MODEL DEVELOPMENT DECISIONS UNDER UNCERTAINTY IN CONCEPTUAL DESIGN

A Thesis

Presented to

The Academic Faculty

by

Thomas M. Stone

In Partial Fulfillment

of the Requirements for the Degree

Master of Science in the

George W. Woodruff School of Mechanical Engineering

Georgia Institute of Technology

August 2012

MODEL DEVELOPMENT DECISIONS UNDER UNCERTAINTY IN CONCEPTUAL DESIGN

Approved by:

Dr. Seung-Kyum Choi, Co-Advisor
George W. Woodruff School of Mechanical Engineering
Georgia Institute of Technology

Dr. Dirk Schaefer, Co-Advisor
George W. Woodruff School of Mechanical Engineering
Georgia Institute of Technology

Dr. Jianxin (Roger) Jiao
George W. Woodruff School of Mechanical Engineering
Georgia Institute of Technology

Date Approved: June 21, 2012

To my family

for their unconditional

love and support

ACKNOWLEDGEMENTS

First of all, I thank Dr. Seung-Kyum Choi and Dr. Dirk Schaefer for their superb advisement of my research efforts. I could not have asked for better direction and guidance. In only two years, I have matured from amateur research skills to a profound understanding of academic research, and I am confident that our future endeavors will be successful and meaningful. In the teaching sphere, I would like to thank them for their supervision of my teaching assistant experience; their professional advice and counsel will prove invaluable in my life.

I thank God for the transformation He has wrought in my life. It is an understatement to say that I would not be in this propitious position today without the grace He has shown to me. Also, it is no small thing that God has made His creation with such complexity and given men curious minds, eager to explore the breadth and depth of it. I am so thankful that I can do something with my life that I enjoy. My fundamental desire is that I can bring Glory to Him through Jesus Christ.

I would like to thank my colleagues—Daniel Wu and Jiten Patel—for their support and friendship. Also, efforts by undergraduate research students—Justin Brown and Kevin Strike— have been instrumental in my graduate research and teaching experience. Dennis Page has provided great encouragement and friendship as a fellow worker at the Georgia Tech Savannah campus. And my church family and friends—namely, Chris Bond and Kevin Summit—have been instrumental in my personal growth and guidance.

Last (but not least), I would like to thank my family. From my father, I acquired a work-ethic—without which I would never be able to complete my Masters studies. My mother has shown unconditional love and support through many years of school and life’s many circumstances. As my brothers have grown, they have become my best friends, and I wish the best for their futures. My extended family has also continually been a source of great support.

TABLE OF CONTENTS

Page

LIST OF TABLES

Page

LIST OF FIGURES

Page

LIST OF ABBREVIATIONS

MSD	Mass Spring Damper
CA	Conjoint Analysis
DM	Decision Maker
FEA	Finite Element Analysis
DEM	Discrete Element Method
PMF	Probability Mass Function
IRTD	Intelligent Real Time Design
LDV	Laser Doppler Vibrometer

SUMMARY

Model development decisions are an important feature of engineering design. The quality of simulation models often dictates the quality of design decisions, seeing as models guide decision makers (DM) in choosing design decisions. A quality model accurately represents the modeled system and is helpful for exploring what-if scenarios, optimizing design parameters, estimating design performance, and predicting the effect of design changes. However, obtaining a quality model comes at a cost in terms of model development—in experimentation, labor, model development time, and simulation time. Thus, DMs must make appropriate trade-offs when considering model development decisions.

The primary challenge in model development is making decisions under significant uncertainty. This thesis addresses model development in the conceptual design phase where uncertainty levels are high. In the conceptual design phase, there are many information constraints which may include an incomplete requirements list, unclear design goals, and/or undefined resource constrains. During the embodiment design phase, the overall objective of the design is more clearly defined, and model development decisions can be made with respect to an overall objective function. For example, the objective may be to maximize profit, where the profit is a known function of the model output. In the conceptual design phase, this level of clarity is not always present, so the DM must make decisions under significant model uncertainty and objective uncertainty. In this thesis, conjoint analysis is employed to solicit the preferences of the decision maker for various model attributes, and the preferences are used to formulate a quasi-objective function during the conceptual design phase—where the overall design goals are vague. Epistemic uncertainty (i.e., imprecision) in model attributes is represented as intervals and propagated through the proposed model development framework.

The model development framework is used to evaluate the best course of action (i.e., model development decision) for a real-world packaging design problem. The optimization of medical product packaging is assessed via mass spring damper models which predict contact forces experienced during shipping and handling. Novel testing techniques are employed to gather information from drop tests, and preliminary models are developed based on limited information. Imprecision in preliminary test results are quantified, and multiple model options are considered. Ultimately, this thesis presents a model development framework in which decision makers have systematic guidance for choosing optimal model development decisions.

CHAPTER 1

INTRODUCTION

1.1 Motivation

Simulation models are used in engineering design as representations of real-world systems. They are invaluable in engineering design because they enable DMs to explore what-if scenarios, optimize design parameters, estimate design performance, and predict the effects of design changes. In engineering design, significant effort and resources are allocated toward model development, because accurate models have the potential to improve design decisions. Oftentimes, this improvement in the design decision far outweighs the cost of developing the model; however, this is not always the case. There is always the potential that developed models can lead to minimal improvements or even bad model development decisions. Thus, the model development can cost more than the improvement achieved via the design decision.

Moreover, simulation models have infinite improvement potential—and thus, infinite cost potential. FEA models can be discretized into smaller elements, and mass spring damper (MSD) models can have more masses or spring/damper elements. Model abstractions can be continually mitigated/removed as the model becomes a better representation of reality. Each of these model development decisions must be weighed against the associated development cost. Model development incurs experimentation costs, labor/time, increased solution time, etc. Figure 1 depicts the problem at hand. The three MSD models are used to represent the responses of a human body subject to vibrations when seated in an automobile. From left to right, the models increase in complexity, and one might assume that the most complex model is the model on the right. However, the most complex model is not always the best model to use in engineering design. Consider the fact that the complex model has over three times the number of parameters as the simple model (on the left); thus, significant experimentation cost must be allocated toward defining these parameters. Also, complex models generally require more simulation time during design analysis/optimization.

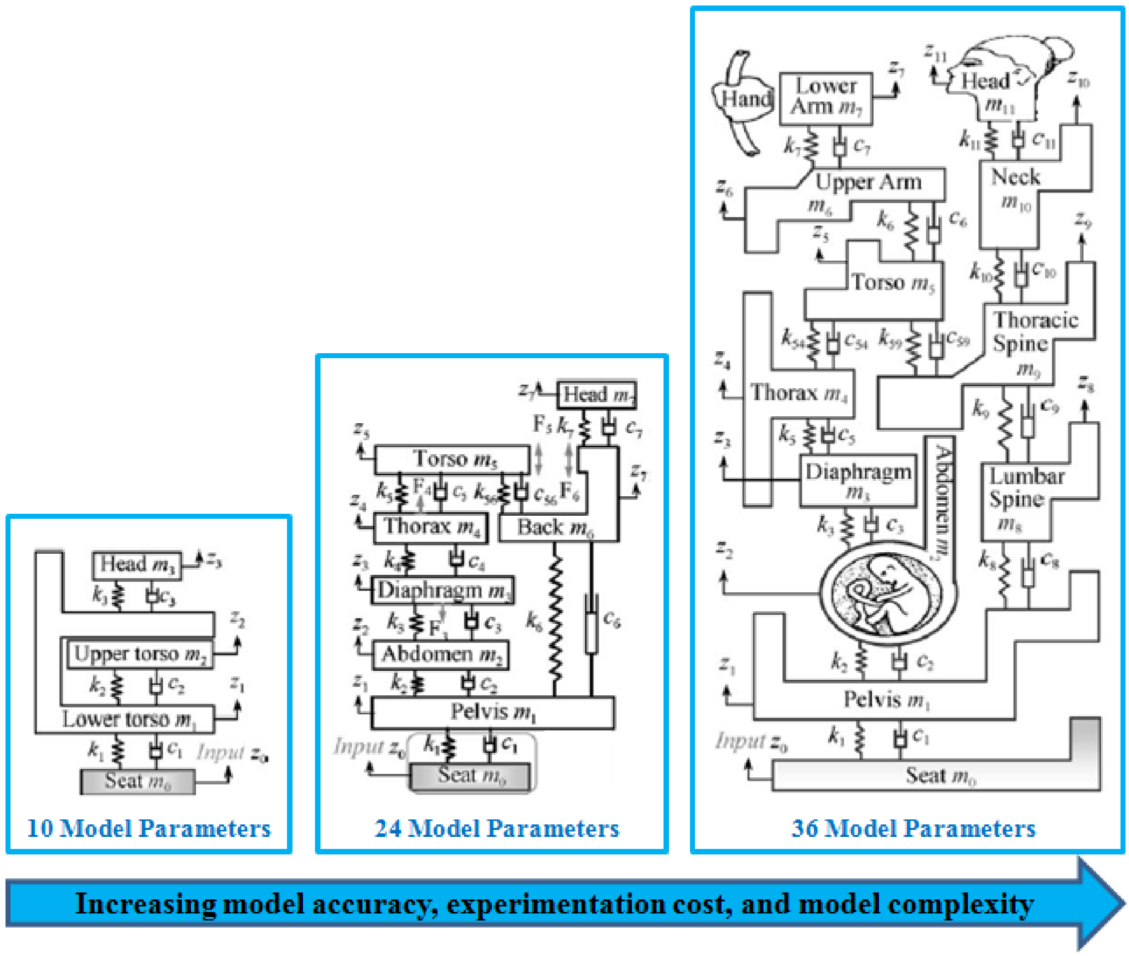


Figure 1. MSD models with varying complexity [1]

Hence, not only do decision makers (DM) need to make the best design decisions; they must also make the best model development decisions. Model development decision can be considered a sub-decision of the overall design decision. Figure 2 depicts the particular problem addressed by this thesis—the DM has completed preliminary experimentation in order to evaluate multiple preliminary models. Now the DM needs to make a model development decision—in this case, determining the final experimentation setup. If the DM knew precisely which model would be best to use in engineering design, he could allocate experimentation resources exclusively to the development of that model. However, the DM does not yet know which model *will be* best, so the best model development decision may be to develop all potential models—keeping the model-selection options open—and then choose the best model. Of course, this would incur more costs in time and experimentation, but uncertainty often dictates that the DM keep more options open. Thus, model development decisions are not simple or easy. This thesis provides a framework for making the best model development decision according to uncertain information.

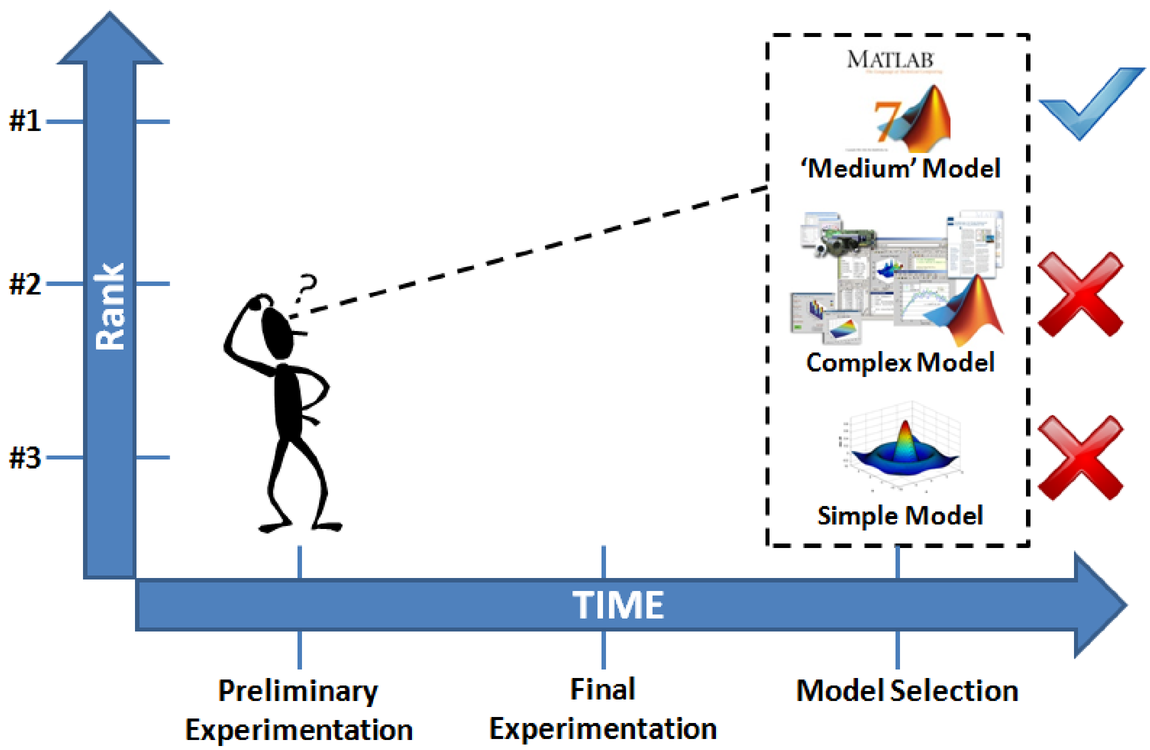


Figure 2. Decision-making problem addressed by this thesis

1.2 Research Question 1 and Hypothesis

Design is popularly viewed as having four phases: task clarification, conceptual design, embodiment design, and detail design [2]. Much of the model development research addresses problems in the embodiment design phase, and limited attention is given to the conceptual design phase. The primary reason for this is that the conceptual design phase presents the DM with a significant level of uncertainty including an incomplete requirements list, unclear overall design goals, undefined resource constrains, etc. During the embodiment design phase, the overall objective of the design is more clearly defined, and model development decisions can be made with respect to an overall objective function. For example, the objective may be to maximize profits, where the profit is a known function of the model output. In the conceptual design phase, this level of clarity is not always present, so the DM must make decision under significant model uncertainty and objective uncertainty.

Question: How can the DM choose a model development decision in the conceptual design phase, where there is significant model uncertainty and objective uncertainty?

Hypothesis: Conjoint analysis is used to elicit the DMs preferences during the conceptual design phase, and the uncertainty in model parameters is represented with intervals such that imprecision is appropriately considered.

Conjoint analysis (CA) is a method for eliciting the preferences of DMs for different levels of attributes. The preferences can then be used to formulate a quasi-objective function during the conceptual design phase when the overall design goals are vague. Also, when uncertainty levels are high, it is important to consider a specific type of uncertainty—imprecision. In the case of a numerical data-set, imprecision denotes that the true mean is not equal to the sample mean, which is often the case when limited preliminary experimentation has been completed, since bias and other forms of systematic error can grossly skew the preliminary data. This should be accounted for in order to make the correct model development decision.

