and which should be chosen?

**Research Question 5.3:** What missions should be modeled in order to gain confidence in the results of the methodology?

These models had to be selected such that they interfaced well with the selected interoperability method. In the end, a quasi-discrete-time-Markov-Chain model was chosen that had previously reproduced one historical mission with relative accuracy given adequate calibration. This model was selected due to its speed, its ability to model different types of assets (for asset design capability) along with their functional characteristics, its ability to incorporate interoperability into system- and mission-level effects, and its ability to model a relatively large number of asset simultaneously. The generation of mission model selection criteria, and the selection of this specific mission model in order to showcase the methodology, addressed Research Question 5 as a whole.

The thesis of this dissertation was combining these various solutions can allow an analyst to study whether interoperability acts to improve the adaptability of force plans. To that end, experiments were carried out as a sort of demonstration of the methodology. The goal of these experiments was not to definitely prove that interoperability was a boon to fleet plan adaptability, as it is unlikely that this is always the case (especially given the various costs of interoperability mentioned earlier). Rather, it was to show that by using this methodology, investigation of problems of this sort was an attainable goal. The steps necessary to fully flesh out the framework developed here are discussed in the Future Work section.

Before showing the type of analysis that can be conducted, various developments and additions to the traditional fleet planning methodology had to be tested. These three developments and additions consist of interoperability-enabled mission models, the fleet scaling method, and the adaptability criterion. The primary determination of the methodology with respect to interoperability is that there are a few requirements that must be satisfied if an interoperability model is to be adapted for use in the methodology. These are as follows:

1. As realistic as possible
2. Quantitative
3. Rapid yet scalable to large SoS
4. Provide a way to modify existing missions with interoperability effects
5. Be technology-agnostic to allow for determining functional capabilities

To instantiate these requirements and show an interoperability model, coupled with a mission model, in action, a reliability-based interoperability model was integrated into a collaborative-effects model, both from the literature. These were applied inside a quasi-Markov-Chain combat model of the OMAHA beach landings, and the interoperability of the entire force was varied in order to determine the effects on measures of effectiveness. While some measures of effectiveness were less affected than others, it was clear that this instantiation did reproduce similar results to those found in the literature, as seen in Figure 72.

This result was a product of varying the levels of interoperability while keeping the other inputs of the combat model constant. Because the model was deterministic in its current implementation, there was no need to run replication studies. The results were affected by the selection of the number of "transmitting" assets per each asset population. This number was determined via historical data, even though in some cases this did result in a decreased run-time. However, this result addressed Hypothesis 2 by showing that interoperability could be modeled and have an effect on mission-level variables, even for a low-fidelity model.

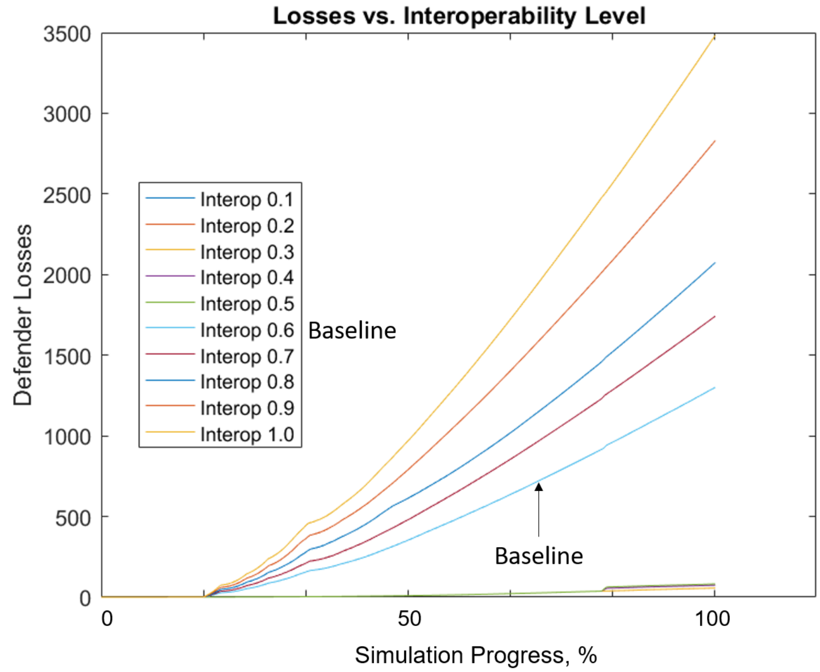



Figure 72: Enemy (defender) casualties versus force-wide interoperability level

The weaknesses for this demonstration are, of course, that this abstracted interoperability model would require either calibration to test the true values of interoperability that are achievable, or else testing results after-the-fact to determine how such a high level of interoperability might be achievable. However, because the purpose of this methodology is to set functional characteristic requirements (and capability requirements) for the fleet, this weakness was not deemed to be overly problematic, though of course any methods addressing it would be welcome.

The development of the fleet scaling method was more difficult to test. The method makes the unintuitive assumption that a force is nothing more than all of the assets operating all potential mission types, with some simultaneous repetitions, and that these missions are “average” missions or else that probability is adequately mitigated with replication studies. The imposition of the “average” assumption was to momentarily dispense with the difficulty that no two missions, no matter how identical on paper, are likely to be performed with the same exact statistics and results.

Testing this method with historical data, as was attempted, thus necessarily provided challenges: find missions that are simultaneously operated, with identical performance, that also have sufficient data regarding their performance and the assets operating in them. The best that could be done without an exhaustive search of the entirety of military history was again the OMAHA beach battle, which satisfied two of these requirements. It is one of the best-documented battles in history due to its importance and its brutality. It also has four sibling missions - the other beaches in the Normandy landings, which were assaulted at the same time. However, the assumption that it does violate is the "averageness" assumption.

To mitigate this shortcoming in the data, the averageness of OMAHA beach was examined and from this, predictions were drawn regarding what the fleet scaling method would output. Because of the comparatively heavy casualties on OMAHA beach, when scaling up to the other beaches, the scaling method used up its "friendly casualty budget" before it used up the "enemy casualty budget", and underestimated the number of enemy casualties and thus the assaulting forces as well. This was determined to be a sufficient result, as it was entirely predictable and reproducible. Even with probabilistics, the scaling method would have rarely produced the proper result because the wrong mission was being modeled, and thus the averageness assumption was not entirely at fault. This was deemed sufficient to address Hypothesis 3.

The final sub-problem that had to be examined was whether the adaptability criterion selected from literature was sufficient for capturing the desired tradeoff: mainly, one between the quality of a fleet and the quantity of options. Fleet planning problems typically involve thousands or tens of thousands of fleet plans and the decision between them can quickly get out of hand for an analyst working by hand. Instead, a hand-crafted set of fleets and fleet plans was created. The fleets were created such that the difference between them would create a set of fleet plans where one branch of fleets was superior but had fewer directions to evolve, and the second branch of fleets was inferior but had more choice.

Furthermore, the fleets were designed such that sometimes the differences between the

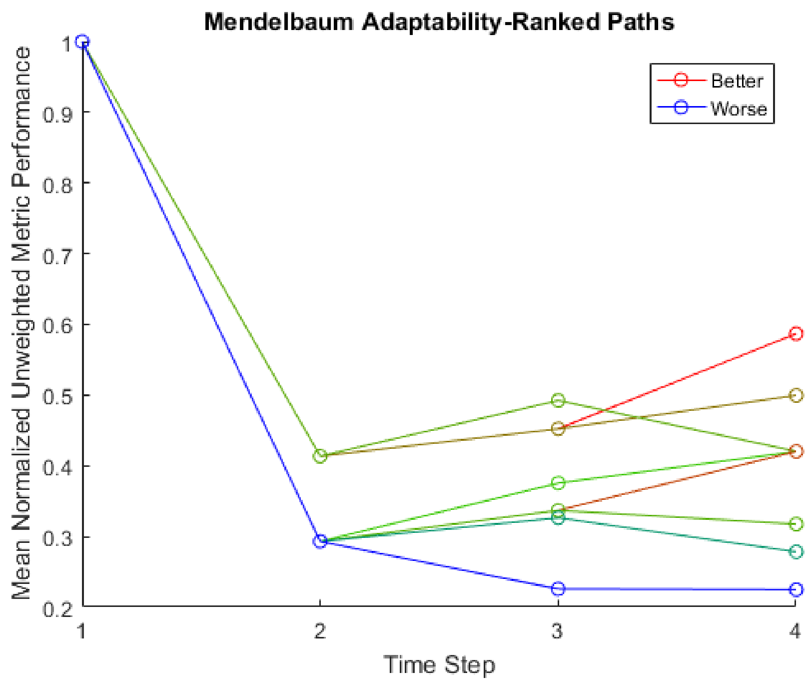



Figure 73: Normalized fleet performance, colored by criterion ranking

performance of fleets in the top branch and bottom branch was rather minimal. Thus, a few scenarios were examined: a completely inferior fleet plan with no options, a somewhat inferior fleet plan with more options, a somewhat superior fleet plan with few options, and a superior fleet plan with few options. The map of these fleet plans is shown in Figure 73.

In general, the adaptability criterion did capture the trade-off well. Ranked from best (red) to worst (blue), it can be seen that the highest-ranked fleet plan was one a high-performing that had a few more options available to it. However, the second highest-ranked plan was noticeably inferior, performance-wise, to two other plans. Instead, it had more options available along time step 2 and 3. As a result, this outweighed its relative undesirability from a performance standpoint.

There remains more work to be done - the benefits of this criterion are that it is easy to calculate and understand, and it accounts for forecasting uncertainty. However, a criterion that better captures flexibility of sub-decisions in a plan would be more desirable. Furthermore, this criterion can likely be gamed by artificially increasing the number of options, for example by improperly costing fleets such that the cost differences between them are not too great. However, for the purposes of this methodology, Hypothesis 4 was accepted based on these promising results.

With the three methods evaluated and found sufficient for examining the problem, a demonstration was done in the following way: an asset was designed and tested together with the SoS to assess the effects of infusing interoperability into the fleet. This demonstration consisted of the methodology, with some parts simplified, as seen in figure 74 This asset was included under two mutually exclusive cases - one in which the interoperability was always a fixed value, and one in which the interoperability was allowed to change between fleets along the path. If interoperability increases adaptability, then the variable-interoperability case ought to have a lower criterion (more adaptable) than the fixed-interoperability case. This was found to indeed be the case, as shown in Figure 75.

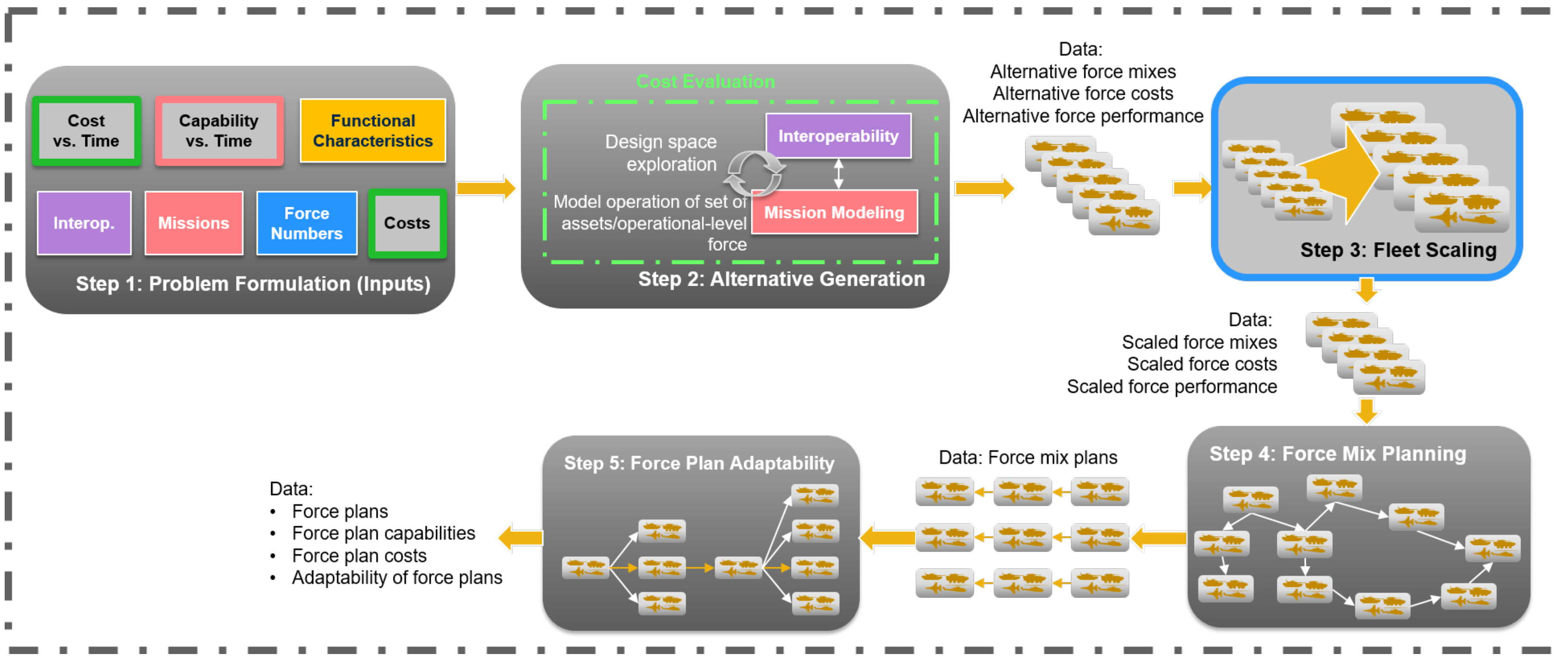



Figure 74: Simplified instantiation of methodology for purposes of demonstration

This figure shows the full methodology, as used for this demonstration. The squares with a solid gray fill and a colored outline are ones which have some sort of defaulting or nominal values. This includes the use of nominal costs, the defaulting of the capability and budget uncertainties to be highly permissive, and the use of the scaling method without asset overlap.

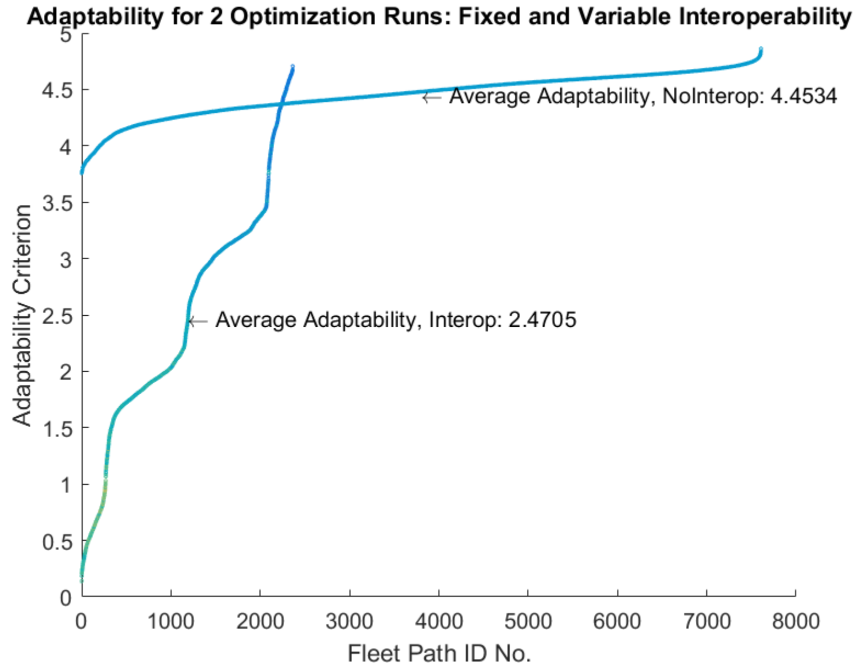



Figure 75: Adaptability of fixed- and variable-interoperability fleet paths, colored by interoperability

In fact, this effect was unique for interoperability out of all of the asset design variables studied, including lethality and fire rate (which were both multiplied by interoperability-based collaboration effects to produce the effect on target), failure rate, effective radius and endurance. An important contributor to this result is insufficient costing built in to the demonstration of the methodology. However, there is also undoubtedly an effect due to the simple fact that increasing the interoperability of an asset improves not only its own effectiveness, but the effectiveness of all assets it can interoperate with. Thus, even if interoperability contributes the same number of choices at each decision point (a way to "game" the example criterion), it undoubtedly still improved mission effectiveness, which decreased the "losses" associated with choosing that force even if the force was somewhat more expensive as a result.

As a final reminder, these experiments walk through the process of selecting and evaluating the viability of methods that can be used to instantiate this methodology for studying a specific class of problems. So long as the general structure and requirements of the methodology are followed, any number of methods can be used in place of the ones outlined here, especially if they are superior. Thus, various gaps in the current implementation, such as the lack of a sufficiently robust costing method for interoperability, the simplistic force scaling method, or the basic adaptability criterion, can be improved and substituted prior to an analysis. However, as the final experiment shows, following this method can enable decision makers to begin to answer one big question by answering many smaller ones: “how can I choose a sufficiently capable yet adaptable fleet evolution plan, such that I do not commit myself to potentially expensive pivots down the line”, and “which technology decisions must I make now and in the future which can improve the adaptability of my force plans”.