1.3 Research Question 2 and Hypothesis

Various avenues have been explored in model development and decision-based-design, but limited effort has been put toward to considering multiple models and model dependencies. Real-world conceptual design situations often involve multiple preliminary models, which are eventually narrowed down to a single, ultimate decision model. Eliminating preliminary models results in reduced model development costs, but there is always the chance that the misinterpretation of preliminary experimentation results leads to the elimination of a potentially useful model. So a systematic framework is required for the model elimination decision. Moreover, multiple models often are variations of each other with dependencies that come from common information sources. For example, a complex model may require some of the same basic experimentation that a simple model also requires. This dependency must be properly handled in a decision-based-design tool called a decision tree.

Question: How can a DM choose correct model development decision when there are multiple models with common information sources?

Hypothesis: A model development decision with multiple models is appropriately evaluated with decision-based-design techniques that account for the dependencies that exist between the models—perhaps, due to common sources of information

1.4 Research Question 3 and Hypothesis

This thesis includes a unique feature in the fact that real-world models are tested and developed for use in the model development framework demonstration. Mass spring damper (MSD) models are used to determine the contact forces experienced by medical product packaging during shipping and handling. The MSD models simulate an impact (drop test) and predict the contact force between individual packages. The models include design parameters such as box length and height, number of packages, and package orientation—which can be used to optimize the packaging design.

Much research has been completed concerning MSD topics including drop testing and vibration response. However, this particular packaging design problem presents some key challenges. The individual packages weight less than 10 grams each, so measurements are difficult to acquire without interfering with the system. Also, the packaged products consist of a soft outer packaging with a hard enclosed product, and the interaction between approximately one hundred of these packages in one shipping box is difficult to model.

Question: How can the proposed decision framework be applied to a practical model development problem?

Hypothesis: The proposed decision framework can be used to choose model development decisions in a packaging design problem with complex interactions and experimentation/measurements.

This thesis research takes advantage of both novel testing techniques and traditional MSD theory in order to model the complex interaction of the packages. A non-contact sensor—laser doppler vibrometer—and light-weight accelerometers are used to take measurements. Appropriate assumptions are explored in order to remove some of the complexity of the problem while still achieving acceptable results.

1.5 Thesis Organization

Figure 3 presents the organization of this thesis. Chapter 1 motivates the thesis topic and provides specific research questions that are addressed by the thesis research. In Chapter 2, the design problem that is used to demonstrate the thesis research is introduced. Also, the state-of-the-art MSD and model development techniques are presented. Research gaps are identified, and the solutions provided by this thesis are introduced. The proposed methods for model development are described in Chapter 3—along with the MSD models and experimentation techniques. Chapter 4 includes the demonstration of the model development framework and relevant results. Then in Chapter 5, the research questions are re-stated and evaluated in terms of completion.

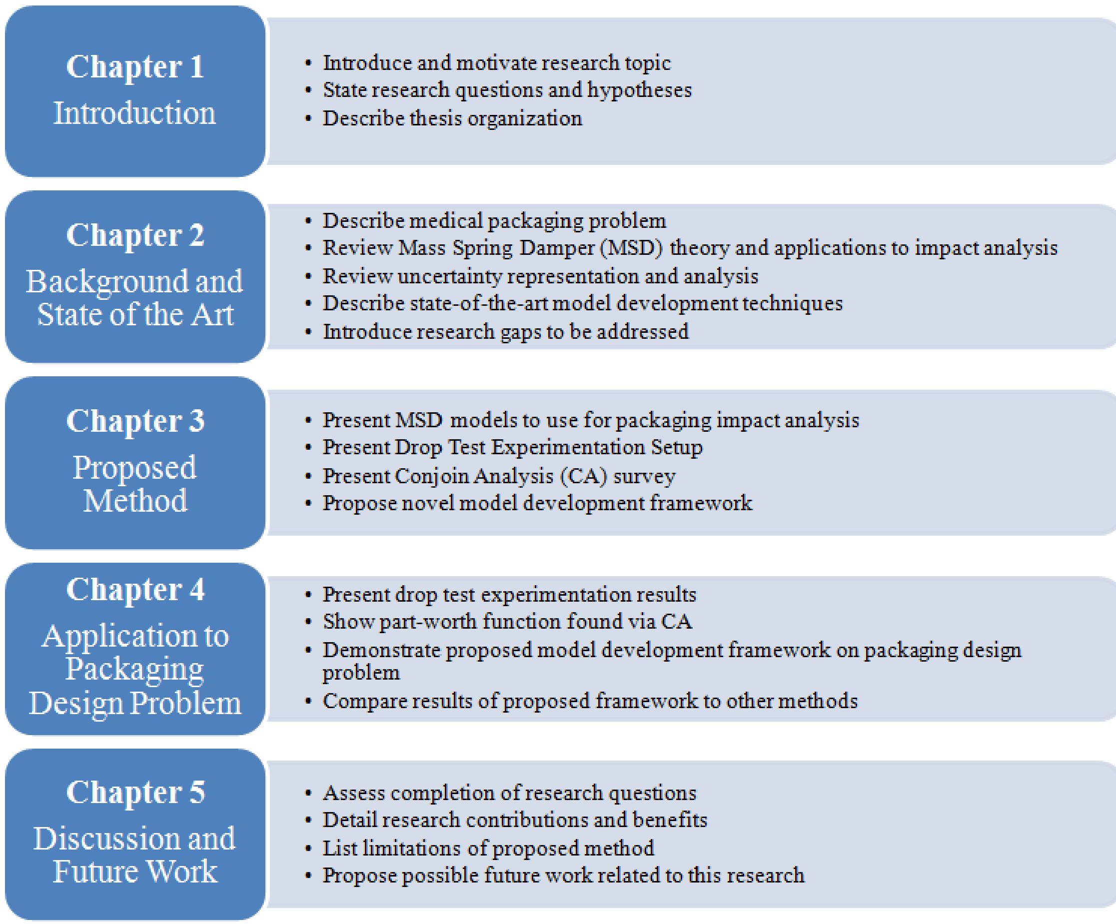


Figure 3. Outline of thesis organization

CHAPTER 2

BACKGROUND AND STATE-OF-THE-ART

This chapter begins with an introduction to the packaging design problem that motivates this thesis. The problem plays a significant role in directing the research toward real-world applicability. Significant testing and experimentation is completed regarding the packaging problem in order to produce actual models for use in model development. The primary focus of this thesis is still on model development, but an appreciable amount of research is also conducted on MSD theory in impact analysis and novel MSD testing/measurement techniques.

The latter sections in this chapter provide the background needed to understand the proposed model development framework: uncertainty representation, decision-making under uncertainty, and conjoint analysis (CA). The state-of-the-art model development and decision-making techniques are analyzed, and research gaps are identified. Finally, the scope of this research is outlined, describing how this thesis 'fills the gaps.'

2.1 Medical Product Packaging Problem

In completing this thesis, the author collaborated with a medical company to solve a product packaging problem. The medical company, a leading supplier of medical devices, manufactures and ships a variety of medical products in the United States. Needles and syringes are one of the primary products in production—designed, sold, and shipped by the company. Syringes and needles are designed to reduce the spread of infection, enhance diabetes treatment, and advance drug delivery. Product package and shipment must ensure that a sterile environment is maintained throughout the delivery process. Medical syringes are encased in polypropylene film with a paper backing. This packaged product is sealed via a thermoforming process which creates a sterile housing for the medical device. An example is shown in Figure 4. A single sealed package is called a primary package.

Figure 4. Primary sterile packaging

Batches of approximately 100 primary packages are then placed in corrugated cardboard shipping cartons called secondary packaging, as shown in Figure 5. Primary packages are stacked in either the configuration of moderately nested, fully nested or randomly nested. Consideration of different orientations is not within the scope of this thesis, but this feature can be handled by the proposed MSD model.

Figure 5. Secondary packaging

Secondary packages are stacked and shrink-wrapped into groups of four. This final phase of packaging, illustrated in Figure 6, is termed tertiary packaging. Tertiary packaging is the packaging structure which is transported from one location to another in the shipping process.

Figure 6. Tertiary packaging, shrink-wrapped

One could also consider palletized cartons as a fourth scale of packaging (i.e., palletized), but the scope of this thesis is limited to analysis of the primary and secondary packaging.

Figure 7. Multi-scale packaging design

Optimization of Cost and Reliability of Packaging

If the primary packaging is compromised by way of a tear or hole, the enclosed product is considered unsterile and must be disposed of. Damages to the primary packaging occur during shipping and handling as the packaging is subject to drops and vibrations during transit. Even a pin-hole in the polymer film can render a syringe unsterile and useless. Of course, this is undesirable for the user and the company. The obvious solution is to increase the thickness of the polymer film that is the dominant failed component. However, the cost of manufacturing for the syringe is very low such that the packaging cost is significant with respect to the overall product cost. Thus, additions to the packaging cost cannot be made haphazardly. When considering cost-effective solutions, the entire packaging system must be taken into account; the syringe, carton, primary packaging, and other packaging materials are all significant with respect to overall product cost.

Complexities in Packaging Design

Packaging design and development for a disposable medical device is a complex and challenging task. The reason for complexity is because of the involvement of multiple overlapping dimensions including a) device b) sterilization, and c) package. According to ISO standards [3], the goal of medical packaging is to allow sterilization, provide physical protection, maintain sterility up to the point of use and allow aseptic presentation.

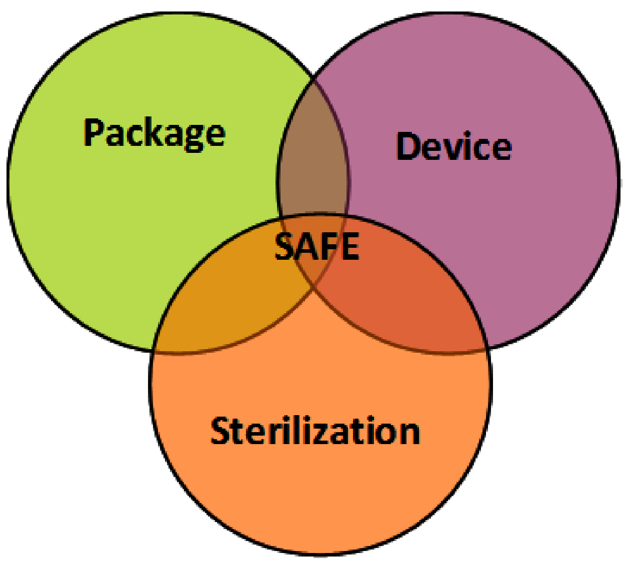


Figure 8. Multiple dimensions for safe medical device packaging

This thesis focuses on two complexities in particular: (1) the high number of design parameters that must be considered in the packaging design and (2) the complex interaction between primary and secondary packages. Shipping cartons (secondary packaging) can be tested according to ASTM standards, where the carton is dropped in certain orientations and the packaging contents are then checked for damage [4]. However, the ASTM testing does not provide any insight into the relationship between packaging parameters and failures/damage—and thus, there is no clear direction for redesign. An incomplete list of packaging design parameters includes the following (starred '*' items are within the scope of this thesis):

- Number of primary packages*
- Rows/columns of primary packages*
- Length/width/height of carton*
- Orientation of primary packages*
- Type of carton
- Primary package design
- Product (syringe) design

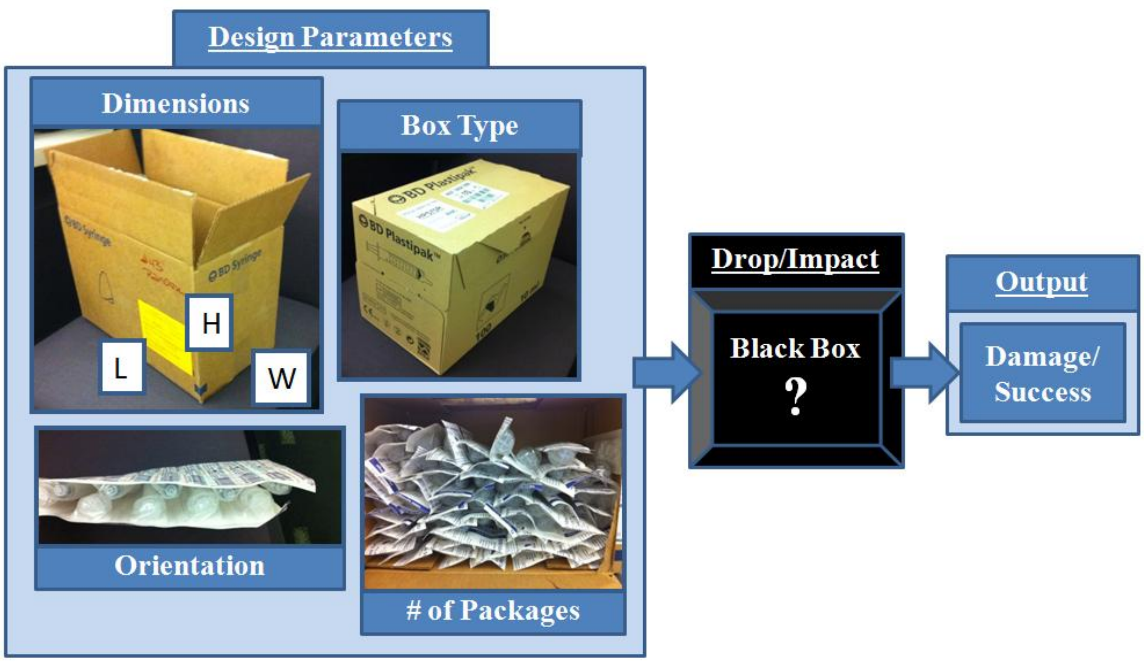


Figure 9. Packaging design modeling problem

The relationship between all of these parameters and the reliability of the packaging design is complex. This thesis also focuses on the latter complexity (2): the primary packages interact with each other and with the carton throughout the shipping process. Of particular interest is the contact force that is experience between adjacent primary packages during drops. The scope of this thesis excludes other modes of failure such as vibration and crushing since the drop (impact) mode is assumed to be the primary cause of failure.

Figure 10. Cut-away view of packaging carton

2.2 MSD Theory in Impact Analysis

MSD theory is helpful for many types of mechanical engineering problems—impact, vibration, complex motion, etc.—and is used in a multitude of industries including automotive, aerospace, and packaging. The theory revolves around three basic components: masses, springs, and dampers. A mass and its acceleration represents the inertia of the rigid body. The damper and the relative velocity of its ends represents the damping forces. The spring and the relative position of its ends represents the spring force. Any number of these components can be combined in complex ways to model the behavior of real-world systems. The most basic MSD model is shown in Figure 11.

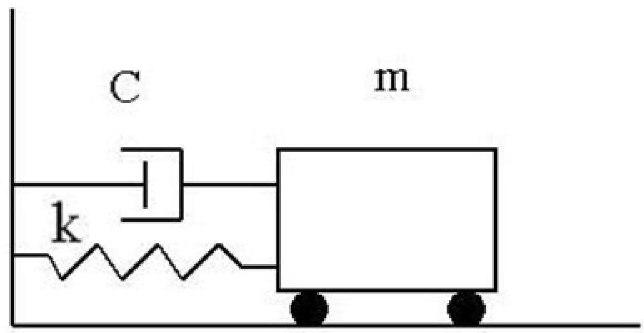


Figure 11. Simple MSD model

Useful information can be gathered from MSD models. The model can describe the position, velocity, and acceleration of rigid bodies as well as contact forces between moving parts. Consider the automobile crash test depicted in Figure 12. The actual problem is very complex, but a simple MSD model can provide helpful information concerning the accelerations experienced by the driver and passengers. Of course, complex MSD models are required to accurately represent the details of the system. Measurements and testing must be completed in order to define MSD model parameters: masses, spring constants, and damping coefficients.

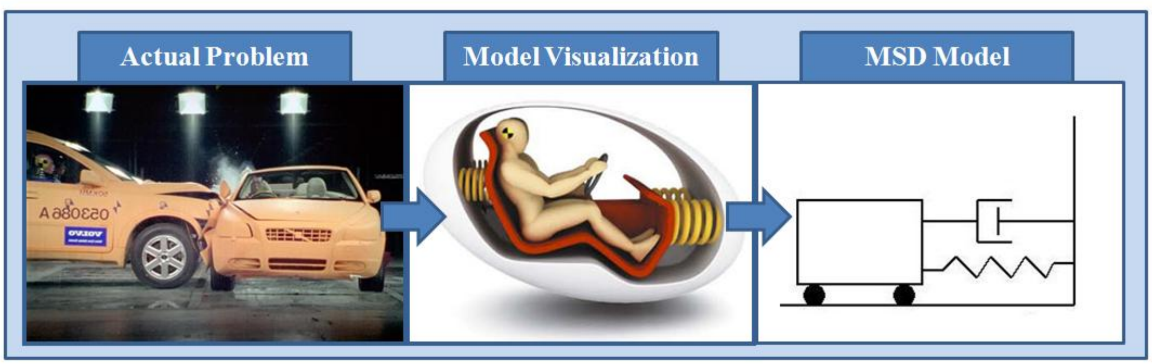


Figure 12. MSD modeling of car impact test

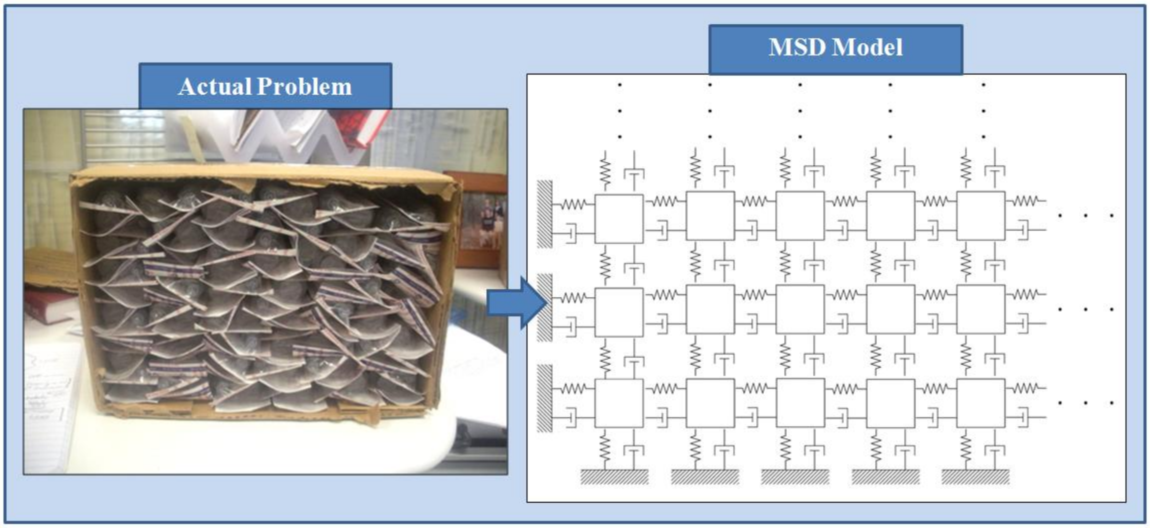


Figure 13. MSD modeling of medical packaging

Advantages over Comprehensive FEA Models

One might question the use of MSD models instead of finite element analysis (FEA) models. Complex FEA models can be used to capture the effects/responses of complex geometry and subtle features of the system. However, there are key reasons why the author chooses to use MSD theory for the packaging design problem in this thesis:

- *Time:* FEA models of complex systems can be computationally expensive. The author's past experience dictates that FEA simulations of drop tests have a long 'run time' for this particular application. In particular, the complexities of the primary packaging shape and the large deformations may result in simulation errors (or at least long run times).
- *Material Models:* FEA requires material model parameters that may be difficult to obtain, e.g, the thin polymer film on the primary packaging. Finding these parameters would only be worthwhile if the details of the deformation of the polymer film were of importance.
- *Defining MSD Parameters:* The MSD model can be set up such that the spring and damper parameters have a physical meaning. i.e., the springs and dampers represent the interaction of the primary packages, and the forces experienced by

these elements represent the contact forces between the primary packages. Moreover, the MSD model parameters are found by empirical observations (with accelerometers and velocity sensors). This is demonstrated in later chapters.

- *Design Parameter Modifications:* MSD design parameters can be easily modified. The packaging design problem is essentially an optimization problem, where different settings for the carton dimensions, primary package orientation, etc. need to be explored until an optimum solution is found. The MSD model parameters such as length, height, spring constants, damping coefficients, etc, are readily adjustable.

MSD Impact Modeling Techniques

It is helpful to briefly review some research concerning MSD models, especially those directly related to impact analysis. The model that is proposed for the medical packaging problem is a combination of original ideas/research as well as many of the existing features noted in the MSD modeling examples that follow.

Kelvin-Voigt Model

The basic Kelvin-Voigt model for spring and damper components is the fundamental tool of MSD theory:

$$m\ddot{\delta} = k\delta + c\dot{\delta} \tag{1}$$

where δ is the deformation of the spring, $\dot{\delta}$ is the velocity of the mass, $\ddot{\delta}$ is the acceleration of the mass, m is the mass of the object, k is the spring constant, and c is the damping coefficient. Equation (1) states that the contact force contributed by the spring is proportional to distance, and the contact force contributed by the damper is proportional to velocity. However, this simple model is not sufficient to accurately describe complex systems.

Nonlinear models

The spherical contact model was first explored by Hertz [5]:

$$F_c = k\delta^n \tag{2}$$

where n is an exponential value for the spring deformation. Empirical models also exist for systems with complex geometries (e.g., non-spherical).

Hunt and Crossley presented one of the first nonlinear viscoelastic contact force model with a nonlinear damping element [6]. An example of a nonlinear model for impact modeling is shown in Equation (3)

$$F_c = k\delta^{3/2} + c\dot{\delta}^{3/2} \tag{3}$$

where F_c is the contact force.

Elastic stops

A critical feature of many real-world vibration systems is that objects may collide and then disengage (and collide again). Due to the existence of colliding components, system models must incorporate elastic stops. The vibro-impact characteristics of an MSD model with elastic stops were investigated in Ref. [7], including an investigation into the dynamics and stability during oscillation. Solutions for these types of MSD models are highly nonlinear, so care must be taken in evaluating computation cost.

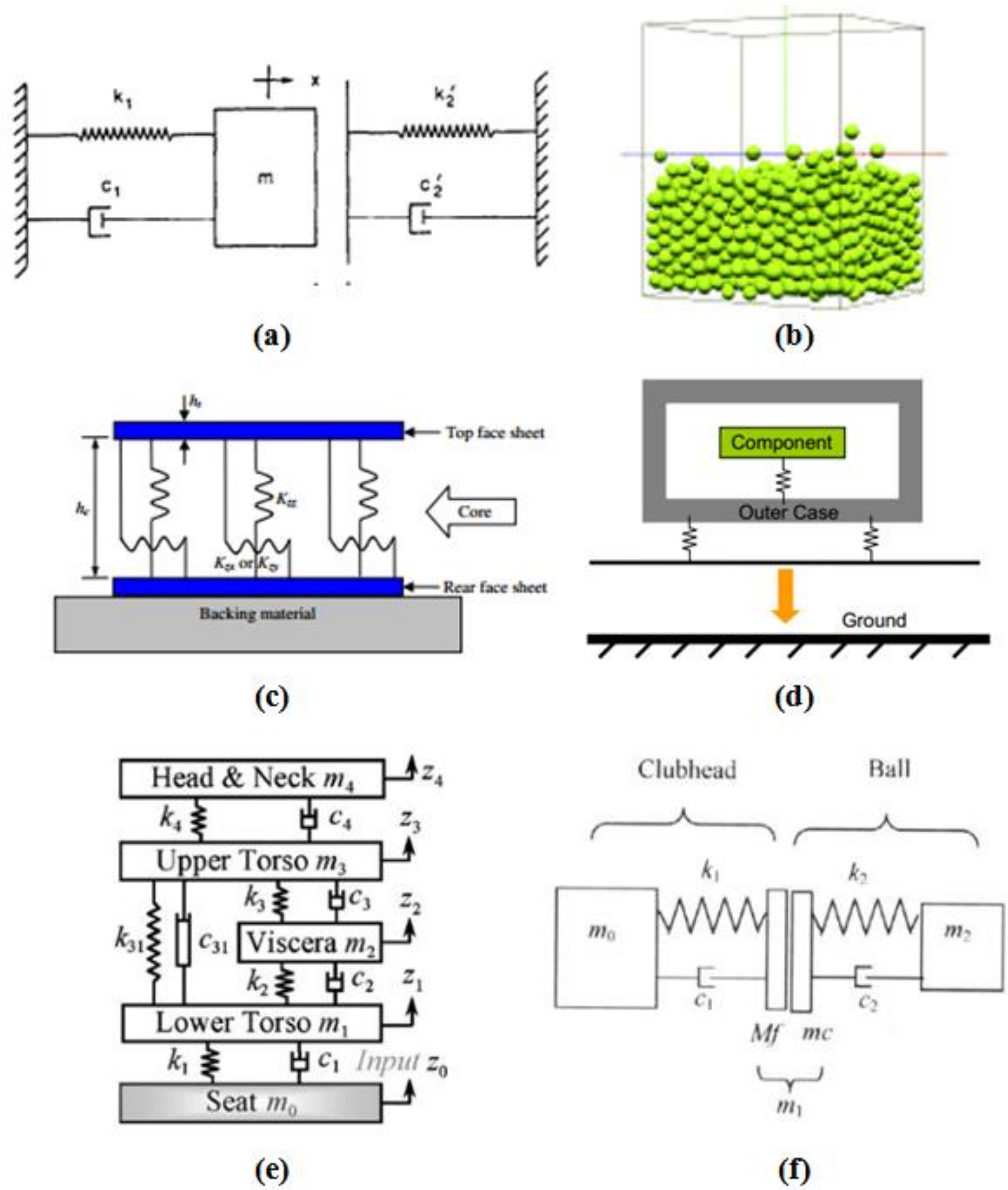


Figure 14. (a) MSD model with elastic stops [7], (b) discrete element method for MSD modeling [8], (c) MSD model for sandwich structure [12], (d) MSD model for portable electronics impact [13], (e) MSD model for automobile passenger [1], and (f) MSD model for golf ball impact [11]

MSD Impact Applications

Fruit

Zeebroeck et al. explored the damage incurred by fruit during shipping and handling via the discrete element method (DEM) [8]. The contact force models and bruise prediction models are determined through novel testing techniques [9] with spring and damping constants determined experimentally [10]. The DEM simulation demonstrates how shipping and handling conditions relate to fruit bruising.

Golf Balls

In Ref. [11], a golf ball impact is modeled by two masses connected by a nonlinear spring in parallel with a nonlinear damper. Spring and damper models incorporate up to eight unknown variables, which are determined experimentally. The coefficient of restitution is determined for 16 clubheads—using three variations of a MSD model for each clubhead. It is shown that added model complexity does not significantly affect the results.

Impact on Sandwich Structures

In Ref. [12], Hertz contact law is employed to model the impact response of laminate sheets. The analytical model is compared with numerical and experimental results. The comparison shows that the analytical model is useful and accurate in modeling the nonlinear impact response.

Vibration on Humans

In Ref. [1], a number of human body vibration models are investigated. This biodynamic study explores the effects of vibrations experienced while driving an automobile. Various lumped parameter models are systematically validated, and a relatively simple model is found to be best according to existing test results.

Impact Analysis of Portable Electronics

In Ref. [13], theoretical models are used to guide the design of portable electronics. A flexible beam structure is compared to a mass-spring model as the force on connectors is observed. It is shown that the simple mass-spring model can be used with acceptable accuracy under certain drop parameters.

2.3 Model Development Background

Models are broadly defined as system-representations that help decision-makers (DM) make better decisions. For instance, consider the decision of where to locate your next party: outside or inside. An accurate weather model will help you choose the action with highest probability of having the best outcome. Better models generally lead to better decisions, and there-in lies the need for model development. However, the field of model development is itself broad and diverse. There are a multitude of actions that fall under model development—to name a few:

- Conduct experimentation/testing
- Add model features
- Refine FEA (add elements)
- Choose among multiple models

Factors influenced by these actions are no-less numerous including experimentation cost, computation time, model performance, etc. This section provides help in navigating the prominent features of the field.

Categories of Model Development

Model development can range from choosing among different preliminary models to refining an existing model—and everywhere in between. It is useful to refer to Pahl and Beitz' engineering design phases: task clarification, conceptual design, embodiment design, and detail design [2]. Almost all model development activities fall in either the conceptual or embodiment design phase. Refer back to the example of party planning based on weather models; a conceptual design activity would be choosing from different weather indicators such as a barometer, the weather station, or simply observing the sky. An example of embodiment design would be conducting final experimentations to refine the weather model used by the weather station. Poh and Horvitz attempt to categorize model development (referred to as model 'refinement') in three different 'dimensions': (1) quantitative refinement, (2) conceptual refinement, and (3) structural refinement [14]

1) Quantitative refinement: allocating resources toward refining uncertainty and preference information in a model
2) Conceptual refinement: refining the 'semantic content' in a model; i.e., modifying how actions, outcomes, or random variables are defined
3) Structural refinement: adding or removing components of a model

Figure 15 shows how the Pahl and Beitz design phases relate to the model refinement dimensions proposed by Poh and Horvitz. The conceptual design phase is highlighted because that phase is the focus of this thesis.