Furthermore, by selecting a few potential settings for interoperability, or any other advanced technology to be modeled, and setting those fleet plans aside for more thorough and high-fidelity analysis to either prove or disprove their potential viability, decision makers can choose the extent to which a good technology is applied to any one asset, answering the question of “where must I apply my expensive technologies such that they give me the most benefit down the line, given that threat scenarios may change and I must remain adaptable throughout.” The ability to answer these types of questions, enabled by this methodology, allows Hypothesis 1 to be accepted - that given the various sub-problems that have been used to augment a traditional fleet mix planning methodology, the methodology would allow analysts to answer these types of questions.

## 6.2 Contributions

As hinted at previously, this dissertation is merely the beginning of an effort to incorporate adaptability into strategic fleet planning for the defense community. As such, its role in highlighting the challenges associated with this problem, as well as where literature has done the most work regarding this problem, is as important as the results that were obtained in the experiments. It is a “down payment” for this problem type - a problem type that, with all of its various complications on traditional fleet mix planning problems, has not been addressed in prior literature.

Perhaps the largest challenge discovered was the lack of sufficient costing and complexity analysis methods for interoperability that can be readily introduced into a high-level (low-fidelity) capability requirements analysis method. The number of fleet plans that can be created with a set number of candidate fleets is highly related to the "distance" of those fleets to each other, and this distance is most often defined as a distance in asset-cost space. If the goal is to confirm that interoperability has a positive correlation with fleet plan adaptability, being confident in the cost of that interoperability is important as cost directly affects the number of options at each decision, which adaptability attempts to capture in one way or another.

A second challenge discovered was the difficulty in translating the effects of interoperability into mission-level effects while maintaining a high-level of analysis. This requirement was necessary because missions models must be called hundreds or thousands of times during the fleet plan generation step, thus putting an emphasis on mission model run-time, and secondly because it is desirable that interoperability analysis remains technology agnostic to enable its use for decades-long analyses.

A final challenge was the lack of sufficient fleet scaling literature. It appears that relatively little attention has been paid to bridging the gap between mission-level forces (systems of systems) and strategic-level forces ("fleets" or "armies", etc.). However, this bridge is paramount to utilizing traditional fleet-planning methodologies to solve strategic defense problems, as there are quite simply two (or even more) different orders of magnitude when dealing with the military.

Conversely, there is a highly robust fleet mix planning community that analyzes many perturbations of the fleet mix planning problem. There was no difficulty in finding many different fleet plan generation methods, although in the end a very simple one was selected, and there was no difficulty in finding many examples of defense applications for this problem type, although they did not address the same problems as this methodology. This was even true for examinations of technology insertion into fleet planning methods, as evidenced by papers regarding reduction of aircraft emissions in air transportation fleets via technology insertion over time.

In terms of the more narrow contributions from these particular results and this particular instantiation, we can see that a first implementation of the Mandelbaum and Buzacott loss criterion, which takes into account flexibility of the decision space, has produced promising results for capturing trade-offs associated with strategic fleet planning. Of course, there are many potential routes that capturing this trade-off can take, including totally divorcing the quality of a fleet from the subsequent decisions associated with it such that the decision maker must explicitly show their preferential weightings for these two aspects of the problem.

Another contribution was the explicit discussion of assumptions required to perform scaling of mission-level SoS to strategic-level fleets or forces, as well as the resulting scaling method. Given that only one other method was found that addressed a similar challenge, and that this other method required nested optimization, the relative simplicity of the fleet scaling method should go in its favor. In fact, the method trades mathematical complexity for conceptual complexity.

For example, the ability of a decision maker to define "overlapping" assets can essentially circumvent the "simultaneous mission" assumption while remaining computationally inexpensive. Furthermore, the burden is shifted onto the analyst (or analyst and decision maker) to determine the proper number of simultaneous missions that can be performed by the fleet. While the problems in terms of complexity of the task are apparent, the benefit is that once this analysis is performed once, it can be reused multiple times and therefore greatly accelerate the run-time of the methodology (trading one-time up-front work instead of repeated later-on work).

The final contribution of this work is the outline of a methodology that essentially aims to generalize the fleet mix planning process by abstracting fleets away from mission-level systems and thereby allowing (via "overlapping assets") multi-mission systems to be modeled more simply, while simultaneously beginning to incorporate more decision-theory-based solutions past the point where other fleet mix planning processes conclude their work.

As stated such, there is not very much in this methodology that is directly related to defense applications. Only the work done regarding incorporating interoperability into mission models is more defense-specific. Thus this methodology could potentially serve as guide for many different applications where assets may perform multiple missions, where all the assets operating in single mission models do not constitute the entirety of the fleet in question, and where decision makers desire a way to analyze the potential fleet plans once they have been generated.

## *6.3 Areas for Future Research*

Future work will consist of addressing some of the challenges highlighted in the previous section, expanding or improving on certain new methods developed, and finally broadening the capabilities outlined here.

To discuss the challenges first, assessing the best way to incorporate the costs of interoperability into a low-fidelity interoperability-modeling approach would significantly aid in gaining confidence in the results of this methodology. This is a multi-faceted problem, as costs of interoperability are not just captured in terms of monetary value. As mentioned in previous chapters, even the active use of signals interoperability, i.e. transmission of data between assets, can have an effect on the effectiveness of interoperability.

While some of this has been discussed via the network complexity modifications to collaborative interoperability effects, there are other challenges as well, such as decrease of available bandwidth and increase of interference which further decrease marginal utility of higher levels of interoperability in more and more assets. Furthermore, it is likely that the level of interoperability modeled here is too abstracted from the actual improvements that interoperability provides. It is possible that some more direct way of modeling improvements to collaboration, or enhanced situational awareness, are desired in order to more accurately reflect the benefits of interoperability as well as teh drawbacks. Added to this are the monetary costs of developing higher levels of interoperability and implementing them in acquisition programs, as well as managing all of the standards, metadata, and protocols associated with this technology.

A related challenge is integration of robust costing methods to various assets under consideration, should the decision-maker desire this methodology be used for asset design. This challenge is likely implementation-specific, but requires some sort of parametrized conceptual-design costing code that can account for various asset types under consideration.

Next, improving on or finding a better fleet scaling method would aid in converting the results from the mission models to strategic fleets such that the analysis can proceed. At issue is the simplification of the assumptions required for the fleet scaling method while not sacrificing on run-time. To summarize, the assumptions are that the fleet is defined as the forces required to operate all mission types and all simultaneous operations of those mission types while accounting for overlapping assets, that each mission model representing a mission type is modeling an average operation of that mission type, and that mission capabilities can be normalized and are additive when normalized.

Especially at issue is the assumption of the average operation of the mission, which can be most simply addressed by stipulating that mission models must be probabilistic (although this solution can increase run-time of the fleet exploration step). Additionally, while assets under routine maintenance were not considered in this analysis, it is likely that “maintenance” can be considered simply another mission type that is scaled based on the average availability of each asset. However, a full exploration of this addition may be required.

Improving the adaptability assessment is of significant interest. The instantiation of this methodology, for the purposes of an example, used an existing adaptability criterion that required little to no modification for inclusion. While the assumptions associated with this criterion did not seem problematic, it is desirable to incorporate greater capability into a newer version of the adaptability assessment.

This greater capability could consist of including 2nd, 3rd, and n-order decision flexibilities into each fleet path such that the adaptability criterion for each fleet path better reflects the adaptability of the entire decision tree to which that fleet path belongs. However, to do this, perhaps a new, even more rigorous definition of adaptability would need to be created. It is likely that a specific case study would greatly aid in the creation of this definition, as well as in the development of this improved criterion.

Related to the discussion of adaptability is a discussion on the generation of scenarios. Mentioned briefly in a previous chapter, scenario planning methods are meant to aid in the continuous decision-making process by serving as thought experiments that serve to jolt decision makers out of a single set of expectations regarding the future. Attempts by these methods to predict or improve an organization's ability to weather black swan events are also numerous yet still challenging. However, the ideas behind these methods have been adapted to fleet sizing and mix methods as a way of generating scenarios for fleets to be analyzed in.

These methods have provided more rigorous yet also limited automatic scenario-generation algorithms that provide some certitude in the relevance of the scenarios examined. In essence, what was proposed was a Design of Experiments (DoE) regarding various scenario settings, e.g. cost of fuel versus available budget. An inclusion of these methods as a post-processing step on the fleet plans, or perhaps as a way to confirm adaptability of fleet plans, could prove beneficial as a decision-making exercise.

We now proceed to a discussion of fleet sizing, mix, and planning methods. These methods, as mentioned in a previous chapter, can take many forms. Some of them have already accounted for the service life or the acquisition time of assets, and inclusion of these types of calculations into the methodology could serve as a likely improvement. Accounting for more realistic acquisitions steps can greatly improve the usability of this methodology as an acquisitions tool. This can further be modified to include not just acquisition cost (as done in the present instantiation) but also operation and decommissioning costs, which would factor in to how long an asset would be kept in service and serve to moderate the amount of money available for new acquisitions.

Yet more factors can be taken into account as well. The inclusion of the risk of an acquisition, perhaps with a resulting distribution on the asset cost or perhaps on the development and production time (acquisition time), would allow the method to account for schedule or cost slippage and thus produce fleet plans that are robust to such inconveniences.

A final improvement to fleet mix planning could include a more explicit inclusion of technology infusion analysis methods as a way to determine what form finalized assets could take and what technology development projects are required to get them there. This could be further modified by risk assessments for those technologies (as is commonly done) as well as estimated development times for them. In fact, it is possible that a robust or adaptable technology development schedule could be developed in parallel (and as an analogue) to fleet development plans from this methodology, with the two working in tandem and modifying each others' risks, costs, and benefits.

Interoperability methods can also see some improvement. Whereas only signals interoperability was considered for the moment, integration of command and control interoperability considerations as well as physical interoperability, could affect the types of decisions that get made. It was argued that command and control is still very human-centric and not amenable to modeling, let alone network graph-based modeling. It was also argued that physical interoperability has more to do with logistics and has a reduced impact directly on the mission, especially when compared to signals interoperability. However, ammunition interoperability, refueling interface interoperability, etc., all have an impact on the readiness of the force.

Inclusion of modularity, both of mission systems and other general sub-systems, presents two challenges - one in determining whether systems are available for a mission, and one in determining how effective they are once they arrive at the mission. The first can be addressed by adding a sort of pre-processing mission to the fleet exploration step which performs logistical analysis of asset types and asset module requirements, module location and quantity, and mission location and module needs. This is of course also a highly geography-dependent problem; results would either need to be parametrized via some type of fit (machine learning, regression, surrogate models, etc.), or missions would need to be location-dependent, or more probabilistics (and therefore even more run-time) would need to be added.

This pre-processing mission could serve to modify the numbers and capabilities of assets that are allowed to operate in the mission, thus tying modular technology to mission performance. The second challenge is determining whether module assets are as effective as traditional assets at operating a mission - this essentially entails quantifying the costs of modularity on asset effectiveness in a mission. This is not a logistical problem but is nevertheless of great interest. However, the way to address this problem is not immediately obvious.

In general, it is desirable to improve the state of mission modeling. At issue are speed, flexibility, and realism. Realism can be improved by accounting for a few different things. Concepts of operation are generally fixed for a given mission model. Even if the mission model is parametric with, e.g., the number of assets, those assets can only use the concepts of operation that have been coded for them to use. A smarter, more flexible, more parametric type of ConOps modeling would be a great boon to mission modeling, as it would allow mission models to attempt to improvise new tactics given the relative strengths and weaknesses of the forces being modeled. This is addressing a longstanding issue with mission modeling, namely that the force would operate with the same ConOps even if the modeler changes some variable. This type of creativity in a rapid mission model is likely a remote possibility at present, yet is required for creating a new class of more representative models.

The inclusion of better-defined tasking in the system dynamics combat model used for this dissertation could work hand-in-hand in enabling it to more accurately capture interoperability effects. Tasks like targeting, fixing, etc., would all contribute to a more understandable and more realistic combat model - however, this was left out of the current iteration due to concerns about run times. Balancing realism and run times, as ever, remains one of the key challenges in combat modeling.

A final candidate for inclusion into mission modeling is weapon ballistics and better damage modeling. The mission model used in the instantiation of this methodology was selected for its speed and relative ability to capture weapon lethality. However, lethality required calibration. Incorporating more physics-based weapon ballistics models without sacrificing speed would help mission models avoid some of the need for calibration.

# APPENDIX A

# OMAHA BEACH MODEL INPUTS

This appendix describes inputs to the OMAHA Beach combat model. This combat model is based on a discrete time hybrid Markov Chain-system dynamics approach. Populations of asset types are defined as objects of a certain type, such as an offensive air asset or a defensive land asset. Each object, or asset population, has a set quantity or number of assets. Each asset has certain functional characteristics, such as its failure rate, its effective combat radius, its fire rate, or its average speed. Furthermore, each asset has its own row and column of the lethality matrices - two matrices that define the lethality of each asset type against each opposing asset type. The two matrices are one for offensive against defensive assets, and one for vice versa. Finally, each asset type has its own scenario variables - these are variables that define when it is launched from the starting point (or base or amphibious assault group), at what rate it is launched, and whether it is carrying any number of other assets to the combat zone.

## *A.1 OMAHA Offensive Asset Definitions*

This section describes the characteristics of the offensive, or friendly assets, in the OMAHA scenario. Because the data set is so large, it is first broken up into the original landing waves from the landing tables [86]. Then, each wave's landing table is split into two pages due to the number of variables that define any given asset. The first page of each wave describes the "Number", "Failure Rate", "Effective Radius", and "Average Speed", while the second describes the "Launch Start", "Launch Rate", "Delivery Capacity", "Delivered Asset ID Numbers", and "Fire Rate". Furthermore, for easier cross-referencing, each page includes the asset population's name and asset population's unique ID number, as well as its type. Type is defined by an “O” or “D” signifying whether the type is offensive or defensive, followed by “Land”, “Strike”, “Air”, or “Water” to describe its general behavior and capabilities. Finally, since the OMAHA scenario was an amphibious landing, land assets do not have a launch start or rate because they are exclusively delivered by water assets.

Table 14: OMAHA Friendly Waves 1-4

| Asset Name | Asset Type | ID # | Number | Failure Rate | Eff. Radius | Avg. Speed |
|---|---|---|---|---|---|---|
| | | WAVE 1 | | | | |
| Infantry | OLand | 1 | | 0.00 | 0.457 | 0.804672 |
| Combat Engineer | OLand | 2 | | 0.00 | 0.457 | 0.804672 |
| LCVP (Higgins Boat) | OWater | 3 | 36 | 0.10 | 1.4 | 16.668 |
| LCT (Landing Craft, Tank) | OWater | 4 | 16 | 0.05 | 1.5 | 14.816 |
| LCA (Landing Craft Assault) | OWater | 5 | 12 | 0.10 | 0.55 | 11.112 |
| LCM (Landing Craft Mechanized) | OWater | 6 | 26 | 0.05 | 1.8 | 14.816 |
| DD Tank | OWater | 7 | 64 | 0.84 | 0.5 | 7.408 |
| DD Tank | OLand | 8 | | 0.07 | 0.5 | 40 |
| | | WAVE 2 | | | | |
| LCVP (Higgins Boat) | OWater | 9 | 38 | 0.05 | 1.4 | 16.668 |
| LCA (Landing Craft Assault) | OWater | 10 | 18 | 0.03 | 0.55 | 11.112 |
| Infantry | OLand | 11 | | 0.00 | 0.457 | 0.804672 |
| | | WAVE 3 | | | | |
| LCA (Landing Craft Assault) | OWater | 12 | 18 | 0.02 | 0.55 | 11.112 |
| LCM (Landing Craft Mechanized) | OWater | 13 | 8 | 0.04 | 1.8 | 14.816 |
| LCVP (Higgins Boat) | OWater | 14 | 12 | 0.04 | 1.4 | 16.668 |
| Combat Engineers | OLand | 15 | | 0.00 | 0.457 | 0.804672 |
| Chem Weapon Bn | OLand | 16 | | 0.00 | 4.02 | 0.804672 |
| Infantry | OLand | 17 | | 0.00 | 0.457 | 0.804672 |
| | | WAVE 4 | | | | |
| LCVP (Higgins Boat) | OWater | 18 | 54 | 0.04 | 1.4 | 16.668 |
| LCM (Landing Craft Mechanized) | OWater | 19 | 2 | 0.04 | 1.8 | 14.816 |
| Infantry | OLand | 20 | | 0.00 | 0.457 | 0.804672 |
| Combat Engineers | OLand | 21 | | 0.00 | 0.457 | 0.804672 |

Table 15: OMAHA Friendly Waves 1-4, Continued

| Asset Name | Asset Type | ID # | Launch Start | Launch Rate | Capacity | Delivering | Fire Rate |
|---|---|---|---|---|---|---|---|
| | | | WAVE 1 | | | | |
| Infantry | OLand | 1 | | | | | 0.13333 |
| Combat Engineer | OLand | 2 | | | | | 0 |
| LCVP (Higgins Boat) | OWater | 3 | 1815.032397 | 6000 | 36 troops | 1 | |
| LCT (Landing Craft, Tank) | OWater | 4 | 1666.911447 | 6000 | 2 tanks | 9 | |
| LCA (Landing Craft Assault) | OWater | 5 | 1222.548596 | 6000 | 36 troops | 1 | |
| LCM (Landing Craft Mechanized) | OWater | 6 | 1666.911447 | 6000 | 60 troops | 2 | |
| DD Tank | OWater | 7 | 0 | 6000 | self | 8 | |
| DD Tank | OLand | 8 | | | | | 0.025 |
| | | | WAVE 2 | | | | |
| LCVP (Higgins Boat) | OWater | 9 | 3615.032397 | 6000 | 36 troops | 11 | |
| LCA (Landing Craft Assault) | OWater | 10 | 3022.548596 | 6000 | 36 troops | 11 | |
| Infantry | OLand | 11 | | | | | 0.13333 |
| | | | WAVE 3 | | | | |
| LCA (Landing Craft Assault) | OWater | 12 | 3622.548596 | 6000 | 36 troops | 17 | |
| LCM (Landing Craft Mechanized) | OWater | 13 | 4066.911447 | 6000 | 60 troops | 15 | |
| LCVP (Higgins Boat) | OWater | 14 | 4215.032397 | 6000 | 12 24 | 15/16 | |
| Combat Engineers | OLand | 15 | | | | | 0.13333 |
| Chem Weapon Bn | OLand | 16 | | | | | 0.01666 |
| Infantry | OLand | 17 | | | | | 0.13333 |
| | | | WAVE 4 | | | | |
| LCVP (Higgins Boat) | OWater | 18 | 4815.032397 | 6000 | 36 troops | 20 | |
| LCM (Landing Craft Mechanized) | OWater | 19 | 4666.911447 | 6000 | 60 troops | 21 | |
| Infantry | OLand | 20 | | | | | 0.13333 |
| Combat Engineers | OLand | 21 | | | | | 0.13333 |

Table 16: OMAHA Friendly Waves 5-9

| Asset Name | Asset Type | ID # | Number | Failure Rate | Eff. Radius | Avg. Speed |
|---|---|---|---|---|---|---|
| WAVE 5 | | | | | | |
| LCVP (Higgins Boat) | OWater | 22 | 28 | 0.04 | 1.4 | 16.668 |
| LCVP (Higgins Boat) | OWater | 23 | 2 | 0.04 | 1.4 | 16.668 |
| LCT (Landing Craft, Tank) | OWater | 24 | 16 | 0.04 | 1.5 | 14.816 |
| LCA (Landing Craft Assault) | OWater | 25 | 24 | 0.04 | 0.55 | 11.112 |
| Infantry | OLand | 26 | | 0.00 | 0.457 | 0.804672 |
| Chem Weapon Bn | OLand | 27 | | 0.00 | 4.02 | 0.804672 |
| DD Tank | OLand | 28 | | 0.05 | 0.5 | 40 |
| Combat Engineers | OLand | 29 | | 0.00 | 0.457 | 0.804672 |
| WAVE 6 | | | | | | |
| LCI (Landing Craft, Infantry) | OWater | 30 | 6 | 0.05 | 1.5 | 27.78 |
| LCM (Landing Craft Mechanized) | OWater | 31 | 2 | 0.04 | 1.8 | 14.816 |
| LCT (Landing Craft, Tank) | OWater | 32 | 4 | 0.04 | 1.5 | 14.816 |
| LCA (Landing Craft Assault) | OWater | 33 | 16 | 0.04 | 0.55 | 11.112 |
| Combat Engineers | OLand | 34 | | 0.00 | 0.457 | 0.804672 |
| Infantry | OLand | 35 | | 0.00 | 0.457 | 0.804672 |
| DD Tank | OLand | 36 | | 0.05 | 0.5 | 40 |
| WAVE 7 | | | | | | |
| LCT (Landing Craft, Tank) | OWater | 37 | 10 | 0.04 | 1.5 | 14.816 |
| DD Tank | OLand | 38 | | 0.05 | 0.5 | 40 |
| WAVE 8 | | | | | | |
| LCI (Landing Craft, Infantry) | OWater | 39 | 2 | 0.04 | 1.5 | 27.78 |
| Combat Engineers | OLand | 40 | | 0.00 | 0.457 | 0.804672 |
| WAVE 9 | | | | | | |
| DUKW (water) | OWater | 41 | 30 | 0.06 | 0 | 10.186 |
| DUKW (land) | OLand | 42 | | 0.06 | 0 | 80 |
| Infantry | OLand | 43 | | 0.00 | 0.457 | 0.804672 |

Table 17: OMAHA Friendly Waves 5-9, Continued

| Asset Name | Asset Type | ID # | Launch Start | Launch Rate | Capacity | Delivering | Fire Rate |
|---|---|---|---|---|---|---|---|
| | | | WAVE 5 | | | | |
| LCVP (Higgins Boat) | OWater | 22 | 5415.032397 | 6000 | 24 12 | 26 27 | |
| LCVP (Higgins Boat) | OWater | 23 | 5415.032397 | 6000 | 36 | 29 | |
| LCT (Landing Craft, Tank) | OWater | 24 | 5266.911447 | 6000 | 2 tanks | 28 | |
| LCA (Landing Craft Assault) | OWater | 25 | 4822.548596 | 6000 | 36 troops | 26 | |
| Infantry | OLand | 26 | | | | | 0.13333 |
| Chem Weapon Bn | OLand | 27 | | | | | 0.01666 |
| DD Tank | OLand | 28 | | | | | 0.025 |
| Combat Engineers | OLand | 29 | | | | | 0.13333 |
| | | | WAVE 6 | | | | |
| LCI (Landing Craft, Infantry) | OWater | 30 | 6489.019438 | 6000 | 133 67 | 34 35 | |
| LCM (Landing Craft Mechanized) | OWater | 31 | 5866.911447 | 6000 | 60 troops | 34 | |
| LCT (Landing Craft, Tank) | OWater | 32 | 5866.911447 | 6000 | 2 tanks | 36 | |
| LCA (Landing Craft Assault) | OWater | 33 | 5422.548596 | 6000 | 36 troops | 35 | |
| Combat Engineers | OLand | 34 | | | | | 0.13333 |
| Infantry | OLand | 35 | | | | | 0.13333 |
| DD Tank | OLand | 36 | | | | | 0.025 |
| | | | WAVE 7 | | | | |
| LCT (Landing Craft, Tank) | OWater | 37 | 7066.911447 | 6000 | 2 tanks | 39 | |
| DD Tank | OLand | 38 | | | | | 0.025 |
| | | | WAVE 8 | | | | |
| LCI (Landing Craft, Infantry) | OWater | 39 | 8289.019438 | 6000 | 133 67 | 40 44 | |
| Combat Engineers | OLand | 40 | | | | | 0.13333 |
| | | | WAVE 9 | | | | |
| DUKW (water) | OWater | 41 | 7660.962105 | 6000 | 1 12 | 42 43 | |
| DUKW (land) | OLand | 42 | | | | | 0 |
| Infantry | OLand | 43 | | | | | 0.13333 |

Table 18: OMAHA Friendly Waves 10-13

| Asset Name | Asset Type | ID # | Number | Failure Rate | Eff. Radius | Avg. Speed |
|---|---|---|---|---|---|---|
| WAVE 10 | | | | | | |
| LCT (Landing Craft, Tank) | OWater | 44 | 12 | 0.04 | 1.5 | 14.816 |
| DD Tank | OLand | 45 | | 0.05 | 0.5 | 40 |
| WAVE 11 | | | | | | |
| Carmick | OStrike | 46 | 60 | 0.00 | 0.025 | 57.6 |
| McCook | OStrike | 47 | 60 | 0.00 | 0.025 | 57.6 |
| Frankford | OStrike | 48 | 60 | 0.00 | 0.025 | 57.6 |
| Frankford | OStrike | 49 | 60 | 0.00 | 0.025 | 57.6 |
| Harding | OStrike | 50 | 60 | 0.00 | 0.025 | 57.6 |
| Harding | OStrike | 51 | 60 | 0.00 | 0.025 | 57.6 |
| Doyle | OStrike | 52 | 60 | 0.00 | 0.025 | 57.6 |
| McCook | OStrike | 53 | 60 | 0.00 | 0.025 | 57.6 |
| Thompson | OStrike | 54 | 60 | 0.00 | 0.025 | 57.6 |
| Baldwin | OStrike | 55 | 60 | 0.00 | 0.025 | 57.6 |
| WAVE 12 | | | | | | |
| LCVP (Higgins Boat) | OWater | 56 | 4 | 0.04 | 1.4 | 16.668 |
| Combat Engineers | OLand | 57 | | 0.00 | 0.457 | 0.804672 |
| WAVE 13 | | | | | | |
| LCI (Landing Craft, Infantry) | OWater | 58 | 2 | 0.04 | 1.5 | 27.78 |
| Combat Engineers | OLand | 59 | | 0.00 | 0.457 | 0.804672 |

Table 19: OMAHA Friendly Waves 10-13, Continued

| Asset Name | Asset Type | ID # | Launch Start | Launch Rate | Capacity | Delivering | Fire Rate |
|---|---|---|---|---|---|---|---|
| | | | WAVE 10 | | | | |
| LCT (Landing Craft, Tank) | OWater | 44 | 8866.911447 | 6000 | 2 tanks | 45 | |
| DD Tank | OLand | 45 | | | | | 0.025 |
| | | | WAVE 11 | | | | |
| Carmick | OStrike | 46 | 7500 | 0.016666667 | | | |
| McCook | OStrike | 47 | 11100 | 0.016666667 | | | |
| Frankford | OStrike | 48 | 12900 | 0.016666667 | | | |
| Frankford | OStrike | 49 | 12900 | 0.016666667 | | | |
| Harding | OStrike | 50 | 15900 | 0.016666667 | | | |
| Harding | OStrike | 51 | 16500 | 0.016666667 | | | |
| Doyle | OStrike | 52 | 16500 | 0.016666667 | | | |
| McCook | OStrike | 53 | 20100 | 0.016666667 | | | |
| Thompson | OStrike | 54 | 20100 | 0.016666667 | | | |
| Baldwin | OStrike | 55 | 20100 | 0.016666667 | | | |
| | | | WAVE 12 | | | | |
| LCVP (Higgins Boat) | OWater | 56 | 0 | 6000 | 36 | 57 | |
| Combat Engineers | OLand | 57 | | | | | 0.13333 |
| | | | WAVE 13 | | | | |
| LCI (Landing Craft, Infantry) | OWater | 58 | 0 | 6000 | 200 | 59 | |
| Combat Engineers | OLand | 59 | | | | | 0.13333 |

Table 20: OMAHA Friendly Waves 14-19

| Asset Name | Asset Type | ID # | Number | Failure Rate | Eff. Radius | Avg. Speed |
|---|---|---|---|---|---|---|
| WAVE 14 | | | | | | |
| LCT with AA batallion | | | 1 | | | |
| LCT with artillery | | | 3 | | | |
| LCM with navy salvage | | | 3 | | | |
| LCT with HQ corps | | | 1 | | | |
| LCT with jeep | | | | | | |
| LCT (Landing Craft, Tank) | OWater | 60 | 2 | 0.04 | 1.5 | 14.816 |
| DD Tank | OLand | 61 | | 0.05 | 0.5 | 40 |
| LCI (Landing Craft, Infantry) | OWater | 62 | 2 | 0.04 | 1.5 | 27.78 |
| Infantry | OLand | 63 | | 0.00 | 0.457 | 0.804672 |
| WAVE 15 | | | | | | |
| LCM (Landing Craft Mechanized) | OWater | 64 | 2 | 0.04 | 1.8 | 14.816 |
| LCVP (Higgins Boat) | OWater | 65 | 18 | 0.04 | 1.4 | 16.668 |
| LCI (Landing Craft, Infantry) | OWater | 66 | 1 | 0.04 | 1.5 | 27.78 |
| Infantry | OLand | 67 | | 0.00 | 0.457 | 0.804672 |
| Infantry | OLand | 68 | | 0.00 | 0.457 | 0.804672 |
| Infantry | OLand | 69 | | 0.00 | 0.457 | 0.804672 |
| WAVE 16 | | | | | | |
| LCI (Landing Craft, Infantry) | OWater | 70 | 9 | 0.04 | 1.5 | 27.78 |
| Infantry | OLand | 71 | | 0.00 | 0.457 | 0.804672 |
| WAVE 17 | | | | | | |
| LCT (Landing Craft, Tank) | OWater | 72 | 10 | 0.04 | 1.5 | 14.816 |
| DD Tank | OLand | 73 | | 0.05 | 0.5 | 40 |
| WAVE 18 | | | | | | |
| LCT (Landing Craft, Tank) | OWater | 74 | 3 | 0.04 | 1.5 | 14.816 |
| DD Tank | OLand | 75 | | 0.05 | 0.5 | 40 |
| WAVE 19 | | | | | | |
| LCVP (Higgins Boat) | OWater | 76 | 8 | 0.04 | 1.4 | 16.668 |
| Combat Engineers | OLand | 77 | | 0.00 | 0.457 | 0.804672 |

Table 21: OMAHA Friendly Waves 14-19, Continued

| Asset Name | Asset Type | ID # | Launch Start | Launch Rate | Capacity | Delivering | Fire Rate |
|---|---|---|---|---|---|---|---|
| | | | WAVE 14 | | | | |
| LCT with AA batallion | | | | | | | |
| LCT with artillery | | | | | | | |
| LCM with navy salvage | | | | | | | |
| LCT with HQ corps | | | | | | | |
| LCT with jeep | | | | | | | |
| LCT (Landing Craft, Tank) | OWater | 60 | 0 | 6000 | 2 tanks | 61 | |
| DD Tank | OLand | 61 | | | | | 0.025 |
| LCI (Landing Craft, Infantry) | OWater | 62 | 0 | 6000 | 200 | 63 | |
| Infantry | OLand | 63 | | | | | 0.13333 |
| | | | WAVE 15 | | | | |
| LCM (Landing Craft Mechanized) | OWater | 64 | 0 | 6000 | 60 troops | 67 | |
| LCVP (Higgins Boat) | OWater | 65 | 0 | 6000 | 36 | 68 | |
| LCI (Landing Craft, Infantry) | OWater | 66 | 0 | 6000 | 200 | 69 | |
| Infantry | OLand | 67 | | | | | 0.13333 |
| Infantry | OLand | 68 | | | | | 0.13333 |
| Infantry | OLand | 69 | | | | | 0.13333 |
| | | | WAVE 16 | | | | |
| LCI (Landing Craft, Infantry) | OWater | 70 | 0 | 6000 | 200 | 71 | |
| Infantry | OLand | 71 | | | | | 0.13333 |
| | | | WAVE 17 | | | | |
| LCT (Landing Craft, Tank) | OWater | 72 | 0 | 6000 | 2 tanks | 73 | |
| DD Tank | OLand | 73 | | | | | 0.025 |
| | | | WAVE 18 | | | | |
| LCT (Landing Craft, Tank) | OWater | 74 | 0 | 6000 | 2 tanks | 75 | |
| DD Tank | OLand | 75 | | | | | 0.025 |
| | | | WAVE 19 | | | | |
| LCVP (Higgins Boat) | OWater | 76 | 0 | 6000 | 36 | 77 | |
| Combat Engineers | OLand | 77 | | | | | 0.13333 |

## A.2 OMAHA Defensive Asset Definitions

This section describes the characteristics of the defensive, or enemy assets, in the OMAHA scenario. Because the data set is so large, it is broken up into multiple pages, with each page listing some number of troops or defensive emplacements [74]. Each page lists the name, type, and ID number, as well as "Number", "Failure Rate", "Effective Radius", "Average Speed", and "Fire Rate". As in the previous section, type is defined by an "O" or "D" signifying whether the type is offensive or defensive, followed by "Land", "Strike", "Air", or "Water" to describe its general behavior and capabilities. Defensive assets currently only have strike or land capabilities, which is representative of the battle.