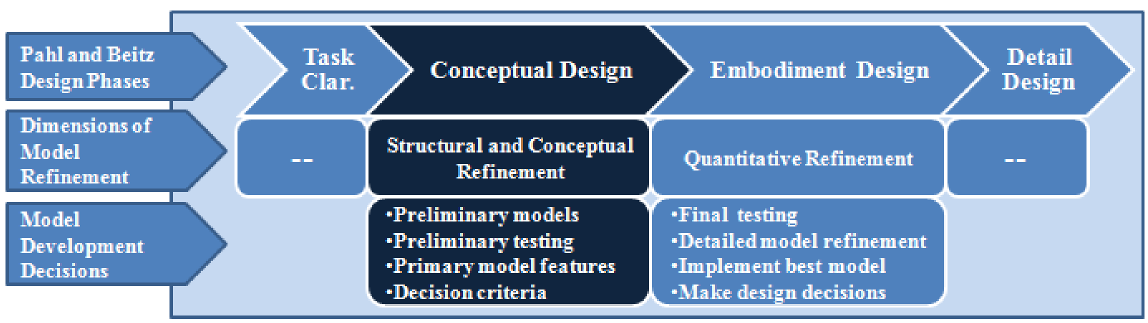


Figure 15. Model development dimensions and the Pahl and Beitz design method

Types of Uncertainty

Uncertainty plays a major role in decision making. The models that decisions are based on are uncertain in almost all cases. In fact, even if the DM collects all of the available information, models with inherent variability will still result in uncertainty in the decision-making process. This statement may seem paradoxical if one does not have a proper understanding of the different types of uncertainty. There are many perspectives on types of uncertainty. For this thesis, it is useful to consider two categories of uncertainty: aleatory uncertainty and imprecision.

Aleatory Uncertainty

All systems that describe a real-world process are subject to variability—also called aleatory or irreducible uncertainty—which is variability that is inherent in a process [15]. Consider the process of rolling a die. No matter how much information is gathered concerning the outcome of a roll, the DM will never by certain of the outcome. There is inherent variability in the process. When considering model development, aleatory uncertainty is not as significant relative to imprecision because by definition aleatory uncertianty cannot be reduced by further improving the model. Aleatory uncertainty definitely needs to be taken into account when making decisions, but it is not the focus of this model development thesis.

Imprecision

Imprecision, also known as epistemic uncertainty, represents the uncertainty that can be reduced by gathering more information (i.e., improving the model). Hence, it has another name—reducible uncertainty. Again, consider the example of rolling a die. Simple analytical analyses shows there is a 1/6 chance that a die roll will produce an integer value from 1 to 6. However, assume that this analytical observation is not known. If the DM rolls the die 20 times, he can make an empirical approximation of the probability that the die will produce each output—the probability mass function (PMF). However, this approximation of the PMF based on 20 die rolls will not be perfectly correct; in technical terms, it is not precise. The DM can choose to gather more information and improve the precision of the PMF by increasing the number of die rolls. By continuing to gather data, the DM will eventually reduce all of the reducible uncertainty (i.e., imprecision), and he will know the PMF precisely. Note the distinction between certainty and precision. The DM can never know the outcome of the die roll with certainty; however, by gathering more information, he can have precise information concerning the outcome (i.e., a precise PMF). Therein lies the grounds for model development. Model development can reduce the reducible uncertainty such that the DM can make better decisions—the primary focus of this thesis.

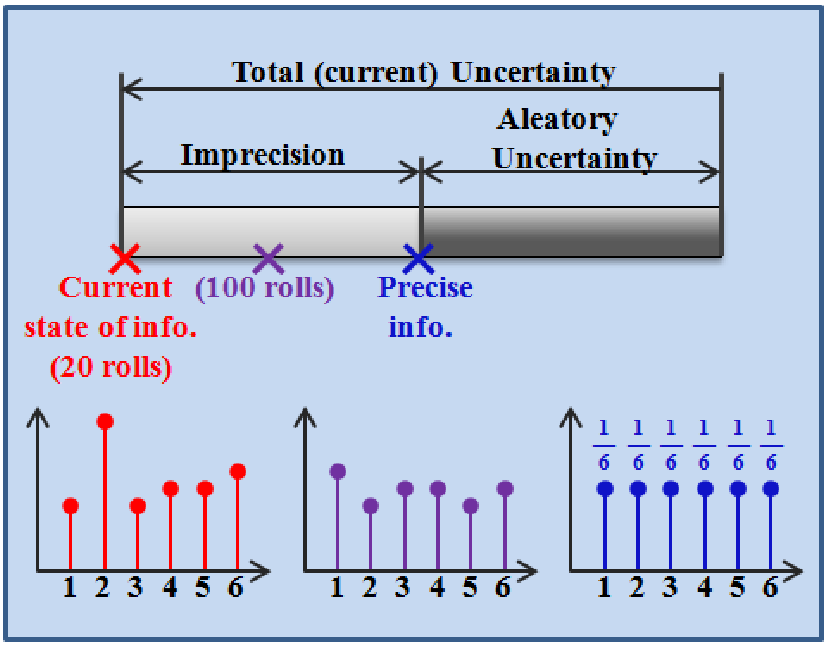


Figure 16. Categories of uncertainty [16]

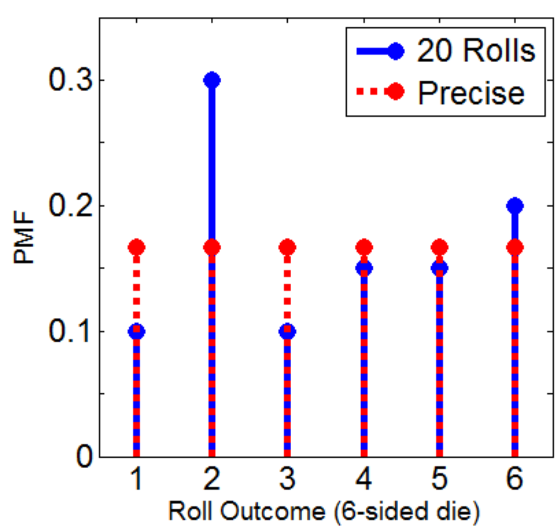


Figure 17. PMF for 6-sided die; precise and imprecise information

Motivating Example

Consider the model development problem depicted in Figure 18. In the 'design problem,' the goal of the DM is to acquire money in a board game. Landing on different spaces produces different outcomes, θ, with different payoffs, y, such as gaining \$200 (θ=2 spaces) or losing \$100 (θ=4 spaces).

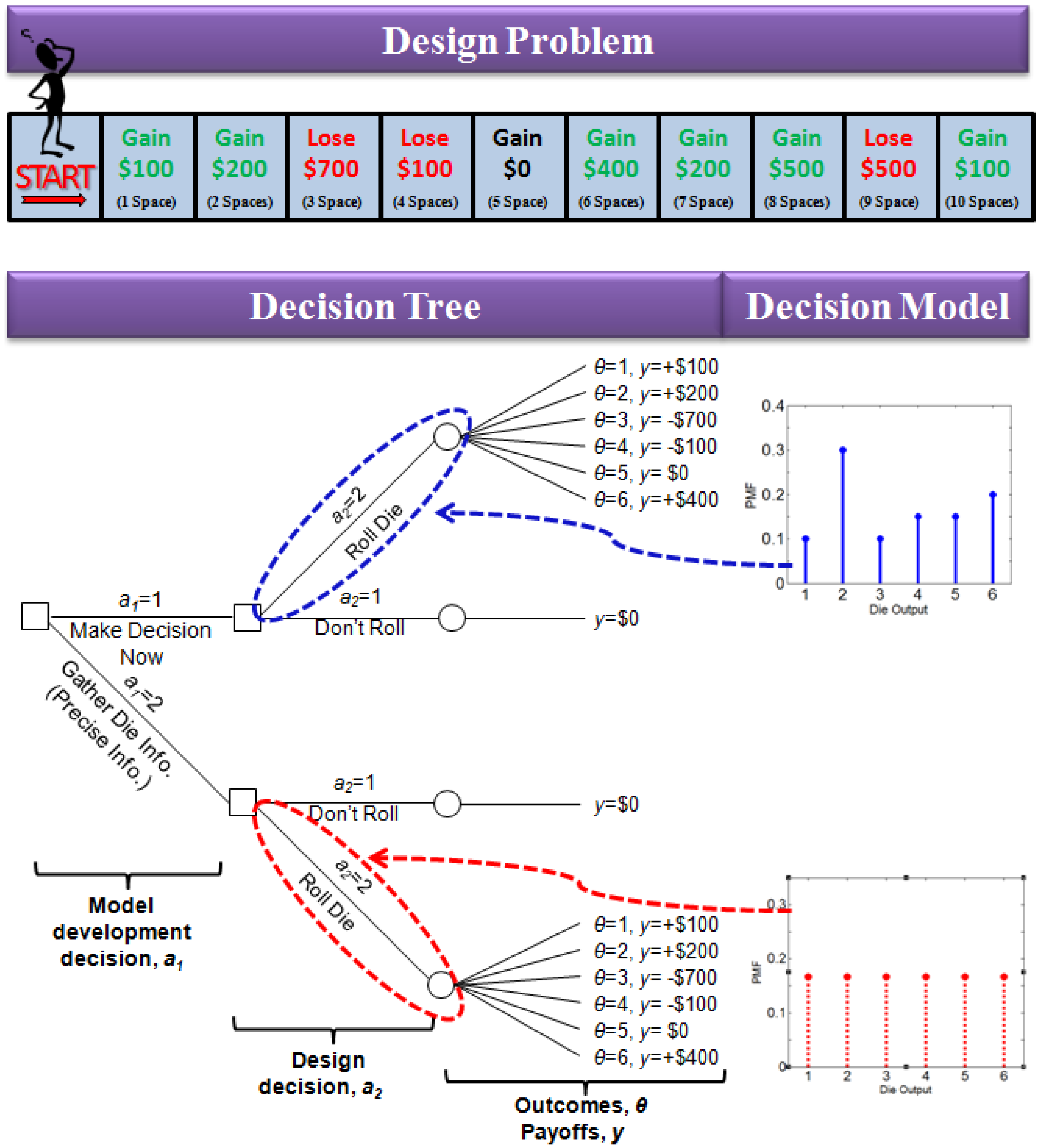


Figure 18. Components of model development problem

In this simple game, there are two design decision options, a_2: roll a 6-sided die and move to the appropriate space (a_2=2), or do not roll the die (a_2=1)—and gain $0.

Precise information

It is common knowledge that the outcome of rolling a fair 6-sided die has a 1/6 chance of being 1, 2, 3, 4, 5, or 6; e.g., P[θ =1]=1/6. Assuming the DM is risk-neutral, he can use this information to make the decision with the highest expected payoff. The expected payoff of decision a_2=1 is $0, and the expected payoff of decision a_2=2 can be calculated according to Equation (4)

$$E[y(a_2 = 2)] = P(\theta = 1)y(\theta = 1) + P(\theta = 2)y(\theta = 2) + \cdots + P(\theta = 6)y(\theta = 6) \qquad (4)$$

where E[] is the expected value operator. For this special case, the expected payoff is simply the average of all possible payoffs, -$16.7. Since the expected payoff of decision a_2=1 is $0, the DM will choose not to roll the die, a_2=1.

Imprecise Information

Consider the situation where the DM does not precisely know the probability information of the 6-sided die. Instead he forms a model of the PMF for the die by rolling it 20 times and making an empirical observation. The DM's die model is shown in Figure 17. Now the DM has another decision to make: he can gather more information about the die model (a_1=2), or he can forgo the extra information and make a design decision now, (a_1=1). If the DM chooses to make a design decision now, the expected payoff of not rolling the die is simple to evaluate, $E[y(a_1=1,a_2=1)]$=$0. If the DM chooses to make a decision now and then roll the die, the expected payoff is evaluated according to the imprecise die model.

$$\begin{aligned} &E[y(a_1 = 1, a_2 = 2)] \\ &= 0.1(\$100) + 0.3(\$200) + 0.1(-\$700) + 0.15(-\$100) + 0.15\cdot(\$0) + 0.3(\$400) = \$65 \end{aligned}$$

Since the DM with imprecise information expects to get a payoff of $65, he chooses to roll the die (a_2=2). However, an omniscient observer knows that the decision to roll the die actually has an expected payoff of -$16.7, which is what the DM with limited information will actually receive. Moreover, the omniscient observer knows that the best design decision is to not roll the die and receive a payoff of $0. Therefore, the value of the precise information is $16.7. In other words, the DM should pay at most $16.7 to acquire precise information about the die model.

Decision Making under Uncertainty

Research efforts have been made toward representing both variability and imprecision as a probability-box, and using the probability-box to inform design decisions. In Ref. [17], imprecise probabilities are used to determine the optimal refinement level of a material model. By using a probability box (p-box), the authors account for both imprecision and aleatory uncertainty. Representation of uncertainty with triangular probabilities is utilized in product design selection [18] and product line design [19] by Li and Azarm. And in Ref. [20], decision alternatives are systematically and efficiently eliminated via uncertainty analysis, considering both imprecision and aleatory uncertainty.

Particular efforts have been made in the field of model development under uncertainty. In Ref. [21], a FEM model of and I-beam structure is analyzed to determine the optimal number of elements to use in the model. A trade-off between improved accuracy, computation cost, etc., is evaluated. The value of the I-beam model is determined in terms of a dollar amount based on a well-defined problem statement. In Radhakrishnan and McAdam's work [22], the values of models are considered in terms of attribute preferences which are elicited via utility theory techniques. The authors also consider uncertainty in the utility values due to attribute uncertainty.

Decision-based Model Development

Decision-based design is a well-explored field with numerous examples of helpful application [20,23,24]. The motivation behind decision-based design is that decisions are the fundamental construct in engineering design. Thus, a large research effort has led to the development of quality decision support tools. In Ref. [24], a decision support framework was demonstrated by choosing rapid prototyping processes and materials to produce a light switch cover plate assembly. The framework facilitated trade-offs among multiple, conflicting attributes, mitigation of risk associated with uncertain parameters, and limited iterations in the product development cycle.

When considering model development, actions such as gathering more information are often considered to be a separate decision from the overall design process. i.e., the design-based design process is used to select the best design, and the development of the decision model is considered separately as its own decision. This methodology has been challenged in multiple works [17,23], particularly in Ref. [23], where the model development decision is formulated in terms of the overall decision problem (i.e., as a sub-decision). The overall decision problem is to choose the thickness of a pressure vessel, and the model development decision is to choose which material to test. Instead of considering the material testing separately, authors evaluate the model decision based on the expected outcome of the pressure vessel design. This connects the model development decision to the outcome of the overall decision problem.

'Correct' Decisions

It is important to note that decision-based-design under uncertainty is a tool for making the *correct* decision, which may or may not turn out to be a *good* decision. The correct decision is the decision that has the highest expected value according to the preferences of the DM. In the example shown in Figure 19, the decision with the highest expected payoff is decision a_2=1: don't roll the die. Thus, this is the correct decision with an expected payoff of \$0. However, the decision to roll the die could potentially result in a payoff of \$200 if the outcome is θ=2. In this case, one could say that the decision a_2=1 is not a good decision. Thus, decision-based-design is only capable of determining the *correct* decision. Note that the preference of the DM for big losses/gains can be handled by considering risk averseness via utility functions, or other tools that elicit the particular preferences of the DM.

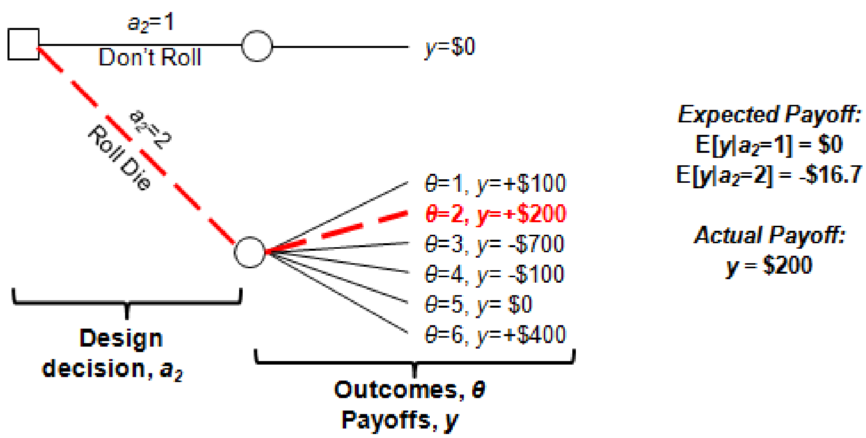


Figure 19. Decision tree for 6-sided die and *lucky* outcome

Ling et al. applied a decision-based-design methodology to the design of a pressure vessel with unknown material strength [17]. The decision to conduct more experimentation was formulated in terms of the expected payoff of the design decision. Imprecise probabilities (p-boxes) were used to model the imprecision and variability of the material strength. In this way, the authors were able to bound the value of information of the additional material strength samples. The authors considered the possibility that the added information could be *bad* information or that the added information could cause an *unlucky* design decision.

Irrevocable Resources

The concept of irrevocable resources is not an abstract one. Simply, irrevocable resources are resources that are allocated (or spent) when a decision is made. The resource allocation is ‘irrevocable’ in that those specific resources cannot be re-allocated. In model development, irrevocable resources primarily include experimentation cost and time spent creating the model (e.g., creating numerical analysis code, forming analytical solutions, etc.). The cost of the allocated resources could potentially be recovered through improvements in the quality of the model-based decision, but the recovery is not guaranteed.

Model development does not come without a cost. Developing a material model requires material testing costs, and improving an FEA model may result in more computational cost. Perhaps, there is even an option to reject the current model and go in a different direction, which will have a cost in terms of time. However, decisions are best supported by the most precise model, and improving the model’s precision is always an option. Thus, the DM is left with the question, ‘is the current model good enough to make a design decision?’ This question has been addressed by multiple research articles where the topics of *information economics* and *expected value-of-information* (EVI) are explored in depth.

In Ref. [25], Bradley and Agogino proposed the intelligent real time design (IRTD) methodology. In their methodology demonstration, the DM is guided toward the best bearing selection from a catalogue while considering resource constraints and the possibility of model development. An uncertain utility function acts as a model that can be developed by gathering more information. EVI is determined by comparing the objective function value based on current information with the objective function value based on a more complete set of data. The expected value of perfect information (EVPI) is introduced to assess the value of gathering more information. After receiving input from the DM, the IRTD methodology suggests the next course of action, which may be bearing selection or model improvement. The DM is then provided with cost suggestions (i.e., value of information) that can be compared to the actual cost of developing the decision model.

Similarly, Panchal et al. seek to utilize model development resources efficiently [26]. Two design problems are proposed, one of which is a pressure vessel design problem. The authors emphasize that before making the best thickness decision, the DM is faced with another decision—'should he make the decision now based on the available information or spend resources to gather more information?' A metric called improvement potential is developed for quantifying the value-of-information obtained through improving the model. The proposed method is used to support model development decisions.

This challenge of irrevocable resources was also addressed by Thompson and Paredis [23], where a decision tree was used to determine the decision with greatest expected payoff. Two separate materials are presented to the DM with limited information on the yield strength of each material. The DMs initial options are to (1) design the pressure vessel based on current information, (2) test the first material, or (3) test the second material. The analysis proves that model development is only worth performing when the trade-offs between cost and quality is appropriate. A similar problem was explored by Ling et al. [17], except in this case, the author considers *how many* yield strength tests should be performed, such that gained precision in the design decision is appropriately 'traded off' with experimentation cost.

Decision Criterion

When variability information is known about a decision model, a decision can be made based on the highest expected payoff. However, there are many situations where the model is not defined in terms of variability. Instead, many models are subject to imprecision, where the model output is best described using an interval. If the payoff is then expressed as an interval, a decision cannot be made based on the highest expected payoff (because there is not a single expected payoff value).

Consider the die example presented in Figure 18. If the only information known about the 6-sided die model is that it will produce an integer value from 1 to 6, the expected payoff is not a single value; instead it is the set of values [$100,$200,-$700,-$100,$0,$400]. There is no probability information that indicates one payoff is more probable than another. However, there are decision policies that can help the DM make a decision based on intervals. Figure 20b presents the outcomes of a 6-sided die roll and a 4-sided die roll without probability information.

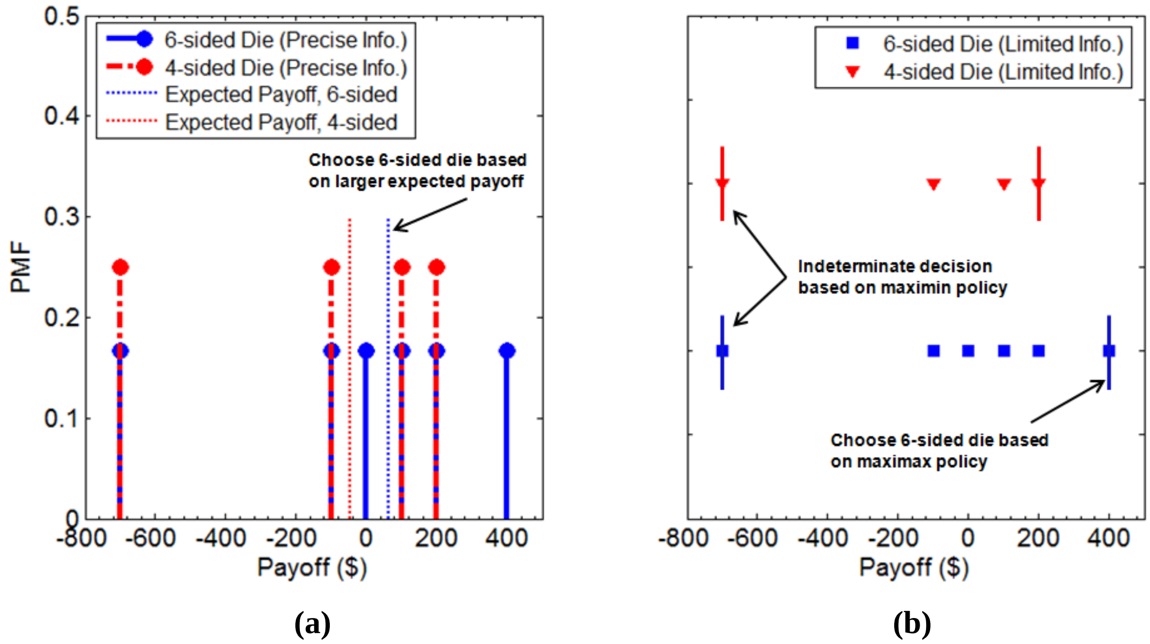


Figure 20. Decision analysis with (a) PMF information and (b) interval information

In Figure 20a (with PMF information), the correct decision is to roll the 6-sided die because the expected payoff is higher for this decision. However, the expected payoff only exists as a single value when the PMF information is available. Other decision policies must be used in the case that PMF information is not available. Under the maximax decision policy, rolling the 6-sided die is chosen because that decision has the highest possible payoff. The DM uses this policy if he is optimistic. On the other hand, the maximin decision policy is used when the DM is pessimistic. In the problem depicted in Figure 20b, the maximin decision policy results in an indeterminate decision because both decisions have the same minimum payoff. The maximin policy mitigates against poor outcomes by choosing he decision with best *bad* outcome.

Conjoint Analysis

The realization that making decisions is an intricate part of engineering design has stimulated a great deal of research in areas such as decision analysis, decision theory, concept generation, modeling customer demand, multi-attribute decision making, enterprise models, product development processes, and decentralized decision making [27]. Using these decision-making processes is intended to improve decision quality and to assist in the creating profitable products and, in general, achieving optimal outcomes.

Techniques to model design decisions can be used to incorporate DM preferences in the development of a product to assist in accomplishing this goal. The modeling of the DM's preferences and trade-off analysis is typically done through surveys or questioning elicitations to gather subjective data that further accompany objective data to determine an optimal design. The traditional decision-making techniques [28,29,30,31] are usually highly iterative and include exhausting questioning for the decision maker. Specifically, methods, such as the lottery elicitation in the Von Neumann–Morgenstern utility theory and the multi-attribute utility theory, require questions to determine indifference points, which are more difficult to use than a simple ranking survey [32]. Relatively new methods, such as hypothetical equivalents and inequivalents (HEIM), are being developed and extended to new applications in order to handle current concerns in multi-attribute decision-making [33,34]. Traditional methods, such as conjoint analysis (CA), quality function deployment, and survey design methods—that reflect a respondent survey technique—are relatively simple to evaluate [35]. Another corresponding research thrust is the inclusion of uncertainty parameters in the respondent preferences [28,31,36,37,38,39]. This thesis assesses uncertainty by propagating parameter uncertainties though the CA preference evaluation. This uncertainty assessment is straightforward, yet critical, to making the best decisions.

Propagation of uncertainties is also possible when using utility theory techniques to solicit DM preferences. Radhakrishnan and McAdams formulate utility functions by linearly interpolating between utility values [22]. Each utility function describes the utility of a model attribute over a continuous range of attribute levels. The authors also consider the uncertainty in the preferences due to attribute uncertainty. However, there is no clear guidance as to how the uncertainty characteristics are to be obtained.

This thesis employs CA because it is useful for quantifying the relative preference of attributes. CA is effective when trade-offs must be made among competing attributes. This is due to the fact that the CA ‘survey’ is presented to the survey respondent in a way that is intuitive and mimics real-world decision-making. In short, the respondent is asked to rank a list of options with varying attributes from most-preferable to least-preferable. For example, the highest ranked option may have the attributes ‘high’ accuracy with ‘low’ experimentation cost. The second-ranked option may have ‘medium’ accuracy with ‘low’ experimentation cost. Then the third option is likely to have ‘high’ accuracy and ‘medium’ experimentation cost. Since the options are presented as a collection of attributes, the respondent makes trade-offs ‘naturally,’ rather than being forced to directly compare accuracy and experimentation cost. The ranking of many options is used to compute the preference of each individual attribute, and the best feasible option is chosen.

2.4 Research Gaps in Model Development

In order to determine the research gaps in model development, an extensive literature review is performed. State-of-the-art methods in the fields of model development, information economics, and decision-based-design are explored. Ten representative works and their features are shown in Table 1 and Table 2.

Table 1. Model development and decision-based-design research

		(2008, Panchal et al.)	(2006, Aughenbaugh and Paredis)	(2005, Radhakrishnan and McAdams)	(1994, Bradley and Agogino)	(1993, Poh and Horvitz)	(2005, Fernandez)	(2010, Thompson and Paredis)	(2006, Ling, Aughenbaugh, and Paredis)	(2006, Ling and Paredis)	(2006, Rekuc et al.)
Topic(s)		Model development Information economics	Model development Information economics	Model development	Model development Information economics	Model development Information economics	Decision-based design	Model development Information economics	Model development Information economics	Model development Information economics	Decision-based design
Type of Uncertainty	**Imprecision**	●	●	○	●	●	●	○	●	●	●
	Variability	●	●	●	●	●	○	●	●	○	●
Overall Objective Function		●	●	○	●	●	●	●	●	●	●
Structural Model Development		○	○	●	○	●	○	●	○	○	N/A
Model Development Dependencies		N/A	N/A	○	N/A	○	N/A	○	N/A	N/A	N/A
No. of Information Sources		1	1	N/A	5	N/A	N/A	2	1	1	N/A
Considers Irrevocable Resources		●	●	○	●	●	N/A	●	●	●	N/A

Table 2. Model development and decision-based-design research

	(2008, Panchal et al.)	(2006, Aughenbaugh and Paredis)	(2005, Radhakrishnan and McAdams)	(1994, Bradley and Agogino)	(1993, Poh and Horvitz)	(2005, Fernandez)	(2010, Thompson and Paredis)	(2006, Ling, Aughenbaugh, and Paredis)	(2006, Ling and Paredis)	(2006, Rekuc et al.)
Topic(s)	Model development Information economics	Model development Information economics	Model development	Model development Information economics	Model development Information economics	Decision-based design	Model development Information economics	Model development Information economics	Model development Information economics	Decision-based design
Description	Determine improvement potential of reducing uncertainty in model	Manage data collection/experimentation according to information economics	Consider resource trade-offs in model selection	Propose systematic framework to help designers balance limited resources with design improvements	Investigates the value of refining decision models	Comprehensive demonstration of decision support under uncertainty	Choose experimentation plan based on costs and expected design outcomes	Manage data collection/experimentation according to information economics	Create the optimal FEA model based on information economics	Systematically eliminating design alternatives under uncertainty
Uncertainty Representation	Intervals	P-box	Piecewise PDF function	Intervals and general PDF	Intervals and triangular PDF	Intervals	Normal PDFs	P-box	Intervals	Intervals and Normal PDFs
Evaluation Metric(s)	Value of Information (payoff of decision), Utility Theory	Value of Information (payoff of decision)	Utility Theory	Value of Information, Utility Theory	Value of Information, Utility Theory	Utility Theory	Value of Information (payoff of decision)	Value of Information (payoff of decision)	Value of Information (payoff of decision), Utility Theory	Payoff of Decision
Design Phase	Embodiment	Embodiment	Conceptual	Conceptual	Embodiment / Conceptual	Embodiment	Embodiment	Embodiment	Embodiment	Embodiment
Description of Application	Refinement of material model to be used in design of pressure vessel (and 2nd example)	Refine material model for pressure vessel design (thickness)	Choose best model for race car sway bar	Choose bearing from catalog	Plan a party (location) subject to weather conditions	Select rapid prototype materials and processes for light switch cover plate assembly	Choose material testing prior to design of pressure vessel	Refine material model for pressure vessel design (thickness)	Refine FEA model to use in beam design	Design gear box for race car

Fundamental concepts and features of model development are identified and noted for each work, including type of uncertainty, design phase, irrevocable resources, etc. Figure 21 and Figure 22 depict the findings of the literature review—showing the predominant features (and omissions) in model development research. Note that the omission of a feature does not detract from the usefulness of the work. Each of the listed works offers significant contributions to the field. It is generally helpful to focus on a limited number of model development features when performing research such that the selected features are comprehensively addressed.