Table 22: OMAHA Enemy Defenders

| Name | Type | ID | Number | EffRadius | AvgSpeed | FailureRate | FireRate |
|---|---|---|---|---|---|---|---|
| Infantrymen | DLand | 78 | 2000 | 0.5 | 1.2 | 0.002 | 0.083333333 |
| 75 mm Gun | DLand | 79 | 1 | 1.8 | 0 | 0.0001 | 0.233333333 |
| Mortar Tobruk | DLand | 80 | 3 | 1 | 0 | 0.0001 | 0.333333333 |
| Mortar Position | DLand | 81 | 1 | 1 | 0 | 0.0001 | 0.333333333 |
| Flamethrowers | DLand | 82 | 2 | 0.025 | 1.2 | 0.002 | 0.000277778 |
| 88mm Pak in pillbox | DLand | 83 | 1 | 14.86 | 0 | 0.0001 | 0.291666667 |
| 50mm Pak in concrete emplacement | DLand | 84 | 1 | 1 | 0 | 0.0001 | 0.216666667 |
| Tobruk with R35 Tank Turret | DLand | 85 | 1 | 1 | 0 | 0.0001 | 0.166666667 |
| Machine Gun Tobruk | DLand | 86 | 2 | 1 | 0 | 0.0001 | 20 |
| Flamethrowers | DLand | 87 | 2 | 0.025 | 1.2 | 0.002 | 0.000277778 |
| 75mm Gun in pillbox | DLand | 88 | 2 | 1.8 | 0 | 0.0001 | 0.233333333 |
| 50mm Pak gun | DLand | 89 | 2 | 1 | 0 | 0.0001 | 0.216666667 |
| Machine Gun position | DLand | 90 | 3 | 1 | 0 | 0.0001 | 20 |
| Machine Gun Tobruk | DLand | 91 | 1 | 1 | 0 | 0.0001 | 20 |
| Mortar Tobruk | DLand | 92 | 2 | 1 | 0 | 0.0001 | 0.333333333 |
| Flamethrowers | DLand | 93 | 2 | 0.025 | 1.2 | 0.002 | 0.000277778 |
| 76,2mm Gun | DLand | 94 | 1 | 1 | 0 | 0.0001 | 0.183333333 |
| Mortar Tobruk | DLand | 95 | 2 | 1 | 0 | 0.0001 | 0.333333333 |
| 50mm Pak in pillbox | DLand | 96 | 1 | 1 | 0 | 0.0001 | 0.216666667 |
| 50mm Pak in concrete emplacement | DLand | 97 | 1 | 1 | 0 | 0.0001 | 0.216666667 |
| 75mm Gun | DLand | 98 | 1 | 1.8 | 0 | 0.0001 | 0.233333333 |
| Mortar Tobruk | DLand | 99 | 2 | 1 | 0 | 0.0001 | 0.333333333 |
| 50mm Pak in concrete emplacement | DLand | 100 | 1 | 1 | 0 | 0.0001 | 0.216666667 |
| Anti-Tank Gun | DLand | 101 | 1 | 1 | 0 | 0.0001 | 0.833333 |

Table 23: OMAHA Enemy Defenders, Continued

| Name | Type | ID | Number | EffRadius | AvgSpeed | FailureRate | FireRate |
|---|---|---|---|---|---|---|---|
| Tank Turret Tobruk | DLand | 102 | 2 | 1 | 0 | 0.0001 | 0.166666667 |
| Heavy Mortar in concrete emplacement | DLand | 103 | 2 | 1 | 0 | 0.0001 | 0.333333333 |
| Double Embrasure Pillbox | DLand | 104 | 1 | 1 | 0 | 0.0001 | 0.83333333 |
| 50mm Pak in concrete emplacement | DLand | 105 | 1 | 1 | 0 | 0.0001 | 0.216666667 |
| Anti-Tank Gun | DLand | 106 | 1 | 1 | 0 | 0.0001 | 0.833333 |
| Tank Turret Tobruk | DLand | 107 | 2 | 1 | 0 | 0.0001 | 0.166666667 |
| Double Embrasure Pillbox | DLand | 108 | 1 | 0 | 0 | 0.0001 | 0.83333333 |
| 75mm gun in pillbox | DLand | 109 | 1 | 1.8 | 0 | 0.0001 | 0.233333333 |
| 75mm gun | DLand | 110 | 1 | 1.8 | 0 | 0.0001 | 0.233333333 |
| Machine Gun Tobruk | DLand | 111 | 4 | 1 | 0 | 0.0001 | 20 |
| Mortar in concrete emplacement | DLand | 112 | 2 | 1 | 0 | 0.0001 | 0.333333333 |
| Machine Gun Tobruk | DLand | 113 | 1 | 1 | 0 | 0.0001 | 20 |
| Mortar with concrete emplacement | DLand | 114 | 1 | 1 | 0 | 0.0001 | 0.333333333 |
| Machine Gun position | DLand | 115 | 1 | 1 | 0 | 0.0001 | 20 |
| Double Embrasure Pillbox | DLand | 116 | 1 | 1 | 0 | 0.0001 | 0.83333333 |
| 88mm Pak in pillbox | DLand | 117 | 1 | 14.86 | 0 | 0.0001 | 0.333333333 |
| 50mm in double embrasure pillbox | DLand | 118 | 1 | 1 | 0 | 0.0001 | 0.216666667 |
| Machine Gun position | DLand | 119 | 1 | 1 | 0 | 0.0001 | 20 |
| Machine Gun Tobruk | DLand | 120 | 1 | 1 | 0 | 0.0001 | 20 |
| Double Embrasure Pillbox | DLand | 121 | 1 | 1 | 0 | 0.0001 | 0.83333333 |
| 75mm Gun in pillbox | DLand | 122 | 1 | 1.8 | 0 | 0.0001 | 0.233333333 |
| Mortar Tobruk | DLand | 123 | 3 | 1 | 0 | 0.0001 | 0.333333333 |
| Machine Gun position | DLand | 124 | 1 | 1 | 0 | 0.0001 | 20 |
| 75mm Gun | DLand | 125 | 2 | 1.8 | 0 | 0.0001 | 0.233333333 |

## A.3 OMAHA Offensive Asset Lethality Matrix

As mentioned previously, lethality matrices describe the lethality of some asset in a row against some asset in a column. Assets are listed in terms of their unique population ID numbers, which can be referenced in the previous tables. In almost all cases, lethality should be taken to mean the fractional damage produced by each use of a weapon - because any asset in the "attacking" state fires its weapon continuously (according to its fire rate) and never misses, these lethalities are lower than one would typically see because they must represent a sort of average per-shot lethality. The only asset where lethality is not used in the "per shot" sense is the strike asset, where the lethality is a per-asset lethality because strike assets are single-use.

The offensive lethality matrix is broken up into 9 tables due to size. The tables move from left to right through the matrix, starting with offensive assets 1 through 25 against defensive assets 80 through 96.

Table 24: OMAHA Offensive Lethality Matrix, Part 1 of 9

| 0 | 80 | 81 | 82 | 83 | 84 | 85 | 86 | 87 | 88 | 89 | 90 | 91 | 92 | 93 | 94 | 95 | 96 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.05 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 6 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 7 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 8 | 0.15 | 3 | 0 | 0.015 | 0.15 | 3 | 3 | 0 | 0 | 0.15 | 3 | 3 | 0.15 | 0 | 0 | 0.15 | 3 |
| 9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 11 | 0.075 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 12 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 13 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 14 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 15 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 16 | 0.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 17 | 0.25 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 18 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 19 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 20 | 0.25 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 21 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 22 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 23 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 24 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 25 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Table 25: OMAHA Offensive Lethality Matrix, Part 2 of 9

| 0 | 97 | 98 | 99 | 100 | 101 | 102 | 103 | 104 | 105 | 106 | 107 | 108 | 109 | 110 | 111 | 112 | 113 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 6 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 7 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 8 | 0 | 3 | 3 | 3 | 0 | 3 | 3 | 0 | 3 | 3 | 3 | 3 | 0 | 3 | 3 | 3 | 0 |
| 9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 11 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 12 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 13 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 14 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 15 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 16 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 17 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 18 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 19 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 20 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 21 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 22 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 23 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 24 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 25 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Table 26: OMAHA Offensive Lethality Matrix, Part 3 of 9

| 0 | 114 | 115 | 116 | 117 | 118 | 119 | 120 | 121 | 122 | 123 | 124 | 125 | 126 | 127 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 6 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 7 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 8 | 3 | 0 | 3 | 0.15 | 3 | 3 | 3 | 0.15 | 0 | 3 | 3 | 0 | 0.15 | 3 |
| 9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 11 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 12 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 13 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 14 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 15 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 16 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 17 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 18 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 19 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 20 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 21 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 22 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 23 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 24 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 25 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Table 27: OMAHA Offensive Lethality Matrix, Part 4 of 9

| 0 | 80 | 81 | 82 | 83 | 84 | 85 | 86 | 87 | 88 | 89 | 90 | 91 | 92 | 93 | 94 | 95 | 96 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 27 | 0.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 28 | 0.3 | 3 | 0 | 0.015 | 0.15 | 3 | 3 | 0 | 0 | 0.15 | 3 | 3 | 0.15 | 0 | 0 | 0.15 | 3 |
| 29 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 30 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 31 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 32 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 33 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 34 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 35 | 0.5 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 36 | 7.5 | 3 | 0 | 0.015 | 0.15 | 3 | 3 | 0 | 0 | 0.15 | 3 | 3 | 0.15 | 0 | 0 | 0.15 | 3 |
| 37 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 38 | 7.5 | 3 | 0 | 0.015 | 0.15 | 3 | 3 | 0 | 0 | 0.15 | 3 | 3 | 0.15 | 0 | 0 | 0.15 | 3 |
| 39 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 40 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 41 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 42 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 43 | 25 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 44 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 45 | 7.5 | 3 | 0 | 0.015 | 0.15 | 3 | 3 | 0 | 0 | 0.15 | 3 | 3 | 0.15 | 0 | 0 | 0.15 | 3 |
| 46 | 0.8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 47 | 0.8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 48 | 0.8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 49 | 0.8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1.1 |
| 50 | 0.8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1.1 |
| 51 | 0.8 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 0 |
| 52 | 0.8 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 0 |

Table 28: OMAHA Offensive Lethality Matrix, Part 5 of 9

| 0 | 97 | 98 | 99 | 100 | 101 | 102 | 103 | 104 | 105 | 106 | 107 | 108 | 109 | 110 | 111 | 112 | 113 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 27 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 28 | 0 | 3 | 3 | 3 | 0 | 3 | 3 | 0 | 3 | 3 | 3 | 3 | 0 | 3 | 3 | 3 | 0 |
| 29 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 30 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 31 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 32 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 33 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 34 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 35 | 0.1 | 0.1 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 36 | 0 | 3 | 3 | 3 | 0 | 3 | 3 | 0 | 3 | 3 | 3 | 3 | 0 | 3 | 3 | 3 | 0 |
| 37 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 38 | 0 | 3 | 3 | 3 | 0 | 3 | 3 | 0 | 3 | 3 | 3 | 3 | 0 | 3 | 3 | 3 | 0 |
| 39 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 40 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 41 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 42 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 43 | 0.1 | 0.1 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 44 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 45 | 0 | 3 | 3 | 3 | 0 | 3 | 3 | 0 | 3 | 3 | 3 | 3 | 0 | 3 | 3 | 3 | 0 |
| 46 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.9 | 1 | 1 | 0.9 | 0.9 | 1 | 1 |
| 47 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.9 | 1 | 1 | 0.9 | 0.9 | 1 | 1 |
| 48 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.9 | 1 | 1 | 0.9 | 0.9 | 1 | 1 |
| 49 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 50 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 51 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 52 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Table 29: OMAHA Offensive Lethality Matrix, Part 6 of 9

| 0 | 114 | 115 | 116 | 117 | 118 | 119 | 120 | 121 | 122 | 123 | 124 | 125 | 126 | 127 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 27 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 28 | 3 | 0 | 3 | 0.2 | 3 | 3 | 3 | 0.15 | 0 | 3 | 3 | 0 | 0.15 | 3 |
| 29 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 30 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 31 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 32 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 33 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 34 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 35 | 0.05 | 0.1 | 0.05 | 0.1 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 36 | 3 | 0 | 3 | 0.2 | 3 | 3 | 3 | 0.15 | 0 | 3 | 3 | 0 | 0.15 | 3 |
| 37 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 38 | 3 | 0 | 3 | 0.2 | 3 | 3 | 3 | 0.15 | 0 | 3 | 3 | 0 | 0.15 | 3 |
| 39 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 40 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 41 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 42 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 43 | 0.05 | 0.1 | 0.05 | 0.1 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 44 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 45 | 3 | 0 | 3 | 0.2 | 3 | 3 | 3 | 0.15 | 0 | 3 | 3 | 0 | 0.15 | 3 |
| 46 | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 | 1 |
| 47 | 0.9 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 |
| 48 | 0.9 | 1.2 | 1.2 | 1.2 | 1.2 | 1.2 | 1.2 | 1.2 | 1.2 | 1.2 | 1.1 | 1 | 0.9 | 0 |
| 49 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 50 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 51 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 52 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Table 30: OMAHA Offensive Lethality Matrix, Part 7 of 9

| 0 | 80 | 81 | 82 | 83 | 84 | 85 | 86 | 87 | 88 | 89 | 90 | 91 | 92 | 93 | 94 | 95 | 96 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 53 | 0.8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 54 | 0.8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 55 | 0.8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 56 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 57 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 58 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 59 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 60 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 61 | 7.5 | 3 | 0 | 0.015 | 0.15 | 3 | 3 | 0 | 0 | 0.15 | 3 | 3 | 0.15 | 0 | 0 | 0.15 | 3 |
| 62 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 63 | 0.5 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 64 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 65 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 66 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 67 | 0.5 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 68 | 0.5 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 69 | 0.5 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 70 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 71 | 0.5 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 72 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 73 | 7.5 | 3 | 0 | 0.015 | 0.15 | 3 | 3 | 0 | 0 | 0.15 | 3 | 3 | 0.15 | 0 | 0 | 0.15 | 3 |
| 74 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 75 | 7.5 | 3 | 0 | 0.015 | 0.15 | 3 | 3 | 0 | 0 | 0.15 | 3 | 3 | 0.15 | 0 | 0 | 0.15 | 3 |
| 76 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 77 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 78 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 79 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Table 31: OMAHA Offensive Lethality Matrix, Part 8 of 9

| 0 | 97 | 98 | 99 | 100 | 101 | 102 | 103 | 104 | 105 | 106 | 107 | 108 | 109 | 110 | 111 | 112 | 113 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 53 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.9 | 1 | 1 | 0.9 | 0.9 | 1 | 1 |
| 54 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.9 | 1 | 1 | 0.9 | 0.9 | 1 | 1 |
| 55 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.9 | 1 | 1 | 0.9 | 0.9 | 1 | 1 |
| 56 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 57 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 58 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 59 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 60 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 61 | 0 | 3 | 3 | 3 | 0 | 3 | 3 | 0 | 3 | 3 | 3 | 3 | 0 | 3 | 3 | 3 | 0 |
| 62 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 63 | 0.1 | 0.1 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 64 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 65 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 66 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 67 | 0.1 | 0.1 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 68 | 0.1 | 0.1 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 69 | 0.1 | 0.1 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 70 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 71 | 0.1 | 0.1 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 72 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 73 | 0 | 3 | 3 | 3 | 0 | 3 | 3 | 0 | 3 | 3 | 3 | 3 | 0 | 3 | 3 | 3 | 0 |
| 74 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 75 | 0 | 3 | 3 | 3 | 0 | 3 | 3 | 0 | 3 | 3 | 3 | 3 | 0 | 3 | 3 | 3 | 0 |
| 76 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 77 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 78 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 79 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Table 32: OMAHA Offensive Lethality Matrix, Part 9 of 9

| 0 | 114 | 115 | 116 | 117 | 118 | 119 | 120 | 121 | 122 | 123 | 124 | 125 | 126 | 127 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 53 | 0.9 | 0.8 | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 |
| 54 | 0.9 | 0.8 | 0.9 | 0.9 | 0.9 | 1.2 | 1.2 | 1.2 | 1.2 | 1.2 | 0.9 | 0.9 | 0.9 | 0.9 |
| 55 | 0.9 | 0.8 | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 |
| 56 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 57 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 58 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 59 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 60 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 61 | 3 | 0 | 3 | 0.2 | 3 | 3 | 3 | 0.15 | 0 | 3 | 3 | 0 | 0.15 | 3 |
| 62 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 63 | 0.05 | 0.1 | 0.05 | 0.1 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 64 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 65 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 66 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 67 | 0.05 | 0.1 | 0.05 | 0.1 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 68 | 0.05 | 0.1 | 0.05 | 0.1 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 69 | 0.05 | 0.1 | 0.05 | 0.1 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 70 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 71 | 0.05 | 0.1 | 0.05 | 0.1 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 72 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 73 | 3 | 0 | 3 | 0.2 | 3 | 3 | 3 | 0.15 | 0 | 3 | 3 | 0 | 0.15 | 3 |
| 74 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 75 | 3 | 0 | 3 | 0.2 | 3 | 3 | 3 | 0.15 | 0 | 3 | 3 | 0 | 0.15 | 3 |
| 76 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 77 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 78 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 79 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

## A.4 OMAHA Defensive Asset Lethality Matrix

Repeated here for easier reference, the lethality matrices describe the lethality of some asset in a row against some asset in a column. Assets are listed in terms of their unique population ID numbers, which can be referenced in the previous tables. In almost all cases, lethality should be taken to mean the fractional damage produced by each use of a weapon - because any asset in the “attacking” state fires its weapon continuously (according to its fire rate) and never misses, these lethalities are lower than one would typically see because they must represent a sort of average per-shot lethality. The only asset where lethality is not used in the “per shot” sense is the strike asset, where the lethality is a per-asset lethality because strike assets are themselves ordnance and are single-use.