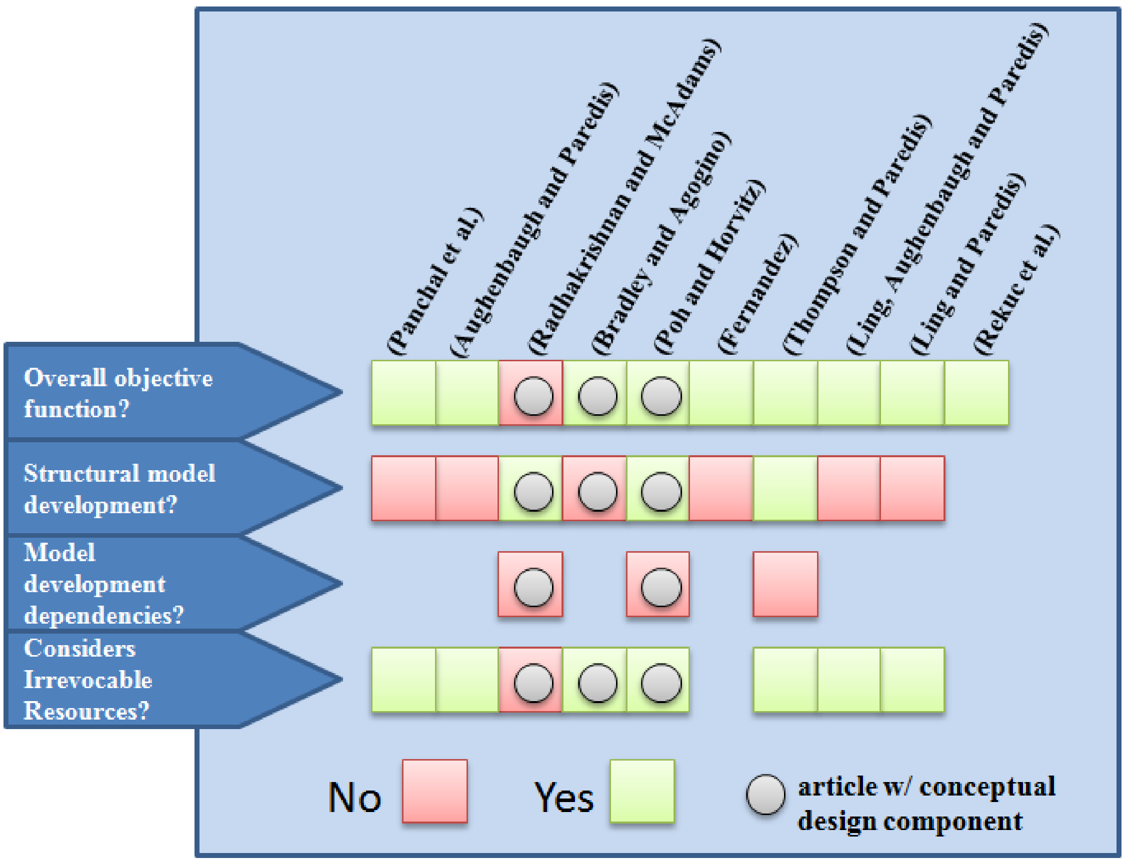


Figure 21. Analysis of literate review on decision-based-design and model development

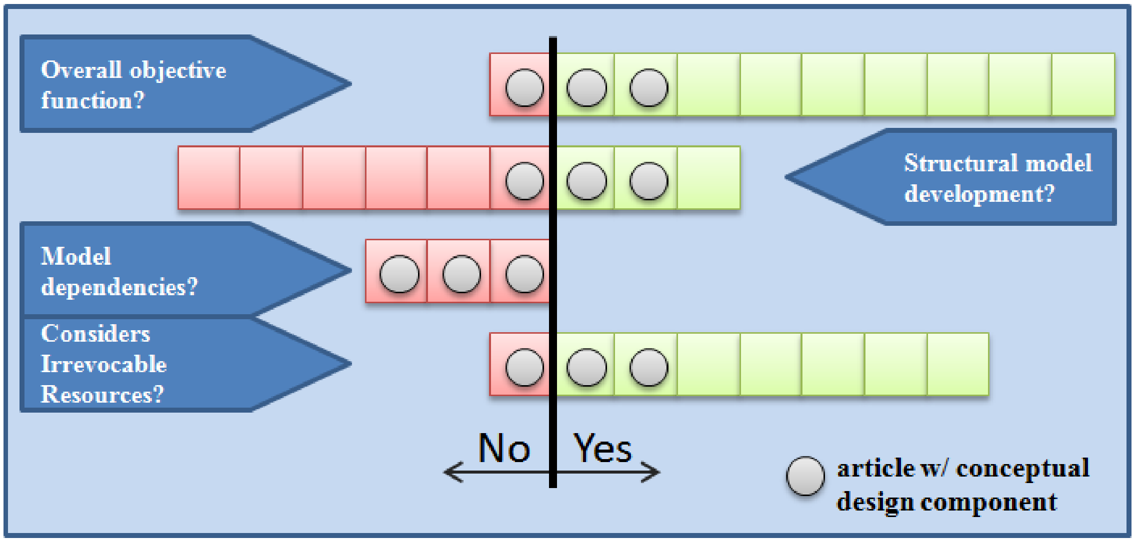


Figure 22. Analysis of literate review on decision-based-design and model development

Model Development in Conceptual Design Phase

The first observation from Figure 21 and Figure 22 is that most of the model development research focuses on embodiment design applications, rather than conceptual design. The difficulty in addressing this design phase is no doubt related to the high level of uncertainty that exits during conceptual design. In the conceptual design phase, there are many information constraints which may include an incomplete requirements list, unclear design goals, undefined resource constrains, etc.

Overall Objective Function

In particular, an objective function is generally not clearly defined in the early stages of design. In other words, the DM does not precisely know the overall goal of the decision model. The DM may have a vague idea of the general goals such as reduce probability of failure, decrease manufacturing cost, reduce weight, etc. But he does not have enough information to formulate a precise objective function based on these design parameters. Referring back to Figure 18, this is comparable to refining the die model without having the playing board. In this case, the DM must find a way to assess the die model without knowing the potential payoffs of the decision.

Two of the articles that claim to address the conceptual design phase assume that the objective function is known. Bradley and Agogino implement an objective function that depends on many factors such as cost-per-bearing, cost of failure, reliability of the bearing, mission duration, etc. Technically, the bearing selection problem may be considered a conceptual design problem, but a concise, well-defined objective function is oftentimes not available during the conceptual design phase. Poh and Horvitz also make some key assumptions, namely, that the objective function is available and that the exact value of each of the parameters is known. The objective function is required to calculate the expected value of information (EVI), and the exact parameter values are required to calculate the expected value of perfect information (EVPI). This is comparable to the board game example, where the precise PMF for the die is needed to compute the EVPI. Typically, this precise information is not known, and special methodologies must be implemented to overcome this challenge. Thus, this thesis focuses on model development in the conceptual design phase when an objective function is not known and imprecision exists in preliminary information.

Figure 22 shows that there is one work which addresses the unknown objective function. Radhakrishnan and McAdams do not incorporate an objective function based on the overall design decision [22]. This represents a true conceptual design problem, where multiple models are available for development, but the precise, overall goals are either vague or unknown. The authors simply consider model attributes that are potentially valuable to the DM such as accuracy, time, etc. Then, the preference for different attribute levels are solicited via utility theory techniques. However, the primary limitation is the lack of consideration of irrevocable resources. e.g., the ‘time’ is allocated toward creating and evaluating models before the best model is chosen. The time cannot be recovered retroactively, and thus, is not appropriately considered.

This presents a challenge when assessing conceptual model development. ‘How can the models be assessed before committing irrevocable resources?’ This thesis presents a solution to this problem by splitting model development into phasese. The first phase is preliminary testing, in which a small number of tests are implemented. Then the models are assessed based on the limited data before final testing begins; thus, the model developing decision is framed around choosing the final testing tasks such that resources are allocated optimally.

Multiple Sources of Information

Table 1 shows that there are only two works that consider more than one source of additional model information. Thompson and Paredis provide a comprehensive investigation into the effects of including two information sources (different materials). i.e., the DM has more than the standard two options: gathering information or making a decision now. The DM can choose to (1) make the decision now based on current information, (2) test the first material, or (3) test the second material. By implementing a decision tree, the authors handle the dependency of the outcome on the order of decisions.

Bradley and Agogino don't handle the order of events, but they do consider far more sources of information. Five potential sources are considered including cost of failure, number of units to be produced, and bearing load. This provides the DM with a diverse set of options, which is the case in most real-world situations.

This work considers two sources of information for model development. Moreover, there is a unique focus on the dependency of models based on common sources of information.

'Structural' Model Development and Model Dependencies

Poh and Horvitz describe structural model refinement as a 'modeling effort that leads to the addition or deletion of conditioning variables or dependencies in a decision model.' Consider a comparable board game example with an additional option that includes a 4-sided die. Choosing to develop the 6-sided die over the 4-sided die, or vice versa, is a structural model development decision. Predicting the outcome of the 6-sided die involves a structurally different model than that of the 4-sided die.

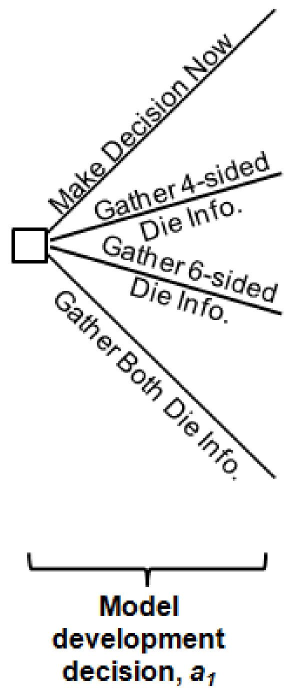


Figure 23. Model development decision with multiple die
Structural model development is only considered in three of the works listed works

Poh and Horvitz use the concept of irrevocable resources to define the net expected value of refinement (NEVR) as the difference between the expected value of refinement (EVR) and the cost of the refinement (including the added cost of the more complex model). Radhakrishnan and McAdams separately evaluate three different analytical models of a torsion bar, along with a FEA model. Thompson and Paredis include two different materials when making a decision to improve one or both material models.

However, none of these efforts directly consider possible dependencies between the models. For example, consider the board game example with a 4-sided die and 6-sided die. The model of the 4-sided die outcome is independent from the model of the 6-sided die outcome. However, this is not the case when another design decision is considered—

rolling both dice. The decision to roll both dice also needs a model, and this model for the summed outcome of both dice is dependent on each of the single-die models. One could now consider four model development decision options: (1) make a decision now, (2) get information on the 4-sided die, (3) get information on the 6-sided die, or (4) get information on both dice. Choosing the correct model development decision requires consideration of the model dependencies.

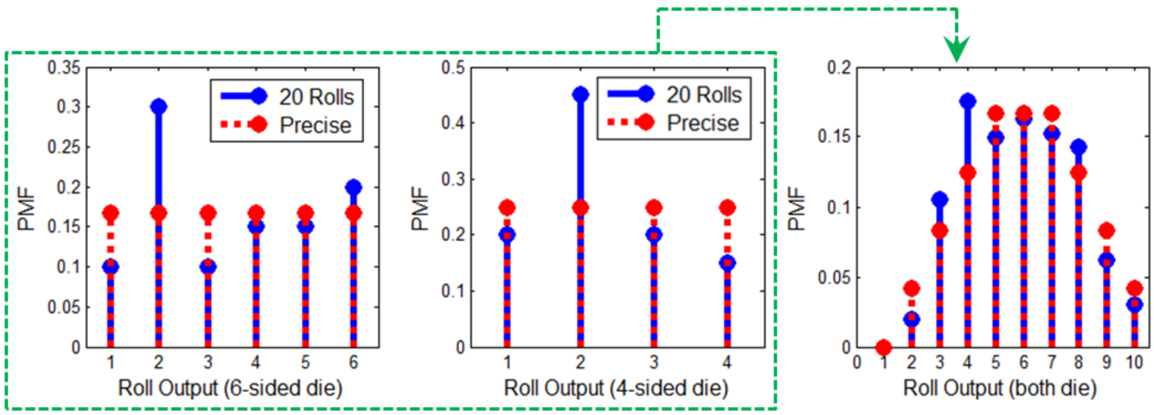


Figure 24. Dependency of models for different die roll decisions

Model dependency becomes increasingly important when considering imprecision in information sources. The die dependency is a relatively simple example, but this paper considers a more complex example where the dependency between two complex models does not have a simple, analytical relationship. In this thesis, a framework is developed which handles model dependencies created by common sources of information.

Scope of this Work

Multiple works in the field of model development have been presented—each making significant contributions to the field. There is great value in focusing on the detailed analysis of a few model development features. Novel or uncommon focuses are starred (*). These items represent research avenues that have not yet been explored and/or fully investigated.

1) MSD model for predicting contact forces between small packages during impact

2) *Novel testing/measurement techniques for retrieving drop test data and calibrating drop test model
3) *Model development in the conceptual design phase—in particular, when the objectives of the overall design are not clearly defined
4) Using CA to solicit DM preferences, propagate uncertainties, and evaluate decision outcomes (rather than an overall objective function)
5) Address structural model development with multiple model options
6) *Accommodate model dependencies and common sources of information
7) Consider uncertainty in model development, namely, imprecision in information sources

CHAPTER 3

PROPOSED METHODOLOGY

3.1 Drop Test Modeling

This section includes details on preliminary model development. In an attempt to understand the interaction of the individual packages during shipping and handling, the DM implements drop tests according to ASTM standards [4]. In ASTM D7386-08, cartons are dropped in different orientations, and then the individual packages are subject to a bubble pressure test according to ISO standards to check for damages [3]. Gathering drop test data for different carton dimensions would require new cartons to be produced, and exploring the entire design space (all feasible dimensions, package orientations, etc.) would require many weeks of testing. Thus, a drop test model is developed in order to efficiently explore the design space and optimize the packaging design parameters. Experimental acceleration and velocity data is used to develop a MSD model that is useful for predicting the contact force experienced by individual packages.