The OMAHA defensive lethality matrix is broken up into 10 tables due to size. The tables move from left to right through the matrix, starting with the lethality of defensive assets 80 through 104 against offensive assets 1 through 17.

Table 33: OMAHA Defensive Lethality Matrix, Part 1 of 10

| 0 | 1 | 2 | 4 | 3 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 80 | 0.023 | 0.03 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.023 | 0 | 0 | 0 | 0.03 | 0.023 | 0.023 |
| 81 | 0.25 | 0.375 | 1 | 1 | 1 | 1 | 0 | 5 | 1 | 1 | 0.25 | 1 | 1 | 1 | 0.375 | 0.25 | 0.25 |
| 82 | 0.375 | 0.5 | 0 | 0 | 0 | 0 | 0 | 2.5 | 0 | 0 | 0.375 | 0 | 0 | 0 | 0.5 | 0.5 | 0.375 |
| 83 | 0.375 | 0.5 | 0 | 0 | 0 | 0 | 0 | 2.5 | 0 | 0 | 0.375 | 0 | 0 | 0 | 0.5 | 0.5 | 0.375 |
| 84 | 1.25 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1.25 | 0 | 0 | 0 | 0 | 0 | 1.25 |
| 85 | 0.25 | 0.375 | 0 | 0 | 0 | 0 | 0 | 7.5 | 0 | 0 | 0.25 | 0 | 0 | 0 | 0.375 | 0.25 | 0.25 |
| 86 | 0.175 | 0.25 | 0 | 0 | 0 | 0 | 0 | 5 | 0 | 0 | 0.175 | 0 | 0 | 0 | 0.25 | 0.175 | 0.175 |
| 87 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 88 | 0.02 | 0.025 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.02 | 0 | 0 | 0 | 0.025 | 0.02 | 0.02 |
| 89 | 1.25 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1.25 | 0 | 0 | 0 | 0 | 0 | 1.25 |
| 90 | 0.25 | 0.375 | 0 | 0 | 0 | 0 | 0 | 7.5 | 0 | 0 | 0.25 | 0 | 0 | 0 | 0.375 | 0.25 | 0.25 |
| 91 | 0.175 | 0.25 | 0 | 0 | 0 | 0 | 0 | 5 | 0 | 0 | 0.175 | 0 | 0 | 0 | 0.25 | 0.175 | 0.175 |
| 92 | 0.02 | 0.025 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.02 | 0 | 0 | 0 | 0.025 | 0.02 | 0.02 |
| 93 | 0.02 | 0.025 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.02 | 0 | 0 | 0 | 0.025 | 0.02 | 0.02 |
| 94 | 0.375 | 0.5 | 0 | 0 | 0 | 0 | 0 | 2.5 | 0 | 0 | 0.375 | 0 | 0 | 0 | 0.5 | 0.5 | 0.375 |
| 95 | 1.25 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1.25 | 0 | 0 | 0 | 0 | 0 | 1.25 |
| 96 | 0.25 | 0.375 | 1 | 1 | 1 | 1 | 0 | 5 | 1 | 1 | 0.25 | 1 | 1 | 1 | 0.375 | 0.25 | 0.25 |
| 97 | 0.375 | 0.5 | 0 | 0 | 0 | 0 | 0 | 2.5 | 0 | 0 | 0.375 | 0 | 0 | 0 | 0.5 | 0.5 | 0.375 |
| 98 | 0.175 | 0.25 | 0 | 0 | 0 | 0 | 0 | 5 | 0 | 0 | 0.175 | 0 | 0 | 0 | 0.25 | 0.175 | 0.175 |
| 99 | 0.175 | 0.25 | 0 | 0 | 0 | 0 | 0 | 5 | 0 | 0 | 0.175 | 0 | 0 | 0 | 0.25 | 0.175 | 0.175 |
| 100 | 0.25 | 0.375 | 1 | 1 | 1 | 1 | 0 | 5 | 1 | 1 | 0.25 | 1 | 1 | 1 | 0.375 | 0.25 | 0.25 |
| 101 | 0.375 | 0.5 | 0 | 0 | 0 | 0 | 0 | 2.5 | 0 | 0 | 0.375 | 0 | 0 | 0 | 0.5 | 0.5 | 0.375 |
| 102 | 0.175 | 0.25 | 0 | 0 | 0 | 0 | 0 | 5 | 0 | 0 | 0.175 | 0 | 0 | 0 | 0.25 | 0.175 | 0.175 |
| 103 | 0.175 | 0.25 | 0 | 0 | 0 | 0 | 0 | 5 | 0 | 0 | 0.175 | 0 | 0 | 0 | 0.25 | 0.175 | 0.175 |
| 104 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Table 34: OMAHA Defensive Lethality Matrix, Part 2 of 10

| 0 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 | 29 | 30 | 31 | 32 | 33 | 34 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 80 | 0 | 0 | 0.023 | 0.03 | 0 | 0 | 0 | 0 | 0.023 | 0.023 | 0 | 0.03 | 0 | 0 | 0 | 0 | 0.03 |
| 81 | 1 | 1 | 0.25 | 2.5 | 1 | 1 | 1 | 1 | 0.25 | 37.5 | 5 | 5 | 1 | 1 | 1 | 1 | 5 |
| 82 | 0 | 0 | 0.375 | 0.5 | 0 | 0 | 0 | 0 | 0.375 | 0.375 | 2.5 | 0.5 | 0 | 0 | 0 | 0 | 0.5 |
| 83 | 0 | 0 | 0.375 | 0.5 | 0 | 0 | 0 | 0 | 0.375 | 0.375 | 2.5 | 0.5 | 0 | 0 | 0 | 0 | 0.5 |
| 84 | 0 | 0 | 1.25 | 0 | 0 | 0 | 0 | 0 | 1.25 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 85 | 0 | 0 | 0.25 | 0.375 | 0 | 0 | 0 | 0 | 0.25 | 0.25 | 7.5 | 0.375 | 0 | 0 | 0 | 0 | 0.375 |
| 86 | 0 | 0 | 0.175 | 0.25 | 0 | 0 | 0 | 0 | 0.175 | 0.175 | 5 | 0.25 | 0 | 0 | 0 | 0 | 0.25 |
| 87 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2.5 | 0 | 0 | 0 | 0 | 0 | 0 |
| 88 | 0 | 0 | 0.02 | 0.025 | 0 | 0 | 0 | 0 | 0.02 | 0.02 | 0 | 0.025 | 0 | 0 | 0 | 0 | 0.025 |
| 89 | 0 | 0 | 1.25 | 0 | 0 | 0 | 0 | 0 | 1.25 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 90 | 0 | 0 | 0.25 | 0.375 | 0 | 0 | 0 | 0 | 0.25 | 0.25 | 7.5 | 0.375 | 0 | 0 | 0 | 0 | 0.375 |
| 91 | 0 | 0 | 0.175 | 0.25 | 0 | 0 | 0 | 0 | 0.175 | 0.175 | 5 | 0.25 | 0 | 0 | 0 | 0 | 0.25 |
| 92 | 0 | 0 | 0.02 | 0.025 | 0 | 0 | 0 | 0 | 0.02 | 0.02 | 0 | 0.025 | 0 | 0 | 0 | 0 | 0.025 |
| 93 | 0 | 0 | 0.02 | 0.025 | 0 | 0 | 0 | 0 | 0.02 | 0.02 | 0 | 0.025 | 0 | 0 | 0 | 0 | 0.025 |
| 94 | 0 | 0 | 0.375 | 0.5 | 0 | 0 | 0 | 0 | 0.375 | 0.375 | 2.5 | 0.5 | 0 | 0 | 0 | 0 | 0.5 |
| 95 | 0 | 0 | 1.25 | 0 | 0 | 0 | 0 | 0 | 1.25 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 96 | 1 | 1 | 0.25 | 5 | 1 | 1 | 1 | 1 | 0.25 | 37.5 | 5 | 5 | 1 | 1 | 1 | 1 | 5 |
| 97 | 0 | 0 | 0.375 | 0.5 | 0 | 0 | 0 | 0 | 0.375 | 0.375 | 2.5 | 0.5 | 0 | 0 | 0 | 0 | 0.5 |
| 98 | 0 | 0 | 0.175 | 0.25 | 0 | 0 | 0 | 0 | 0.175 | 0.175 | 5 | 0.25 | 0 | 0 | 0 | 0 | 0.25 |
| 99 | 0 | 0 | 0.175 | 0.25 | 0 | 0 | 0 | 0 | 0.175 | 0.175 | 5 | 0.25 | 0 | 0 | 0 | 0 | 0.25 |
| 100 | 1 | 1 | 0.25 | 1.25 | 1 | 1 | 1 | 1 | 0.25 | 37.5 | 5 | 1.25 | 1 | 1 | 1 | 1 | 1.25 |
| 101 | 0 | 0 | 0.375 | 0.5 | 0 | 0 | 0 | 0 | 0.375 | 0.375 | 2.5 | 0.5 | 0 | 0 | 0 | 0 | 0.5 |
| 102 | 0 | 0 | 0.175 | 0.25 | 0 | 0 | 0 | 0 | 0.175 | 0.175 | 5 | 0.25 | 0 | 0 | 0 | 0 | 0.25 |
| 103 | 0 | 0 | 0.175 | 0.25 | 0 | 0 | 0 | 0 | 0.175 | 0.175 | 5 | 0.25 | 0 | 0 | 0 | 0 | 0.25 |
| 104 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2.5 | 0 | 0 | 0 | 0 | 0 | 0 |

Table 35: OMAHA Defensive Lethality Matrix, Part 3 of 10

| 0 | 35 | 36 | 37 | 38 | 39 | 40 | 41 | 42 | 43 | 44 | 45 | 46 | 47 | 48 | 49 | 50 | 51 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 80 | 0.023 | 0 | 0 | 0 | 0 | 0.03 | 0 | 0 | 0.023 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 81 | 0.25 | 5 | 1 | 5 | 1 | 5 | 1 | 2.5 | 0.25 | 1 | 5 | 0 | 0 | 0 | 0 | 0 | 0 |
| 82 | 0.375 | 2.5 | 0 | 2.5 | 0 | 0.5 | 0 | 0.25 | 0.375 | 0 | 2.5 | 0 | 0 | 0 | 0 | 0 | 0 |
| 83 | 0.375 | 2.5 | 0 | 2.5 | 0 | 0.5 | 0 | 0.25 | 0.375 | 0 | 2.5 | 0 | 0 | 0 | 0 | 0 | 0 |
| 84 | 1.25 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1.25 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 85 | 0.25 | 7.5 | 0 | 7.5 | 0 | 0.375 | 0 | 5 | 0.25 | 0 | 7.5 | 0 | 0 | 0 | 0 | 0 | 0 |
| 86 | 0.175 | 5 | 0 | 5 | 0 | 0.25 | 0 | 2.5 | 0.175 | 0 | 5 | 0 | 0 | 0 | 0 | 0 | 0 |
| 87 | 0 | 2.5 | 0 | 2.5 | 0 | 0 | 0 | 2.5 | 0 | 0 | 2.5 | 0 | 0 | 0 | 0 | 0 | 0 |
| 88 | 0.02 | 0 | 0 | 0 | 0 | 0.025 | 0 | 0.013 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 89 | 1.25 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1.25 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 90 | 0.25 | 7.5 | 0 | 7.5 | 0 | 0.375 | 0 | 2.5 | 0.25 | 0 | 7.5 | 0 | 0 | 0 | 0 | 0 | 0 |
| 91 | 0.175 | 5 | 0 | 5 | 0 | 0.25 | 0 | 2.5 | 0.175 | 0 | 5 | 0 | 0 | 0 | 0 | 0 | 0 |
| 92 | 0.02 | 0 | 0 | 0 | 0 | 0.025 | 0 | 0.013 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 93 | 0.02 | 0 | 0 | 0 | 0 | 0.025 | 0 | 0.013 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 94 | 0.375 | 2.5 | 0 | 2.5 | 0 | 0.5 | 0 | 0.25 | 0.375 | 0 | 2.5 | 0 | 0 | 0 | 0 | 0 | 0 |
| 95 | 1.25 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1.25 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 96 | 0.25 | 5 | 1 | 5 | 1 | 5 | 1 | 2.5 | 0.25 | 1 | 5 | 0 | 0 | 0 | 0 | 0 | 0 |
| 97 | 0.375 | 2.5 | 0 | 2.5 | 0 | 0.5 | 0 | 0.25 | 0.375 | 0 | 2.5 | 0 | 0 | 0 | 0 | 0 | 0 |
| 98 | 0.175 | 5 | 0 | 5 | 0 | 0.25 | 0 | 2.5 | 0.175 | 0 | 5 | 0 | 0 | 0 | 0 | 0 | 0 |
| 99 | 0.175 | 5 | 0 | 5 | 0 | 0.25 | 0 | 2.5 | 0.175 | 0 | 5 | 0 | 0 | 0 | 0 | 0 | 0 |
| 100 | 0.25 | 5 | 1 | 5 | 1 | 1.25 | 1 | 2.5 | 0.25 | 1 | 5 | 0 | 0 | 0 | 0 | 0 | 0 |
| 101 | 0.375 | 2.5 | 0 | 2.5 | 0 | 0.5 | 0 | 1.25 | 0.375 | 0 | 2.5 | 0 | 0 | 0 | 0 | 0 | 0 |
| 102 | 0.175 | 5 | 0 | 5 | 0 | 0.25 | 0 | 2.5 | 0.175 | 0 | 5 | 0 | 0 | 0 | 0 | 0 | 0 |
| 103 | 0.175 | 5 | 0 | 5 | 0 | 0.25 | 0 | 2.5 | 0.175 | 0 | 5 | 0 | 0 | 0 | 0 | 0 | 0 |
| 104 | 0 | 2.5 | 0 | 2.5 | 0 | 0 | 0 | 1.25 | 0 | 0 | 2.5 | 0 | 0 | 0 | 0 | 0 | 0 |

Table 36: OMAHA Defensive Lethality Matrix, Part 4 of 10

| 0 | 52 | 53 | 54 | 55 | 56 | 57 | 58 | 59 | 60 | 61 | 62 | 63 | 64 | 65 | 66 | 67 | 68 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 80 | 0 | 0 | 0 | 0 | 0 | 0.03 | 0 | 0.03 | 0 | 0 | 0 | 0.023 | 0 | 0 | 0 | 0.023 | 0.023 |
| 81 | 0 | 0 | 0 | 0 | 1 | 5 | 1 | 5 | 1 | 5 | 1 | 0.25 | 1 | 1 | 1 | 0.25 | 0.25 |
| 82 | 0 | 0 | 0 | 0 | 0 | 0.5 | 0 | 0.5 | 0 | 2.5 | 0 | 0.375 | 0 | 0 | 0 | 0.375 | 0.375 |
| 83 | 0 | 0 | 0 | 0 | 0 | 0.5 | 0 | 0.5 | 0 | 2.5 | 0 | 0.375 | 0 | 0 | 0 | 0.375 | 0.375 |
| 84 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1.25 | 0 | 0 | 0 | 1.25 | 1.25 |
| 85 | 0 | 0 | 0 | 0 | 0 | 0.375 | 0 | 0.375 | 0 | 7.5 | 0 | 0.25 | 0 | 0 | 0 | 0.25 | 0.25 |
| 86 | 0 | 0 | 0 | 0 | 0 | 0.25 | 0 | 0.25 | 0 | 5 | 0 | 0.175 | 0 | 0 | 0 | 0.175 | 0.175 |
| 87 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 88 | 0 | 0 | 0 | 0 | 0 | 0.025 | 0 | 0.025 | 0 | 0 | 0 | 0.02 | 0 | 0 | 0 | 0.02 | 0.02 |
| 89 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1.25 | 0 | 0 | 0 | 1.25 | 1.25 |
| 90 | 0 | 0 | 0 | 0 | 0 | 0.375 | 0 | 0.375 | 0 | 7.5 | 0 | 0.25 | 0 | 0 | 0 | 0.25 | 0.25 |
| 91 | 0 | 0 | 0 | 0 | 0 | 0.25 | 0 | 0.25 | 0 | 5 | 0 | 0.175 | 0 | 0 | 0 | 0.175 | 0.175 |
| 92 | 0 | 0 | 0 | 0 | 0 | 0.025 | 0 | 0.025 | 0 | 0 | 0 | 0.02 | 0 | 0 | 0 | 0.02 | 0.02 |
| 93 | 0 | 0 | 0 | 0 | 0 | 0.025 | 0 | 0.025 | 0 | 0 | 0 | 0.02 | 0 | 0 | 0 | 0.02 | 0.02 |
| 94 | 0 | 0 | 0 | 0 | 0 | 0.5 | 0 | 0.5 | 0 | 2.5 | 0 | 0.375 | 0 | 0 | 0 | 0.375 | 0.375 |
| 95 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1.25 | 0 | 0 | 0 | 1.25 | 1.25 |
| 96 | 0 | 0 | 0 | 0 | 1 | 1.25 | 1 | 1.25 | 1 | 1.25 | 1 | 0.25 | 1 | 1 | 1 | 0.25 | 0.25 |
| 97 | 0 | 0 | 0 | 0 | 0 | 0.5 | 0 | 0.5 | 0 | 2.5 | 0 | 0.375 | 0 | 0 | 0 | 0.375 | 0.375 |
| 98 | 0 | 0 | 0 | 0 | 0 | 0.25 | 0 | 0.25 | 0 | 5 | 0 | 0.175 | 0 | 0 | 0 | 0.175 | 0.175 |
| 99 | 0 | 0 | 0 | 0 | 0 | 0.25 | 0 | 0.25 | 0 | 5 | 0 | 0.175 | 0 | 0 | 0 | 0.175 | 0.175 |
| 100 | 0 | 0 | 0 | 0 | 1 | 1.25 | 1 | 1.25 | 1 | 5 | 1 | 0.25 | 1 | 1 | 1 | 0.25 | 0.25 |
| 101 | 0 | 0 | 0 | 0 | 0 | 0.5 | 0 | 0.5 | 0 | 2.5 | 0 | 0.375 | 0 | 0 | 0 | 0.375 | 0.375 |
| 102 | 0 | 0 | 0 | 0 | 0 | 0.25 | 0 | 0.25 | 0 | 5 | 0 | 0.175 | 0 | 0 | 0 | 0.175 | 0.175 |
| 103 | 0 | 0 | 0 | 0 | 0 | 0.25 | 0 | 0.25 | 0 | 5 | 0 | 0.175 | 0 | 0 | 0 | 0.175 | 0.175 |
| 104 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Table 37: OMAHA Defensive Lethality Matrix, Part 5 of 10

| 0 | 69 | 70 | 71 | 72 | 73 | 74 | 75 | 76 | 77 | 78 | 79 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 80 | 0.023 | 0 | 0.023 | 0 | 0 | 0 | 0 | 0 | 0.03 | 0 | 0 |
| 81 | 0.25 | 1 | 0.25 | 1 | 5 | 1 | 5 | 1 | 5 | 0 | 0 |
| 82 | 0.375 | 0 | 0.375 | 0 | 2.5 | 0 | 2.5 | 0 | 0.5 | 0 | 0 |
| 83 | 0.375 | 0 | 0.375 | 0 | 2.5 | 0 | 2.5 | 0 | 0.5 | 0 | 0 |
| 84 | 1.25 | 0 | 1.25 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 85 | 0.25 | 0 | 0.25 | 0 | 7.5 | 0 | 7.5 | 0 | 0.375 | 0 | 0 |
| 86 | 0.175 | 0 | 0.175 | 0 | 5 | 0 | 5 | 0 | 0.25 | 0 | 0 |
| 87 | 0 | 0 | 0 | 0 | 2.5 | 0 | 2.5 | 0 | 0 | 0 | 0 |
| 88 | 0.02 | 0 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0.025 | 0 | 0 |
| 89 | 1.25 | 0 | 1.25 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 90 | 0.25 | 0 | 0.25 | 0 | 7.5 | 0 | 7.5 | 0 | 0.375 | 0 | 0 |
| 91 | 0.175 | 0 | 0.175 | 0 | 5 | 0 | 5 | 0 | 0.25 | 0 | 0 |
| 92 | 0.02 | 0 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0.025 | 0 | 0 |
| 93 | 0.02 | 0 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0.025 | 0 | 0 |
| 94 | 0.375 | 0 | 0.375 | 0 | 2.5 | 0 | 2.5 | 0 | 0.5 | 0 | 0 |
| 95 | 1.25 | 0 | 1.25 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 96 | 0.25 | 1 | 0.25 | 1 | 5 | 1 | 5 | 1 | 1.25 | 0 | 0 |
| 97 | 0.375 | 0 | 0.375 | 0 | 2.5 | 0 | 2.5 | 0 | 0.5 | 0 | 0 |
| 98 | 0.175 | 0 | 0.175 | 0 | 5 | 0 | 5 | 0 | 0.25 | 0 | 0 |
| 99 | 0.175 | 0 | 0.175 | 0 | 5 | 0 | 5 | 0 | 0.25 | 0 | 0 |
| 100 | 0.25 | 1 | 0.25 | 1 | 5 | 1 | 5 | 1 | 1.25 | 0 | 0 |
| 101 | 0.375 | 0 | 0.375 | 0 | 2.5 | 0 | 2.5 | 0 | 0.5 | 0 | 0 |
| 102 | 0.175 | 0 | 0.175 | 0 | 5 | 0 | 5 | 0 | 0.25 | 0 | 0 |
| 103 | 0.175 | 0 | 0.175 | 0 | 5 | 0 | 5 | 0 | 0.25 | 0 | 0 |
| 104 | 0 | 0 | 0 | 0 | 2.5 | 0 | 2.5 | 0 | 0 | 0 | 0 |

Table 38: OMAHA Defensive Lethality Matrix, Part 6 of 10

| 0 | 1 | 2 | 4 | 3 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 0 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 105 | 0.375 | 0.5 | 0 | 0 | 0 | 0 | 0 | 2.5 | 0 | 0 | 0.375 | 0 | 0 | 0 | 0.5 | 0.5 | 0.375 | 105 |
| 106 | 0.225 | 0.3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.225 | 0 | 0 | 0 | 0.3 | 0.225 | 0.225 | 106 |
| 107 | 0.175 | 0.25 | 0 | 0 | 0 | 0 | 0 | 5 | 0 | 0 | 0.175 | 0 | 0 | 0 | 0.25 | 0.175 | 0.175 | 107 |
| 108 | 0.175 | 0.25 | 0 | 0 | 0 | 0 | 0 | 5 | 0 | 0 | 0.175 | 0 | 0 | 0 | 0.25 | 0.175 | 0.175 | 108 |
| 109 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 109 |
| 110 | 0.225 | 0.3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.225 | 0 | 0 | 0 | 0.3 | 0.225 | 0.225 | 110 |
| 111 | 0.25 | 0.375 | 0 | 0 | 0 | 0 | 0 | 7.5 | 0 | 0 | 0.25 | 0 | 0 | 0 | 0.375 | 0.25 | 0.25 | 111 |
| 112 | 0.25 | 0.375 | 1 | 1 | 1 | 1 | 0 | 5 | 1 | 1 | 0.25 | 1 | 1 | 1 | 0.375 | 0.25 | 0.25 | 112 |
| 113 | 0.02 | 0.025 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.02 | 0 | 0 | 0 | 0.025 | 0.02 | 0.02 | 113 |
| 114 | 0.375 | 0.5 | 0 | 0 | 0 | 0 | 0 | 2.5 | 0 | 0 | 0.375 | 0 | 0 | 0 | 0.5 | 0.5 | 0.375 | 114 |
| 115 | 0.02 | 0.025 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.02 | 0 | 0 | 0 | 0.025 | 0.02 | 0.02 | 115 |
| 116 | 0.375 | 0.5 | 0 | 0 | 0 | 0 | 0 | 2.5 | 0 | 0 | 0.375 | 0 | 0 | 0 | 0.5 | 0.5 | 0.375 | 116 |
| 117 | 0.02 | 0.025 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.02 | 0 | 0 | 0 | 0.025 | 0.02 | 0.02 | 117 |
| 118 | 0.225 | 0.3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.225 | 0 | 0 | 0 | 0.3 | 0.225 | 0.225 | 118 |
| 119 | 0.25 | 0.375 | 0 | 0 | 0 | 0 | 0 | 7.5 | 0 | 0 | 0.25 | 0 | 0 | 0 | 0.375 | 0.25 | 0.25 | 119 |
| 120 | 0.175 | 0.25 | 0 | 0 | 0 | 0 | 0 | 5 | 0 | 0 | 0.175 | 0 | 0 | 0 | 0.25 | 0.175 | 0.175 | 120 |
| 121 | 0.02 | 0.025 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.02 | 0 | 0 | 0 | 0.025 | 0.02 | 0.02 | 121 |
| 122 | 0.02 | 0.025 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.02 | 0 | 0 | 0 | 0.025 | 0.02 | 0.02 | 122 |
| 123 | 0.225 | 0.3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.225 | 0 | 0 | 0 | 0.3 | 0.225 | 0.225 | 123 |
| 124 | 0.25 | 0.375 | 0 | 0 | 0 | 0 | 0 | 7.5 | 0 | 0 | 0.25 | 0 | 0 | 0 | 0.375 | 0.25 | 0.25 | 124 |
| 125 | 0.375 | 0.5 | 0 | 0 | 0 | 0 | 0 | 2.5 | 0 | 0 | 0.375 | 0 | 0 | 0 | 0.5 | 0.5 | 0.375 | 125 |
| 126 | 0.02 | 0.025 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.02 | 0 | 0 | 0 | 0.025 | 0.02 | 0.02 | 126 |
| 127 | 0.25 | 0.375 | 1 | 1 | 1 | 1 | 0 | 5 | 1 | 1 | 0.25 | 1 | 1 | 1 | 0.375 | 0.25 | 0.25 | 127 |

Table 39: OMAHA Defensive Lethality Matrix, Part 7 of 10

| 0 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 | 29 | 30 | 31 | 32 | 33 | 34 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 105 | 0 | 0 | 0.375 | 0.5 | 0 | 0 | 0 | 0 | 0.375 | 0.375 | 2.5 | 0.5 | 0 | 0 | 0 | 0 | 0.5 |
| 106 | 0 | 0 | 0.225 | 0.3 | 0 | 0 | 0 | 0 | 0.225 | 0.225 | 0 | 0.3 | 0 | 0 | 0 | 0 | 0.3 |
| 107 | 0 | 0 | 0.175 | 0.25 | 0 | 0 | 0 | 0 | 0.175 | 0.175 | 5 | 0.25 | 0 | 0 | 0 | 0 | 0.25 |
| 108 | 0 | 0 | 0.175 | 0.25 | 0 | 0 | 0 | 0 | 0.175 | 0.175 | 5 | 0.25 | 0 | 0 | 0 | 0 | 0.25 |
| 109 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2.5 | 0 | 0 | 0 | 0 | 0 | 0 |
| 110 | 0 | 0 | 0.225 | 0.3 | 0 | 0 | 0 | 0 | 0.225 | 0.225 | 0 | 0.3 | 0 | 0 | 0 | 0 | 0.3 |
| 111 | 0 | 0 | 0.25 | 0.375 | 0 | 0 | 0 | 0 | 0.25 | 0.25 | 7.5 | 0.375 | 0 | 0 | 0 | 0 | 0.375 |
| 112 | 1 | 1 | 0.25 | 1.25 | 1 | 1 | 1 | 1 | 0.25 | 37.5 | 5 | 1.25 | 1 | 1 | 1 | 1 | 1.25 |
| 113 | 0 | 0 | 0.02 | 0.025 | 0 | 0 | 0 | 0 | 0.02 | 0.02 | 0 | 0.025 | 0 | 0 | 0 | 0 | 0.025 |
| 114 | 0 | 0 | 0.375 | 0.5 | 0 | 0 | 0 | 0 | 0.375 | 0.375 | 2.5 | 0.5 | 0 | 0 | 0 | 0 | 0.5 |
| 115 | 0 | 0 | 0.02 | 0.025 | 0 | 0 | 0 | 0 | 0.02 | 0.02 | 0 | 0.025 | 0 | 0 | 0 | 0 | 0.025 |
| 116 | 0 | 0 | 0.375 | 0.5 | 0 | 0 | 0 | 0 | 0.375 | 0.375 | 2.5 | 0.5 | 0 | 0 | 0 | 0 | 0.5 |
| 117 | 0 | 0 | 0.02 | 0.025 | 0 | 0 | 0 | 0 | 0.02 | 0.02 | 0 | 0.025 | 0 | 0 | 0 | 0 | 0.025 |
| 118 | 0 | 0 | 0.225 | 0.3 | 0 | 0 | 0 | 0 | 0.225 | 0.225 | 0 | 0.3 | 0 | 0 | 0 | 0 | 0.3 |
| 119 | 0 | 0 | 0.25 | 0.375 | 0 | 0 | 0 | 0 | 0.25 | 0.25 | 7.5 | 0.375 | 0 | 0 | 0 | 0 | 0.375 |
| 120 | 0 | 0 | 0.175 | 0.25 | 0 | 0 | 0 | 0 | 0.175 | 0.175 | 5 | 0.25 | 0 | 0 | 0 | 0 | 0.25 |
| 121 | 0 | 0 | 0.02 | 0.025 | 0 | 0 | 0 | 0 | 0.02 | 0.02 | 0 | 0.025 | 0 | 0 | 0 | 0 | 0.025 |
| 122 | 0 | 0 | 0.02 | 0.025 | 0 | 0 | 0 | 0 | 0.02 | 0.02 | 0 | 0.025 | 0 | 0 | 0 | 0 | 0.025 |
| 123 | 0 | 0 | 0.225 | 0.3 | 0 | 0 | 0 | 0 | 0.225 | 0.225 | 0 | 0.3 | 0 | 0 | 0 | 0 | 0.3 |
| 124 | 0 | 0 | 0.25 | 0.375 | 0 | 0 | 0 | 0 | 0.25 | 0.25 | 7.5 | 0.375 | 0 | 0 | 0 | 0 | 0.375 |
| 125 | 0 | 0 | 0.375 | 0.5 | 0 | 0 | 0 | 0 | 0.375 | 0.375 | 2.5 | 0.5 | 0 | 0 | 0 | 0 | 0.5 |
| 126 | 0 | 0 | 0.02 | 0.025 | 0 | 0 | 0 | 0 | 0.02 | 0.02 | 0 | 0.025 | 0 | 0 | 0 | 0 | 0.025 |
| 127 | 1 | 1 | 0.25 | 1.25 | 1 | 1 | 1 | 1 | 0.25 | 37.5 | 5 | 1.25 | 1 | 1 | 1 | 1 | 1.25 |

Table 40: OMAHA Defensive Lethality Matrix, Part 8 of 10

| 0 | 35 | 36 | 37 | 38 | 39 | 40 | 41 | 42 | 43 | 44 | 45 | 46 | 47 | 48 | 49 | 50 | 51 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 105 | 0.375 | 2.5 | 0 | 2.5 | 0 | 0.5 | 0 | 1.25 | 0.375 | 0 | 2.5 | 0 | 0 | 0 | 0 | 0 | 0 |
| 106 | 0.225 | 0 | 0 | 0 | 0 | 0.3 | 0 | 0 | 0.225 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 107 | 0.175 | 5 | 0 | 5 | 0 | 0.25 | 0 | 2.5 | 0.175 | 0 | 5 | 0 | 0 | 0 | 0 | 0 | 0 |
| 108 | 0.175 | 5 | 0 | 5 | 0 | 0.25 | 0 | 2.5 | 0.175 | 0 | 5 | 0 | 0 | 0 | 0 | 0 | 0 |
| 109 | 0 | 2.5 | 0 | 2.5 | 0 | 0 | 0 | 1.25 | 0 | 0 | 2.5 | 0 | 0 | 0 | 0 | 0 | 0 |
| 110 | 0.225 | 0 | 0 | 0 | 0 | 0.3 | 0 | 0 | 0.225 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 111 | 0.25 | 7.5 | 0 | 7.5 | 0 | 0.375 | 0 | 2.5 | 0.25 | 0 | 7.5 | 0 | 0 | 0 | 0 | 0 | 0 |
| 112 | 0.25 | 5 | 1 | 5 | 1 | 1.25 | 1 | 2.5 | 0.25 | 1 | 5 | 0 | 0 | 0 | 0 | 0 | 0 |
| 113 | 0.02 | 0 | 0 | 0 | 0 | 0.025 | 0 | 0.013 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 114 | 0.375 | 2.5 | 0 | 2.5 | 0 | 0.5 | 0 | 1.25 | 0.375 | 0 | 2.5 | 0 | 0 | 0 | 0 | 0 | 0 |
| 115 | 0.02 | 0 | 0 | 0 | 0 | 0.025 | 0 | 0.013 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 116 | 0.375 | 2.5 | 0 | 2.5 | 0 | 0.5 | 0 | 0.013 | 0.375 | 0 | 2.5 | 0 | 0 | 0 | 0 | 0 | 0 |
| 117 | 0.02 | 0 | 0 | 0 | 0 | 0.025 | 0 | 0.013 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 118 | 0.225 | 0 | 0 | 0 | 0 | 0.3 | 0 | 0 | 0.225 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 119 | 0.25 | 7.5 | 0 | 7.5 | 0 | 0.375 | 0 | 2.5 | 0.25 | 0 | 7.5 | 0 | 0 | 0 | 0 | 0 | 0 |
| 120 | 0.175 | 5 | 0 | 5 | 0 | 0.25 | 0 | 2.5 | 0.175 | 0 | 5 | 0 | 0 | 0 | 0 | 0 | 0 |
| 121 | 0.02 | 0 | 0 | 0 | 0 | 0.025 | 0 | 0.013 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 122 | 0.02 | 0 | 0 | 0 | 0 | 0.025 | 0 | 0.013 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 123 | 0.225 | 0 | 0 | 0 | 0 | 0.3 | 0 | 0 | 0.225 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 124 | 0.25 | 7.5 | 0 | 7.5 | 0 | 0.375 | 0 | 2.5 | 0.25 | 0 | 7.5 | 0 | 0 | 0 | 0 | 0 | 0 |
| 125 | 0.375 | 2.5 | 0 | 2.5 | 0 | 0.5 | 0 | 2.5 | 0.375 | 0 | 2.5 | 0 | 0 | 0 | 0 | 0 | 0 |
| 126 | 0.02 | 0 | 0 | 0 | 0 | 0.025 | 0 | 0.013 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 127 | 0.25 | 5 | 1 | 5 | 1 | 1.25 | 1 | 2.5 | 0.25 | 1 | 5 | 0 | 0 | 0 | 0 | 0 | 0 |