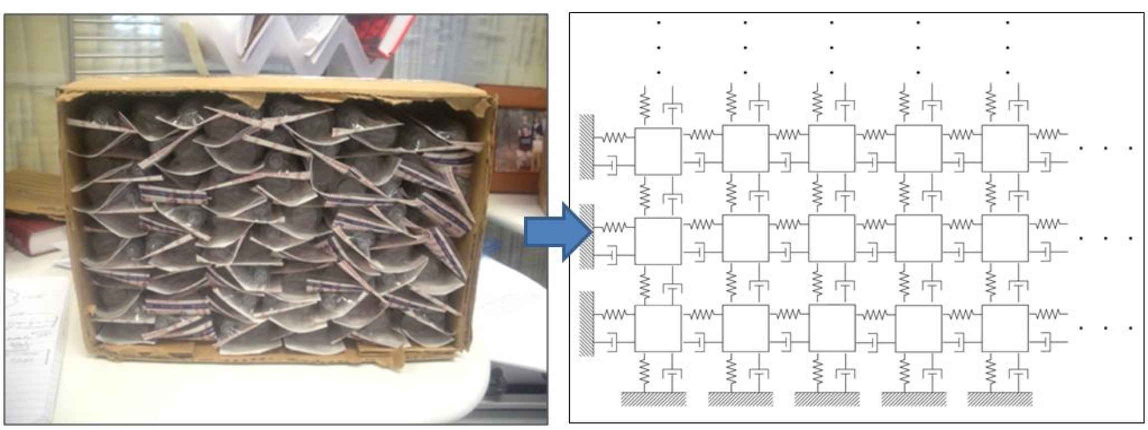


Figure 25. Cut-away of carton and MSD model representation

It is assumed that the failure of the individual packages is directly related to the contact force experienced during drop testing. Various MSD models are considered in terms of their ability to match acceleration and velocity data found experimentally. The experimental set up for low drop test, developed at Georgia Tech, employs a laser doppler vibrometer (LDV) that records the velocity of an individual package within the carton. A high drop test setup is also developed in which the acceleration of an individual package is recorded. Past research considers a variety of MSD models with different numbers of parameters [40]. Three different MSD models are created: a) Simple, b) Medium, and c) Complex—categorized with respect to their relative complexity. The cost associated with developing the model depends on the complexity of the model and the desired accuracy. In general, models with larger numbers of parameters produce more accurate results, but they require more experimentation costs and computation time. Trade-offs must be made with respect to the modeling costs, model accuracy, etc., in the model development process.

Model Assumptions and Development

In this thesis, the generic packaging design consists of individually packaged products inserted into a standard shipping carton. Figure 26a shows a 3D lattice representation of the individually packaged products, and Figure 26b shows the corresponding 2D lattice of the products and the carton. In this particular packaging design, there are 8 rows of product packages and 12 columns of product packages.

Each product package is treated as an individual mass, and the interaction between the masses is modeled using spring and damper models—shown in Figure 26c. In this preliminary model, each mass has 2 degrees of freedom: horizontal and vertical. The model is further simplified by considering only flat drops, where the packaging is not dropped on an edge or corner of the carton. Thus, only one degree of freedom, vertical, must be considered in the simplified model. Also, when assuming a flat drop, each row of

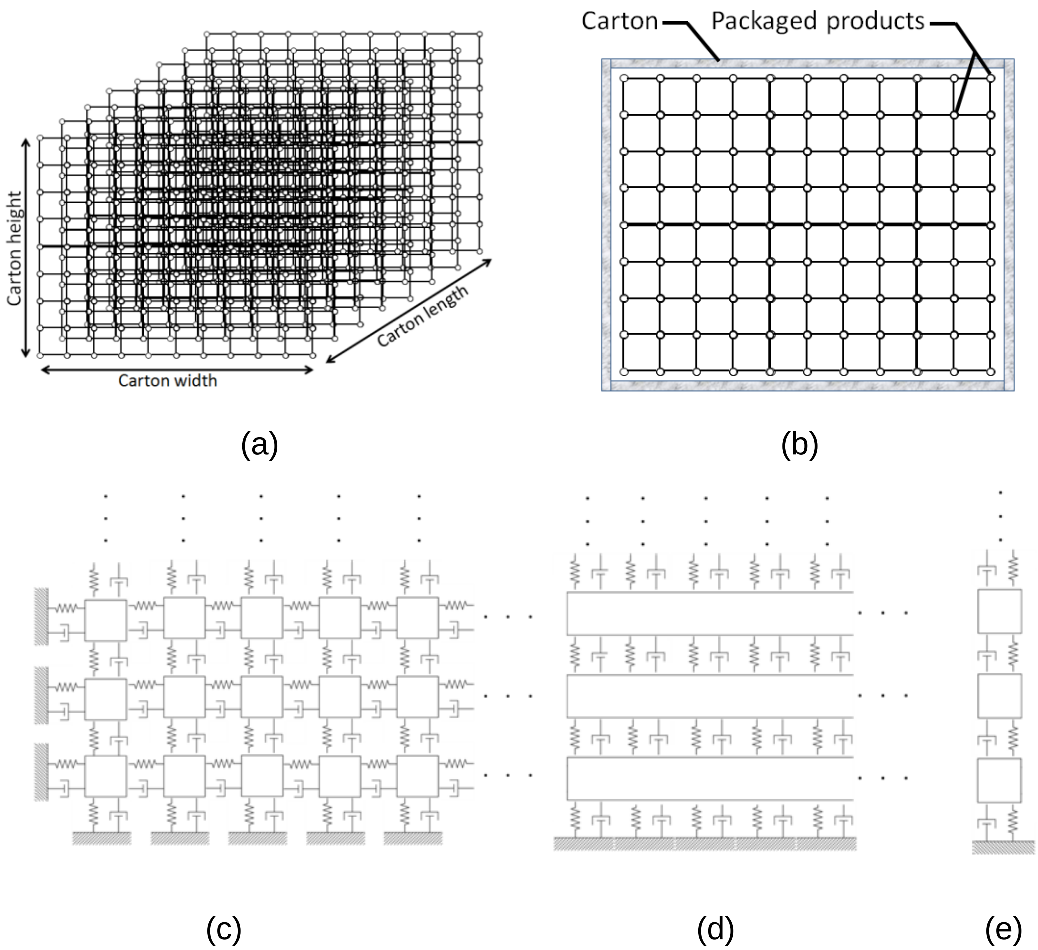


Figure 26. (a) 3D lattice representation of individually packaged products (shown as circles), (b) corresponding 2D lattice composed of products and carton (carton length is into the page), (c) MSD system representation of packaged products (shown as masses), (d) MSD system with combined masses, and (e) MSD system with combined springs and dampers

masses can be consolidated into individual larger masses. The mass combination is depicted in Figure 26d. The springs and dampers in parallel can also be combined.

Proposed Spring/Damper Models

In this section, various spring and damper models are explored for use in the model shown in Figure 27. The spring and damper must be modeled with sufficient intricacy such that results are accurate; however, care must be taken to limit the complexity such that the final model is not too costly.

Nonlinear Viscoelastic Models

Hunt and Crossley presented one of the first nonlinear viscoelastic contact force models, arguing that the linear spring-damper model is not representative of the energy transferred during impact. Such a nonlinear model is shown in Equation (5)

$$F_c = k\delta^{3/2} + c\dot{\delta}^{3/2} \tag{5}$$

where δ is the deformation of the spring and $\dot{\delta}$ is the velocity of the mass. A similar formulation of Equation (5) is presented in Ref. [41].

The k_p value can easily be determined by static experimentation setups. However, researchers investigating Equation (5) identify the damping coefficient, c_p, as a function of a coefficient of restitution, elastic moduli, and/or Poisson ratios—assuming spherical contact. For example, the damping coefficient can be defined as

$$c = {3k(1-e^2)}\big/{4v_i} \tag{6}$$

where e is the coefficient of restitution, and v_i is the initial velocity. The coefficient of restitution is often difficult to determine for product packaging, and contact between product packages is often not characterized as ‘spherical contact.’ Also, elastic moduli and Poisson ratios are not easily acquired for product packaging.

Based on empirical observations, another nonlinear viscoelastic model was introduced in Ref. [42]:

$$F_c = k\delta^{3/2} + c\delta^{1/4}\dot{\delta} \tag{7}$$

The advantage of this model for this thesis is that the damping coefficient is also determined by an empirical relationship. The formulation of the damping parameter is

$$c = \mu m^{1/2} k^{1/2} \tag{8}$$

where μ is an empirically determined constant, and m is the effective mass.

Generalized exponential model

A slightly modified version of the contact force formulation [11] is

$$F_c = k\delta^a + c\delta^b \dot{\delta} \tag{9}$$

where a and b are empirically determined parameters. This model provides freedom in determining an appropriate contact force model for contacts involving non-spherical elements. In the standard Hertz model, a is equal to 3/2, as seen in the aforementioned models. However, non-spherical contact may require different values of a.

Generalized polynomial models

The vibration dynamics of a system were analyzed in Ref. [43], while considering the following spring and damper contact force models:

$$F_{c,spring} = k_1\delta + k_2\delta^3 \tag{10}$$

$$F_{c,damper} = c_1\dot{\delta} + c_2\delta^2\dot{\delta} \tag{11}$$

where $F_{c,spring}$ and $F_{c,damper}$ are the spring contact force, respectively. There are multiple stiffness coefficients—k_1 and k_{s2}—and multiple damping coefficients—c_1 and c_2.

The formulations in Equations (10) and (11) can be generalized according to

$$F_{c,spring} = k_1\delta + k_2\delta^2 + \cdots + k_i\delta^i \tag{12}$$

$$F_{c,damper} = c_1\dot{\delta} + c_2\delta\dot{\delta} + \cdots + c_j\delta^{j-1}\dot{\delta} \tag{13}$$

where k_i is the i^{th} spring coefficient, and c_j is the j^{th} damping coefficient. Note that the units of the k_s and c_s terms change according to the values of i and j, respectively. This model provides a great amount of freedom in empirically matching the actual system, but the number of unknown parameters increases according to the number of terms, $i+j$.

Proportional damping

A popular method of approximating a damping coefficient is assuming that it is proportionally related to the stiffness and mass parameter. Equation (14) describes the relationship between stiffness, K, mass, M, and damping matrices, C, when proportional damping is assumed.

$$C = \alpha M + \beta K \tag{14}$$

where α and β are empirically determined constants. For the case where dampers are parallel to spring elements, rather than being connected to ground, the damping coefficients are exclusively proportional to the stiffness coefficients:

$$C = \beta K \tag{15}$$

This relationship is useful when there are multiple, unique spring and damper coefficients. In this case, only the spring coefficients and one empirical constant, β, must be determined via experimentation.

<u>Multiple Collision Modeling</u>

The interaction of the MSD components must be modeled with sufficient intricacy in order to accurately match actual system behavior. Therefore, care must be taken to limit the number of required modeling features such that the final model can be determined via limited experimentation with low computation costs. A critical feature of the system model is the multiple collisions that occur between the product packages. The product packaging, which enclosing the actual product, is the first system component that interacts with any other system component during impact—contact phase 1. Then, once the product packaging is sufficiently deformed, the actual product begins to interact with other system components—contact phase 2.

Due to the existence of colliding components, the package system is modeled as an n-degree-of-freedom oscillator with elastic stops. The vibro-impact characteristics of an MSD model with elastic stops were investigated in Ref. [7], including dynamics and stability during oscillation. The model shown in Figure 27 is a slight modification of the model used in Ref. [7].

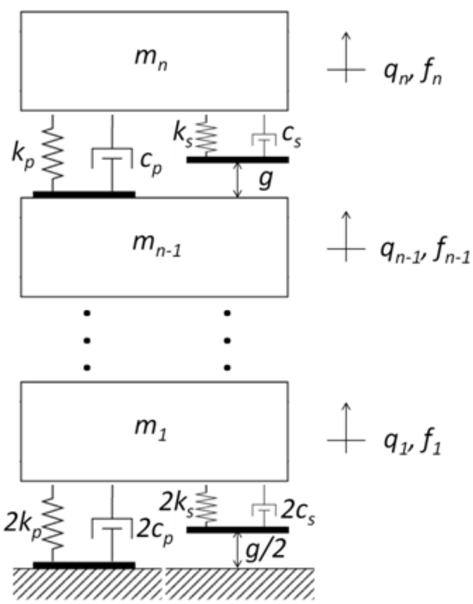


Figure 27. MSD model with elastics stops; elastic stops are capable of 'disengaging' from the adjacent mass

In Figure 27, m_n is the combined mass of the n^{th} row of product packages, k_p and k_s are combined stiffness coefficients, c_p and c_s are damping coefficients, g is the gap between product packaging and the enclosed product, q_n is the generalized position coordinate for mass n, and f_n is the generalized forcing for mass n. Three modes of packaging interaction are possible for the model; the two primary phases are shown in Figure 28.

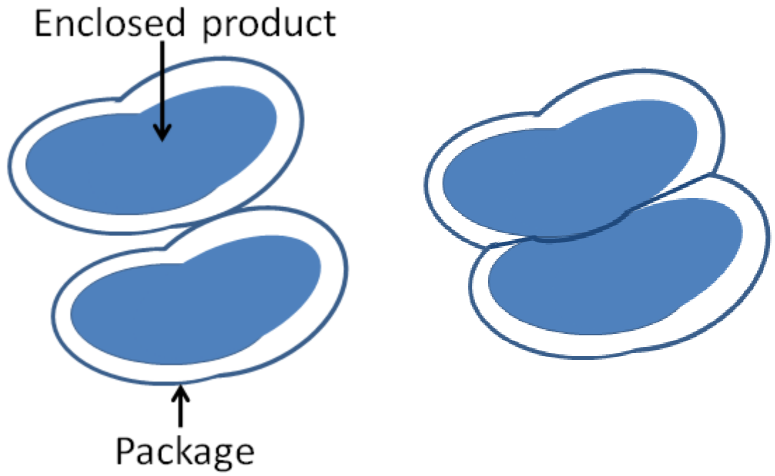


Figure 28. Depiction of (a) contact phase 1 and (b) contact phase 2 for packaged product with arbitrary shape

Contact Phase: Contact phase 1 involves the exclusive interaction of the packaging materials only. The packaging stiffness and damping coefficients are represented as k_p and c_p, respectively.

Contact Phase 2: After the gap, g, decreases to zero, contact phase 2 is initiated. Contact phase 2 involves the interaction of the packaging material along with the interaction of the enclosed product, a syringe. The product stiffness and damping coefficients are represented as k_s and c_s, respectively.