Table 41: OMAHA Defensive Lethality Matrix, Part 9 of 10

| 0 | 52 | 53 | 54 | 55 | 56 | 57 | 58 | 59 | 60 | 61 | 62 | 63 | 64 | 65 | 66 | 67 | 68 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 105 | 0 | 0 | 0 | 0 | 0 | 0.5 | 0 | 0.5 | 0 | 2.5 | 0 | 0.375 | 0 | 0 | 0 | 0.375 | 0.375 |
| 106 | 0 | 0 | 0 | 0 | 0 | 0.3 | 0 | 0.3 | 0 | 0 | 0 | 0.225 | 0 | 0 | 0 | 0.225 | 0.225 |
| 107 | 0 | 0 | 0 | 0 | 0 | 0.25 | 0 | 0.25 | 0 | 5 | 0 | 0.175 | 0 | 0 | 0 | 0.175 | 0.175 |
| 108 | 0 | 0 | 0 | 0 | 0 | 0.25 | 0 | 0.25 | 0 | 5 | 0 | 0.175 | 0 | 0 | 0 | 0.175 | 0.175 |
| 109 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 110 | 0 | 0 | 0 | 0 | 0 | 0.3 | 0 | 0.3 | 0 | 0 | 0 | 0.225 | 0 | 0 | 0 | 0.225 | 0.225 |
| 111 | 0 | 0 | 0 | 0 | 0 | 0.375 | 0 | 0.375 | 0 | 7.5 | 0 | 0.25 | 0 | 0 | 0 | 0.25 | 0.25 |
| 112 | 0 | 0 | 0 | 0 | 1 | 1.25 | 1 | 1.25 | 1 | 1.25 | 1 | 0.25 | 1 | 1 | 1 | 0.25 | 0.25 |
| 113 | 0 | 0 | 0 | 0 | 0 | 0.025 | 0 | 0.025 | 0 | 0 | 0 | 0.02 | 0 | 0 | 0 | 0.02 | 0.02 |
| 114 | 0 | 0 | 0 | 0 | 0 | 0.5 | 0 | 0.5 | 0 | 2.5 | 0 | 0.375 | 0 | 0 | 0 | 0.375 | 0.375 |
| 115 | 0 | 0 | 0 | 0 | 0 | 0.025 | 0 | 0.025 | 0 | 0 | 0 | 0.02 | 0 | 0 | 0 | 0.02 | 0.02 |
| 116 | 0 | 0 | 0 | 0 | 0 | 0.5 | 0 | 0.5 | 0 | 2.5 | 0 | 0.375 | 0 | 0 | 0 | 0.375 | 0.375 |
| 117 | 0 | 0 | 0 | 0 | 0 | 0.025 | 0 | 0.025 | 0 | 0 | 0 | 0.02 | 0 | 0 | 0 | 0.02 | 0.02 |
| 118 | 0 | 0 | 0 | 0 | 0 | 0.3 | 0 | 0.3 | 0 | 0 | 0 | 0.225 | 0 | 0 | 0 | 0.225 | 0.225 |
| 119 | 0 | 0 | 0 | 0 | 0 | 0.375 | 0 | 0.375 | 0 | 7.5 | 0 | 0.25 | 0 | 0 | 0 | 0.25 | 0.25 |
| 120 | 0 | 0 | 0 | 0 | 0 | 0.25 | 0 | 0.25 | 0 | 5 | 0 | 0.175 | 0 | 0 | 0 | 0.175 | 0.175 |
| 121 | 0 | 0 | 0 | 0 | 0 | 0.025 | 0 | 0.025 | 0 | 0 | 0 | 0.02 | 0 | 0 | 0 | 0.02 | 0.02 |
| 122 | 0 | 0 | 0 | 0 | 0 | 0.025 | 0 | 0.025 | 0 | 0 | 0 | 0.02 | 0 | 0 | 0 | 0.02 | 0.02 |
| 123 | 0 | 0 | 0 | 0 | 0 | 0.3 | 0 | 0.3 | 0 | 0 | 0 | 0.225 | 0 | 0 | 0 | 0.225 | 0.225 |
| 124 | 0 | 0 | 0 | 0 | 0 | 0.375 | 0 | 0.375 | 0 | 7.5 | 0 | 0.25 | 0 | 0 | 0 | 0.25 | 0.25 |
| 125 | 0 | 0 | 0 | 0 | 0 | 0.5 | 0 | 0.5 | 0 | 2.5 | 0 | 0.375 | 0 | 0 | 0 | 0.375 | 0.375 |
| 126 | 0 | 0 | 0 | 0 | 0 | 0.025 | 0 | 0.025 | 0 | 0 | 0 | 0.02 | 0 | 0 | 0 | 0.02 | 0.02 |
| 127 | 0 | 0 | 0 | 0 | 1 | 1.25 | 1 | 1.25 | 1 | 5 | 1 | 0.25 | 1 | 1 | 1 | 0.25 | 0.25 |

Table 42: OMAHA Defensive Lethality Matrix, Part 10 of 10

| 0 | 69 | 70 | 71 | 72 | 73 | 74 | 75 | 76 | 77 | 78 | 79 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 105 | 0.375 | 0 | 0.375 | 0 | 2.5 | 0 | 2.5 | 0 | 0.5 | 0 | 0 |
| 106 | 0.225 | 0 | 0.225 | 0 | 0 | 0 | 0 | 0 | 0.3 | 0 | 0 |
| 107 | 0.175 | 0 | 0.175 | 0 | 5 | 0 | 5 | 0 | 0.25 | 0 | 0 |
| 108 | 0.175 | 0 | 0.175 | 0 | 5 | 0 | 5 | 0 | 0.25 | 0 | 0 |
| 109 | 0 | 0 | 0 | 0 | 2.5 | 0 | 2.5 | 0 | 0 | 0 | 0 |
| 110 | 0.225 | 0 | 0.225 | 0 | 0 | 0 | 0 | 0 | 0.3 | 0 | 0 |
| 111 | 0.25 | 0 | 0.25 | 0 | 7.5 | 0 | 7.5 | 0 | 0.375 | 0 | 0 |
| 112 | 0.25 | 1 | 0.25 | 1 | 5 | 1 | 5 | 1 | 1.25 | 0 | 0 |
| 113 | 0.02 | 0 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0.025 | 0 | 0 |
| 114 | 0.375 | 0 | 0.375 | 0 | 2.5 | 0 | 2.5 | 0 | 0.5 | 0 | 0 |
| 115 | 0.02 | 0 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0.025 | 0 | 0 |
| 116 | 0.375 | 0 | 0.375 | 0 | 2.5 | 0 | 2.5 | 0 | 0.5 | 0 | 0 |
| 117 | 0.02 | 0 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0.025 | 0 | 0 |
| 118 | 0.225 | 0 | 0.225 | 0 | 0 | 0 | 0 | 0 | 0.3 | 0 | 0 |
| 119 | 0.25 | 0 | 0.25 | 0 | 7.5 | 0 | 7.5 | 0 | 0.375 | 0 | 0 |
| 120 | 0.175 | 0 | 0.175 | 0 | 5 | 0 | 5 | 0 | 0.25 | 0 | 0 |
| 121 | 0.02 | 0 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0.025 | 0 | 0 |
| 122 | 0.02 | 0 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0.025 | 0 | 0 |
| 123 | 0.225 | 0 | 0.225 | 0 | 0 | 0 | 0 | 0 | 0.3 | 0 | 0 |
| 124 | 0.25 | 0 | 0.25 | 0 | 7.5 | 0 | 7.5 | 0 | 0.375 | 0 | 0 |
| 125 | 0.375 | 0 | 0.375 | 0 | 2.5 | 0 | 2.5 | 0 | 0.5 | 0 | 0 |
| 126 | 0.02 | 0 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0.025 | 0 | 0 |
| 127 | 0.25 | 1 | 0.25 | 1 | 5 | 1 | 5 | 1 | 1.25 | 0 | 0 |

# APPENDIX B

# OPERATION COBRA MODEL INPUTS

This appendix describes inputs to the Operation Cobra combat model, which is based on a limited set of armor-heavy fighting from Operation Cobra. This combat model is based on a discrete time hybrid Markov Chain-system dynamics approach. Populations of asset types are defined as objects of a certain type, such as an offensive air asset or a defensive land asset. Each object, or asset population, has a set quantity or number of assets. Each asset has certain functional characteristics, such as its failure rate, its effective combat radius, its fire rate, or its average speed. Furthermore, each asset has its own row and column of the lethality matrices - two matrices that define the lethality of each asset type against each opposing asset type. The two matrices are one for offensive against defensive assets, and one for vice versa. Finally, each asset type has its own scenario variables - these are variables that define when it is launched from the starting point (or base or amphibious assault group), at what rate it is launched, and whether it is carrying any number of other assets to the combat zone.

## *B.1 Operation Cobra Offensive Asset Definitions*

This section describes the characteristics of the offensive, or friendly assets, in the Operation Cobra scenario [31]. Because the operation is not an amphibious landing, there are significantly fewer populations of assets. Any repetitions are due to a need to increase improve computational speed - this is done by balancing the matrix operations in the interoperability calculations (which benefit from more objects of smaller population sizes) with the matrix operations in the rest of the model (which benefit from fewer objects, i.e. fewer populations and larger population sizes). Each page of the data represents a subset of the attacking force. The columns describe the “Number”, “Failure Rate”, “Fire Rate”, “Effective Radius”, “Average Speed”, and “Endurance” if applicable. Furthermore, each page includes the asset population’s name and asset population’s unique ID number. Type is not listed because all assets were of type “OLand” with the exception of the bombers, which were “OAir”.

Table 43: Operation Cobra Friendly Assets, Part 1 of 3

| | ID | Number | Eff. Radius | Avg. Speed | Failure Rate | Fire Rate |
|---|---|---|---|---|---|---|
| Infantry | 1 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 2 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 3 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 4 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 5 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 6 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 7 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 8 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 9 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 10 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 11 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 12 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 13 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 14 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 15 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 16 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 17 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 18 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 19 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 20 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 21 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 22 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 23 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 24 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 25 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |

Table 44: Operation Cobra Friendly Assets, Part 2 of 3

| | ID | Number | Eff. Radius | Avg. Speed | Failure Rate | Fire Rate |
|---|---|---|---|---|---|---|
| Infantry | 26 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 27 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 28 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 29 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 30 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 31 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 32 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 33 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 34 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 35 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 36 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 37 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 38 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 39 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| Infantry | 40 | 500 | 0.457 | 0.804672 | 0 | 0.13333 |
| M4 Info | 41 | 372 | 0.5 | 40 | 0.01 | 0.01667 |
| M5 | 42 | 154 | 0.5 | 58 | 0.01 | 0.025 |
| M7 105mm Howitzer | 43 | 72 | 2 | 24 | 0.01 | 0.0833 |
| light MG | 44 | 930 | 0.457 | 0.4 | 0.01 | 8.33 |
| MG | 45 | 808 | 0.457 | 0.1 | 0.01 | 8.33 |
| M1 Mortar | 46 | 108 | 1.5 | 0.1 | 0.01 | 0.3 |
| M2 Mortar | 47 | 168 | 0.8 | 0.1 | 0.01 | 0.3 |
| bazooka | 48 | 1214 | 1.5 | 0.3 | 0.01 | 0.0001 |
| M18 | 49 | 108 | 6.7 | 60 | 0.03 | 0.0833 |
| M114 155mm howitzer | 50 | 24 | 7.3 | 0 | 0.01 | 0.0011 |
| Bombers | 51 | 3000 | 2 | 300 | 0.001 | 0.8 |

Table 45: Operation Cobra Friendly Assets, Part 3 of 3

| | ID | Number | Eff. Radius | Avg. Speed | Failure Rate | Fire Rate | Endurance |
|---|---|---|---|---|---|---|---|
| Bombers | 51 | 3000 | 2 | 300 | 0.001 | 0.8 | 300 |

## *B.2 Operation Cobra Defensive Asset Definitions*

This section describes the characteristics of the defensive, or enemy assets, in the Operation Cobra scenario [31]. Because the operation did not have as many fortified emplacements, all assets were condensed into populations of type as opposed to location. The columns describe the “Number”, “Failure Rate”, “Fire Rate”, “Effective Radius”, and “Average Speed”. Furthermore, the table includes the asset population’s name and asset population’s unique ID number. Type is not listed because all assets were of type “OLand”.

Table 46: Operation Cobra Enemy Assets

| | ID | Number | Eff. Radius | Avg. Speed | Failure Rate | Fire Rate |
|---|---|---|---|---|---|---|
| Rifles | 1 | 10000 | 0.5 | 0.8 | 0.002 | 0.0833 |
| Flamethrowers | 2 | 50 | 0.025 | 0.8 | 0.002 | 0.0003 |
| 105mm leFH 18 | 3 | 24 | 3 | 0 | 0.0001 | 0.1 |
| 20mm FLAK | 4 | 24 | 1.1 | 0 | 0.0001 | 2.666 |
| 88mm FLAK | 5 | 12 | 7.43 | 0 | 0.0001 | 0.25 |
| 37mm FLAK | 6 | 8 | 2.1 | 0 | 0.0001 | 2.5 |
| 75mm PAK 40 | 7 | 12 | 2.1 | 0 | 0.0001 | 0.2333 |
| 150mm sFH 18 (Howitzer) | 8 | 18 | 3.5 | 0 | 0.0001 | 0.0666 |
| 120mm Granatwerfer 42 Mortar | 9 | 12 | 1.5 | 0 | 0.0001 | 0.1333 |
| 170mm Kanone 18 | 10 | 12 | 20 | 0 | 0.0001 | 0.0167 |
| 150mm Hummel (SP Gun) | 11 | 18 | 3.5 | 42 | 0.001 | 0.0666 |
| STUG III | 12 | 11 | 2.1 | 40 | 0.0001 | 0.2333 |
| STUG IV | 13 | 11 | 2.1 | 40 | 0.0001 | 0.2333 |
| Panzer IV | 14 | 64 | 1 | 40 | 0.0001 | 0.2333 |
| Panther | 15 | 62 | 1 | 46 | 0.01 | 0.2333 |

## B.3 Operation Cobra Offensive Asset Lethality Matrix

As mentioned previously, lethality matrices describe the lethality of some asset in a row against some asset in a column. Assets are listed in terms of their unique population ID numbers, which can be referenced in the previous tables. In almost all cases, lethality should be taken to mean the fractional damage produced by each use of a weapon - because any asset in the "attacking" state fires its weapon continuously (according to its fire rate) and never misses, these lethalities are lower than one would typically see because they must represent a sort of average per-shot lethality. The only asset where lethality is not used in the "per shot" sense is the strike asset, where the lethality is a per-asset lethality because strike assets are single-use.

The offensive lethality matrix is broken up into 2 tables due to size. The tables move from left to right through the matrix, starting with offensive assets 1 through 26 against defensive assets 54 through 68.

Table 47: Operation Cobra Offensive Lethality Matrix, Part 1 of 2

| 0 | 54 | 55 | 56 | 57 | 58 | 59 | 60 | 61 | 62 | 63 | 64 | 65 | 66 | 67 | 68 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 5 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 6 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 7 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 8 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 9 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 10 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 11 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 12 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 13 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 14 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 15 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 16 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 17 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 18 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 19 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 20 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 21 | 0.005 | 0.005 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.005 | 0.001 | 0 | 0 | 0 | 0 | 0 |
| 22 | 0.01 | 0.01 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.01 | 0.005 | 0 | 0 | 0 | 0 | 0 |
| 23 | 0.016 | 0.016 | 0.0002 | 0.0002 | 0.0002 | 0.0002 | 0.0002 | 0.0002 | 0.0002 | 0.0002 | 0 | 0 | 0 | 0 | 0 |
| 24 | 0.012 | 0.012 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 25 | 0.005 | 0.005 | 0.15 | 0.15 | 0.15 | 0.15 | 0.15 | 0.15 | 0.005 | 0.15 | 0.3 | 0.3 | 0.3 | 0.3 | 0.175 |
| 26 | 0.005 | 0.005 | 0.075 | 0.075 | 0.075 | 0.075 | 0.075 | 0.075 | 0.0005 | 0.075 | 0.15 | 0.15 | 0.15 | 0.15 | 0.1 |

Table 48: Operation Cobra Offensive Lethality Matrix, Part 2 of 2

| 0 | 54 | 55 | 56 | 57 | 58 | 59 | 60 | 61 | 62 | 63 | 64 | 65 | 66 | 67 | 68 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 27 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 28 | 0.002 | 0.002 | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 | 0.002 | 0.025 | 0.039 | 0.039 | 0.039 | 0.04 | 0.03 |
| 29 | 0.001 | 0.001 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.001 | 0.02 | 0.034 | 0.034 | 0.034 | 0.035 | 0.025 |
| 30 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.04 | 0.02 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 |
| 31 | 0.025 | 0.025 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.05 | 0.03 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 32 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 33 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 34 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 35 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 36 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 37 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 38 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 39 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 40 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 41 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 42 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 43 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 44 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 45 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 46 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 47 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 48 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 49 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 50 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 51 | 0.02 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 52 | 0.02 | 0.02 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.02 | 0.1 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 53 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

## B.4 Operation Cobra Defensive Asset Lethality Matrix

Repeated here for easier reference, the lethality matrices describe the lethality of some asset in a row against some asset in a column. Assets are listed in terms of their unique population ID numbers, which can be referenced in the previous tables. In almost all cases, lethality should be taken to mean the fractional damage produced by each use of a weapon - because any asset in the "attacking" state fires its weapon continuously (according to its fire rate) and never misses, these lethalities are lower than one would typically see because they must represent a sort of average per-shot lethality. The only asset where lethality is not used in the "per shot" sense is the strike asset, where the lethality is a per-asset lethality because strike assets are themselves ordnance and are single-use.

The Operation Cobra defensive lethality matrix is broken up into 4 tables due to size. The tables move from left to right through the matrix, starting with the lethality of defensive assets 54 through 68 against offensive assets 1 through 13.

Table 49: Operation Cobra Defensive Lethality Matrix, Part 1 of 4

| 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 54 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |
| 55 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 56 | 0.0085 | 0.0085 | 0.0085 | 0.0085 | 0.0085 | 0.0085 | 0.0085 | 0.0085 | 0.0085 | 0.0085 | 0.0085 | 0.0085 | 0.0085 |
| 57 | 0.0005 | 0.0005 | 0.0005 | 0.0005 | 0.0005 | 0.0005 | 0.0005 | 0.0005 | 0.0005 | 0.0005 | 0.0005 | 0.0005 | 0.0005 |
| 58 | 0.0025 | 0.0025 | 0.0025 | 0.0025 | 0.0025 | 0.0025 | 0.0025 | 0.0025 | 0.0025 | 0.0025 | 0.0025 | 0.0025 | 0.0025 |
| 59 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |
| 60 | 0.0075 | 0.0075 | 0.0075 | 0.0075 | 0.0075 | 0.0075 | 0.0075 | 0.0075 | 0.0075 | 0.0075 | 0.0075 | 0.0075 | 0.0075 |
| 61 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 |
| 62 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 |
| 63 | 0.016 | 0.016 | 0.016 | 0.016 | 0.016 | 0.016 | 0.016 | 0.016 | 0.016 | 0.016 | 0.016 | 0.016 | 0.016 |
| 64 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 |
| 65 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 |
| 66 | 0.006 | 0.006 | 0.006 | 0.006 | 0.006 | 0.006 | 0.006 | 0.006 | 0.006 | 0.006 | 0.006 | 0.006 | 0.006 |
| 67 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 |
| 68 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 |

Table 50: Operation Cobra Defensive Lethality Matrix, Part 2 of 4

| 0 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 54 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.001 |
| 55 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0 | 0 | 0 | 0 | 0 | 0.05 | 0.05 |
| 56 | 0.0085 | 0.0085 | 0.0085 | 0.0085 | 0.0085 | 0.0085 | 0.0085 | 0.02 | 0.02 | 0.02 | 0.02 | 0.025 | 0.0085 | 0.0085 |
| 57 | 0.0005 | 0.0005 | 0.0005 | 0.0005 | 0.0005 | 0.0005 | 0.0005 | 0.01 | 0.01 | 0.01 | 0.01 | 0.025 | 0.0025 | 0.0025 |
| 58 | 0.0025 | 0.0025 | 0.0025 | 0.0025 | 0.0025 | 0.0025 | 0.0025 | 0.004 | 0.004 | 0.004 | 0.004 | 0.014 | 0.006 | 0.006 |
| 59 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.011 | 0.011 | 0.011 | 0.011 | 0.026 | 0.0035 | 0.0035 |
| 60 | 0.0075 | 0.0075 | 0.0075 | 0.0075 | 0.0075 | 0.0075 | 0.0075 | 0.005 | 0.005 | 0.005 | 0.005 | 0.015 | 0.0075 | 0.0075 |
| 61 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.01 | 0.01 | 0.01 | 0.01 | 0.03 | 0.015 | 0.015 |
| 62 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.01 | 0.01 | 0.01 | 0.01 | 0 | 0.01 | 0.01 |
| 63 | 0.016 | 0.016 | 0.016 | 0.016 | 0.016 | 0.016 | 0.016 | 0.011 | 0.011 | 0.011 | 0.011 | 0.031 | 0.016 | 0.016 |
| 64 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.01 | 0.01 | 0.01 | 0.01 | 0.03 | 0.015 | 0.015 |
| 65 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.01 | 0.01 | 0.01 | 0.01 | 0.03 | 0.01 | 0.01 |
| 66 | 0.006 | 0.006 | 0.006 | 0.006 | 0.006 | 0.006 | 0.006 | 0.011 | 0.011 | 0.011 | 0.011 | 0.031 | 0.011 | 0.011 |
| 67 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.01 | 0.01 | 0.01 | 0.01 | 0.02 | 0.01 | 0.01 |
| 68 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.01 | 0.01 | 0.01 | 0.01 | 0.02 | 0.01 | 0.01 |

Table 51: Operation Cobra Defensive Lethality Matrix, Part 3 of 4

| 0 | 28 | 29 | 30 | 31 | 32 | 33 | 34 | 35 | 36 | 37 | 38 | 39 | 40 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 54 | 0 | 0 | 0 | 0 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |
| 55 | 0 | 0 | 0 | 0 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 56 | 0.035 | 0.025 | 0.02 | 0.02 | 0.0085 | 0.0085 | 0.0085 | 0.0085 | 0.0085 | 0.0085 | 0.0085 | 0.0085 | 0.0085 |
| 57 | 0.005 | 0.005 | 0.0075 | 0.01 | 0.0005 | 0.0005 | 0.0005 | 0.0005 | 0.0005 | 0.0005 | 0.0005 | 0.0005 | 0.0005 |
| 58 | 0.014 | 0.014 | 0.006 | 0.006 | 0.0025 | 0.0025 | 0.0025 | 0.0025 | 0.0025 | 0.0025 | 0.0025 | 0.0025 | 0.0025 |
| 59 | 0.01 | 0.01 | 0.011 | 0.011 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |
| 60 | 0.015 | 0.015 | 0.0075 | 0.0075 | 0.0075 | 0.0075 | 0.0075 | 0.0075 | 0.0075 | 0.0075 | 0.0075 | 0.0075 | 0.0075 |
| 61 | 0.03 | 0.03 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 |
| 62 | 0 | 0 | 0.005 | 0.005 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 |
| 63 | 0.031 | 0.031 | 0.016 | 0.016 | 0.016 | 0.016 | 0.016 | 0.016 | 0.016 | 0.016 | 0.016 | 0.016 | 0.016 |
| 64 | 0.03 | 0.03 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 |
| 65 | 0.03 | 0.03 | 0.025 | 0.025 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 |
| 66 | 0.031 | 0.031 | 0.026 | 0.026 | 0.006 | 0.006 | 0.006 | 0.006 | 0.006 | 0.006 | 0.006 | 0.006 | 0.006 |
| 67 | 0.02 | 0.02 | 0.015 | 0.015 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 |
| 68 | 0.02 | 0.02 | 0.015 | 0.015 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 |

Table 52: Operation Cobra Defensive Lethality Matrix, Part 4 of 4

| 0 | 41 | 42 | 43 | 44 | 45 | 46 | 47 | 48 | 49 | 50 | 51 | 52 | 53 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 54 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0 | 0 |
| 55 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0 | 0 |
| 56 | 0.0085 | 0.0085 | 0.0085 | 0.0085 | 0.0085 | 0.0085 | 0.0085 | 0.0085 | 0.0085 | 0.0085 | 0.0085 | 0 | 0 |
| 57 | 0.0005 | 0.0005 | 0.0005 | 0.0005 | 0.0005 | 0.0005 | 0.0005 | 0.0005 | 0.0005 | 0.0005 | 0.0005 | 0.02 | 0 |
| 58 | 0.0025 | 0.0025 | 0.0025 | 0.0025 | 0.0025 | 0.0025 | 0.0025 | 0.0025 | 0.0025 | 0.0025 | 0.0025 | 0.035 | 0 |
| 59 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.025 | 0 |
| 60 | 0.0075 | 0.0075 | 0.0075 | 0.0075 | 0.0075 | 0.0075 | 0.0075 | 0.0075 | 0.0075 | 0.0075 | 0.0075 | 0 | 0 |
| 61 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0 | 0 |
| 62 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0 | 0 |
| 63 | 0.016 | 0.016 | 0.016 | 0.016 | 0.016 | 0.016 | 0.016 | 0.016 | 0.016 | 0.016 | 0.016 | 0 | 0 |
| 64 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 | 0 | 0 |
| 65 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0 | 0 |
| 66 | 0.006 | 0.006 | 0.006 | 0.006 | 0.006 | 0.006 | 0.006 | 0.006 | 0.006 | 0.006 | 0.006 | 0 | 0 |
| 67 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0 | 0 |
| 68 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0 | 0 |

# APPENDIX C

# HAND-CRAFTED FLEET PLAN DATA

This appendix shows the data that was created for Experiment 3. This experiment required the creation of hand-crafted fleet plans, with a "baked in" tradeoff between the number of options and the quality of those options. For the sake of consistency with the rest of the experimental data, the fleet plans use the same number of asset types (25 in all) and the same number of missions (2 missions). However, the fleets themselves are extremely simplified, containing no more than 5 asset types. This is done to simplify the process of ensuring their orthogonality to each other.

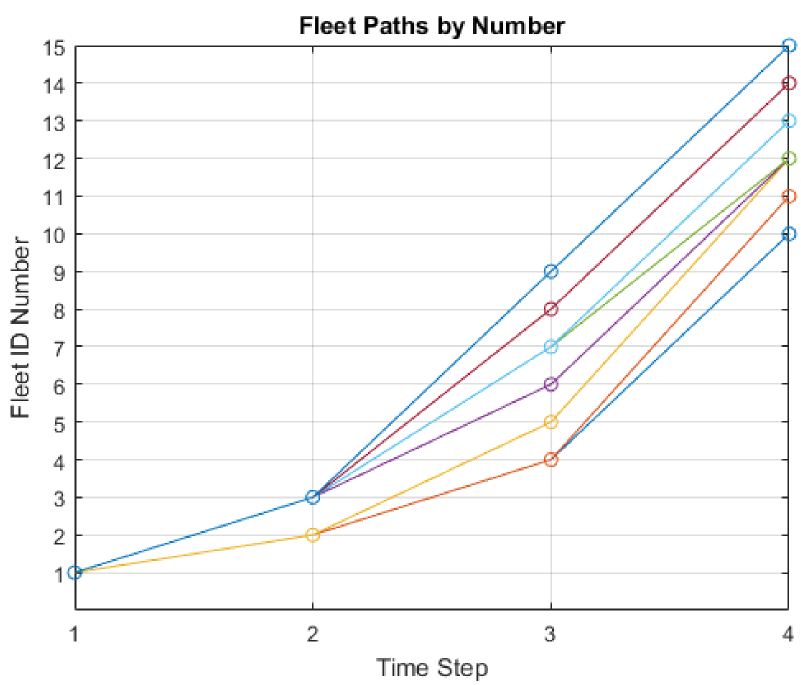



Figure 76: Repeated figure: Hand-crafted fleet paths.

The results of this hand-crafting process are shown in Figure 76, which shows that one branch has significantly more options than the other. The mission performance parameters are also completely notional and are created to ensure that certain fleets are better than others. Once more, the overall goal is that these better fleets are “less close” to the rest of the fleets and therefore fewer fleet mix plans can be created using these better fleets.

## *C.1 Fleet Costs*

$$
\begin{array}{cc}
 & \text{Asset Costs, where } C_i = \text{ cost of asset } i \\
\text{Fleets} &
\begin{bmatrix}
10 \times C_1 & 0 & \dots & \dots & \dots & \dots & \dots & \dots & \dots & 0 \\
5000 \times C_1 & 0 & 1000 \times C_3 & 0 & \dots & \dots & \dots & \dots & \dots & 0 \\
5000 \times C_1 & 5000 \times C_2 & 0 & \dots & \dots & \dots & \dots & \dots & \dots & 0 \\
6500 \times C_1 & 0 & 4000 \times C_3 & 10 \times C_4 & 0 & \dots & \dots & \dots & \dots & 0 \\
5000 \times C_1 & 5000 \times C_2 & 0 & 0 & 30 \times C_5 & 0 & \dots & \dots & \dots & 0 \\
5000 \times C_1 & 5000 \times C_2 & 0 & 0 & 0 & 20 \times C_6 & 0 & \dots & \dots & 0 \\
10 \times C_1 & 0 & 0 & 30 \times C_4 & 0 & \dots & \dots & \dots & \dots & 0 \\
5000 \times C_1 & 0 & 0 & 50 \times C_4 & 0 & \dots & \dots & \dots & \dots & 0 \\
10 \times C_1 & 0 & 3500 \times C_3 & 30 \times C_4 & 0 & \dots & \dots & \dots & \dots & 0 \\
10 \times C_1 & 0 & 0 & 40 \times C_4 & 0 & 50 \times C_6 & 0 & \dots & \dots & 0 \\
10 \times C_1 & 0 & 0 & 30 \times C_4 & 0 & \dots & 0 & 10 \times C_{23} & 0 & 0 \\
5000 \times C_1 & 0 & 4000 \times C_3 & 50 \times C_4 & 0 & \dots & \dots & \dots & \dots & 0 \\
2500 \times C_1 & 0 & 3000 \times C_3 & 30 \times C_4 & 0 & 20 \times C_6 & 0 & \dots & \dots & 0 \\
2500 \times C_1 & 1000 \times C_2 & 0 & 40 \times C_4 & 0 & 50 \times C_6 & 0 & \dots & \dots & 0 \\
10 \times C_1 & 0 & 0 & 30 \times C_4 & 0 & \dots & 0 & 20 \times C_{23} & 0 & 0
\end{bmatrix}
\end{array}
$$

## C.2 Fleet Performance

$$
\begin{array}{ccc}
 & \text{Mission 1} & \text{Mission 2} \\
 & \begin{array}{cc} \text{Metric 1} & \text{Metric 2} \end{array} & \begin{array}{cc} \text{Metric 1} & \text{Metric 2} \end{array} \\
\text{Fleets} &
\begin{bmatrix}
5.22 \times 10^3 & 2.464 \times 10^3 \\
5.25 \times 10^3 & 2.7648 \times 10^3 \\
5.26 \times 10^3 & 3.1 \times 10^3 \\
5.252 \times 10^3 & 2.93648 \times 10^3 \\
5.28 \times 10^3 & 3.3648 \times 10^3 \\
5.278 \times 10^3 & 3.2648 \times 10^3 \\
5.235 \times 10^3 & 2.5648 \times 10^3 \\
5.251 \times 10^3 & 2.6948 \times 10^3 \\
5.247 \times 10^3 & 2.5948 \times 10^3 \\
5.241 \times 10^3 & 2.4948 \times 10^3 \\
5.23 \times 10^3 & 2.38 \times 10^3 \\
5.2511 \times 10^3 & 2.81 \times 10^3 \\
5.239 \times 10^3 & 2.638 \times 10^3 \\
5.238 \times 10^3 & 2.51 \times 10^3 \\
5.228 \times 10^3 & 2.42 \times 10^3
\end{bmatrix}
&
\begin{bmatrix}
3.7465 \times 10^3 & 0.9225 \times 10^3 \\
4.8221 \times 10^3 & 1.3005 \times 10^3 \\
5.2221 \times 10^3 & 1.5005 \times 10^3 \\
5.9221 \times 10^3 & 1.4005 \times 10^3 \\
6.5221 \times 10^3 & 1.8005 \times 10^3 \\
6.1221 \times 10^3 & 1.7005 \times 10^3 \\
4.0000 \times 10^3 & 1.1005 \times 10^3 \\
4.7465 \times 10^3 & 1.2505 \times 10^3 \\
4.5465 \times 10^3 & 1.2005 \times 10^3 \\
4.4465 \times 10^3 & 1.1505 \times 10^3 \\
4.2465 \times 10^3 & 1.0505 \times 10^3 \\
5.5465 \times 10^3 & 1.3755 \times 10^3 \\
5.2465 \times 10^3 & 1.2755 \times 10^3 \\
4.8465 \times 10^3 & 1.1755 \times 10^3 \\
4.4465 \times 10^3 & 1.0755 \times 10^3
\end{bmatrix}
\end{array}
$$

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