No-contact Phase: If the packaging carton is dropped from a sufficient height, the packaged products may rebound and lose contact with each other, resulting in the no-contact phase. A model of the no-contact phase is not necessary when considering only the initial impact (phase 1 and phase 2), but it is useful for parameter estimation.

Of particular interest is the contact force between the masses in the system. The contact force on the bottom of a package, F_c, is

$$F_c = \begin{cases} k_p\delta_p + c_p\dot{\delta}_p & 0 \le \delta_p \le g \\ k_p\delta_p + c_p\dot{\delta}_p + k_s\delta_s + c_s\dot{\delta}_s & \delta_p > g \end{cases} \tag{16}$$

where δ_p and δ_s are the deformations of the product package spring and product spring, respectively. $\dot{\delta}_p$ and $\dot{\delta}_s$ are the deformation rates product package spring and product spring, respectively. Positive values of deformation correspond to spring compression. The gap, g, is approximated by acquiring the distance of product package deflection via experimentation.

Equation (16) describes the interaction of the packages only during contact phases 1 and 2. When the packages are in the no-contact phase, the interaction of the package with the carton wall and gravitational forces dictate the motion of the packages—not depicted in Figure 27 or Figure 28. The low weight of each product package causes the wall interactions to be the prevalent contributor to forcing during the no-contact phase. Consequently, the wall interactions can be approximated by observing the response of the packages during the no-contact phase. The equations of motion during this phase are defined by

$$m_n \ddot{q}_n = -\gamma(k_p q_n + c_p \dot{q}_n) = F_w \qquad q_n - q_{n-1} > 0 \tag{17}$$

where γ is an empirically determined constant, and q_n is the generalized coordinate of the n^{th} mass, and F_w is the wall force acting on the n^{th} package.

Negative deformation values correspond to spring tension. The product package cannot act as a spring in tension; so the dominate forcing is due to interactions between the product package and the carton wall. Equation (17) assumes that the wall interaction force parameters are some proportion, γ, of the product package spring and damper parameters. Also, notice that the wall interaction forces depend on the displacement and speed relative to the carton wall, q_n and $\dot{q}_n$, respectively. The package responses during the no-contact phase are needed for the estimation of other model parameters.

Equations (16) and (17) are then applied to all of the masses in order to develop a system of equations that defines the entire MSD system. The number of equations in the system is equal to the number of rows of product packages in the packaging design. The equations of motion in general matrix form is

$$M\ddot{q} + F_{c,bot} - F_{c,top} + F_{w} = f \tag{18}$$

where M is the inertial matrix, q is the generalized coordinate vector, $F_{\mathrm{c,bot}}$ is the contact force vector for the bottom of the masses, $F_{\mathrm{c,top}}$ is the contact force vector for the top of the masses, F_{w} is the wall interaction force vector, and f is the generalized forcing vector.

The existence of the elastic stop results in piecewise ordinary differential equations. Also, the local solution of an equation of motion for mass n depends on the local solution of the equation of motions for mass n+1 and mass n-1. Thus, traditional analytical solutions are not applicable. Numerical solutions in MATLAB are used to simultaneously solve all of the equations of motion while considering elastic stops and initial conditions.

Selecting a Contact Force (spring/damper) Model

This MSD research compares and contrasts three spring/damper models for the contact phase 2 elements: the Kelvin-Voigt model, Equation (7), and Equations (10) and (11). Contact phase 1 is modeled using Kelvin-Voigt model for all three system models. Table 3 shows the contact force expressions for each system model, where the subscript s denotes the elastic stop elements.

Table 3. Contact force models

	Contact Phase 2 Model	Number of Unknowns
Model 1	$F_c = k_s\delta_s + c_s\dot{\delta}_s$	2
Model 2	$F_c = k_s\delta_s^{3/2} + c\delta_s^{1/4}\dot{\delta}_s$	2
Model 3	$F_{c,spring} = k_{s,1}\delta_s + k_{s,2}\delta_s^{3}$ $F_{c,damper} = c_{s,1}\dot{\delta}_s + c_{s,2}\delta_s^{2}\dot{\delta}_s$	4

Model 1 employs the Kelvin-Voigt model for viscoelastic materials. This is a simple model that results in piecewise linear differential equations; computations of this model are relatively straightforward. However, the Kelvin-Voigt model may not adequately describe the response of the spring and damper elements that represent phase 2 loading. i.e., the phase 2 loading spring force may not be linearly related to spring deformation, and the associated damping force may not be linearly related to the spring deformation rate. Preliminary inspection of packaging design shows that these nonlinearities do exist. Choosing the appropriate models will limit the complexity of the spring and damper models and reduce the experimentation cost, while also delivering sufficiently accurate results.

Experimental Methods

Test Apparatus Construction

Acquiring acceleration data from dropping the syringes involves experimentation with multiple data-capturing methods. An accelerometer is used as the primary impact acceleration-measuring device for the drop tests. In an effort to precisely capture data at the center of the packaged syringes, an accelerometer is encapsulated inside of a syringe. To accomplish this task the syringe is modified by cutting away material and permitting the secure installation of the accelerometer inside the syringe while removing the appropriate amount of plastic to offset the weight added by the accelerometer. The weight of the plunger without the accelerometer is 7.82 g. Then the plunger is removed from the syringe for accessibility. Using a dremel tool, a section of the plunger material is cut out to permit placement of the measuring device into the syringe, as seen in Figure 29.

Figure 29. Plunger before and after modifications

The plunger with the accelerometer placed in its proper orientation is shown in Figure 30.

Figure 30. Plunger with accelerometer in place

Weight measurements are then recorded with the syringe and accelerometer assembled. The weight of the modified syringe is found to be 9.06 g, requiring further removal of 1.24 g of material. A final weight of 7.85 g is eventually achieved, which is within the .03 g of the original syringe weight. After assembling the modified syringe with the accelerometer enclosed, the testing process begins.

LDV Testing

A Polytech PDV-100 Portable laser doppler vibrometer (LDV), illustrated in Figure 31, is used as a method to capture velocity.

Figure 31. Polytech PDV-100 Portable Laser Digital Vibrometer (LDV)

A test setup is devised in which the LDV is suspended over the drop area using a system of stands, as seen in Figure 32 and Figure 33. For the LDV to best capture the velocity of the packages during impact, a piece of reflective tape is attached to the top syringe as viewed in Figure 33. After numerous drops it is noted that the LDV loses its precision on drops which were greater than 5 in. Errors are most likely not the fault of the LDV, as this model is capable of measuring variable working distances from 0.2 m to 30 m. Imprecise signals can be due to the rapid shifting of the reflective tape attached to the 'marker' syringe. Poor reflection back to the LDV is experienced with more violent drops and package shifting. Thus, the LDV drop test height is adjusted to 0.5 in. This produces less sporadic movements in the 'marker' syringe so that a time response can be required of the package velocity throughout the duration of the impact.

Figure 32. LDV setup

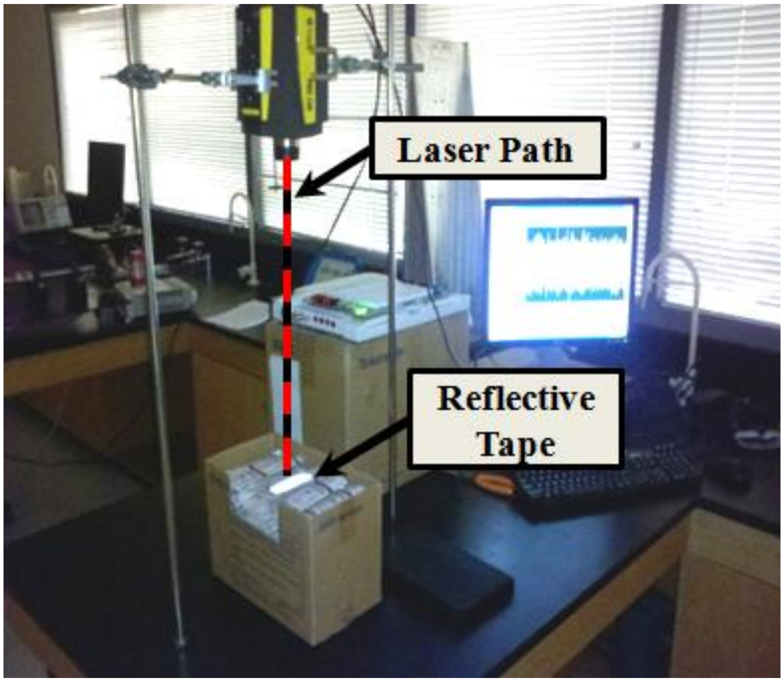


Figure 33. View of LDV setup with reflective tape attached to top syringe

Accelerometer Testing and LabView Instructions

Accelerometer testing is conducted with the assistance of LabView software and the NI Elvis II Instrumentation board which is pictured in Figure 34.

Figure 34. National Instruments Elvis II Instrumentation board

Testing is initiated by starting the LabVIew Signal Express software. This is done by turning on the NI Elvis II Instrumentation board and selecting ‘Begin a Measurement with This Devise Using NI LabView SignalExpress’ in the ‘New Data Acquisition Device’ window, which will appear automatically. When the main testing window opens, delete the ‘DAQmx-Aquire’ box if it is present; it will look like Figure 35.

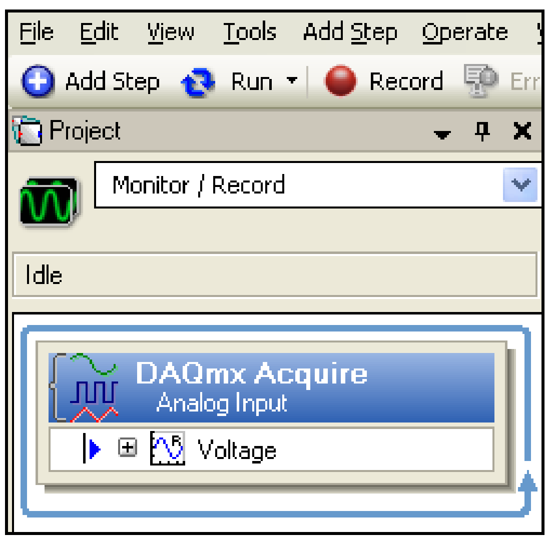


Figure 35. LabView Signal Express DAQmx Acquire box

Click on ‘Add Step’ and open ‘Aquire Signal > DAQmx_Aquire > Analog Input > Voltage’ and select ‘scopeCh1’ from the Physical Tab, then select OK. Configuration of the input device was then accomplished. The window, as viewed below in Figure 36, appeared on the screen after OK was clicked in the previous step.

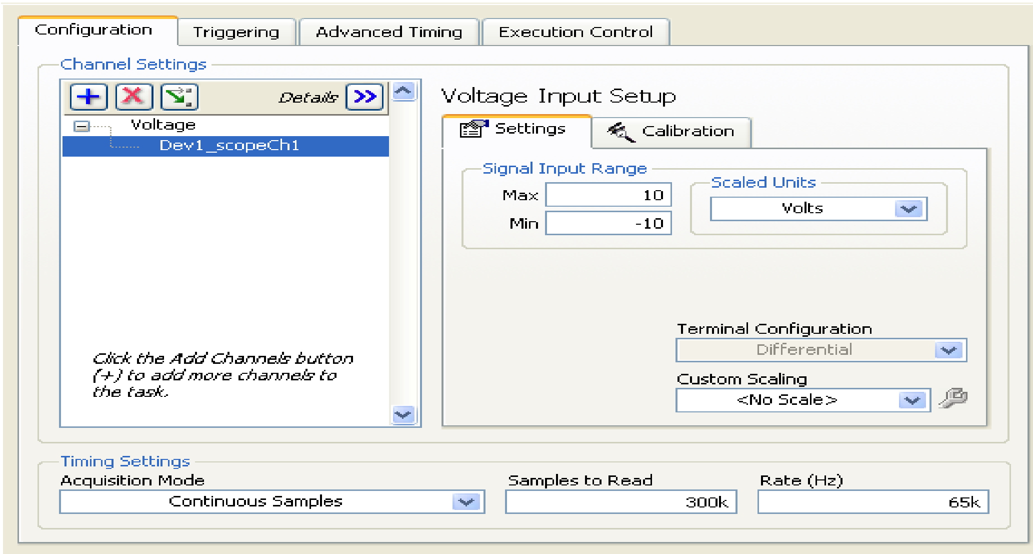


Figure 36. Configuration tab, LabView SignalExpress

The following settings are selected on the Configuration tab:

- Channel Settings:
  - Voltage – Dev1_scopeCh1
  - Voltage Input Setup
- Settings:
  - Signal Input Range: Max = (10 V), Min = (-10 V)
  - Scaled Units: Volts
  - Terminal Configuration: Differential
  - Custom Scaling: <No Scale>
- Timing Settings:
  - Acquisitions Mode: Continuous Samples
  - Samples to Read: 300k
  - Rate(Hz): 65k

The Triggering, Advanced Timing and Execution Control tabs do not require alteration from that which was set to default on software startup. After closing the configuration window it was then possible to select ‘Run’. At this point the accelerometer is collecting random noise and the screen display reflected what is seen in Figure 37. Data is now ready to be collected through LabView.

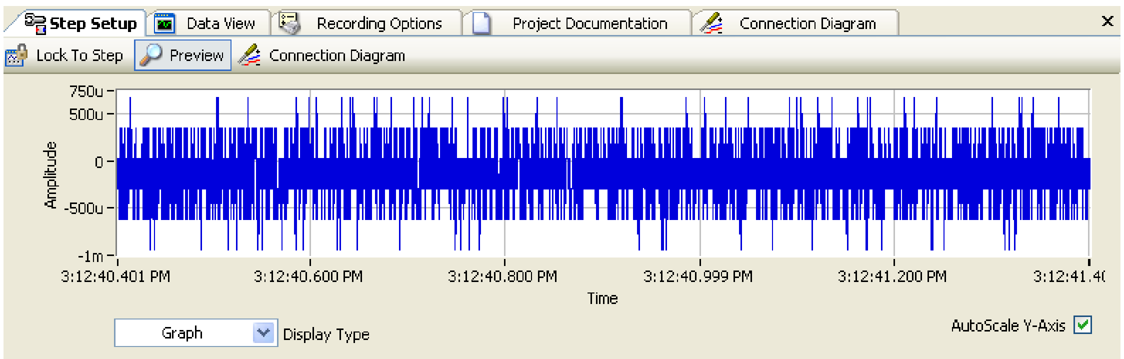


Figure 37. LabView display from accelerometer (‘noise’)

Syringes are oriented in the Moderately Nested packaging style and dropped from a height of 10 in. for the first of two drop cycles. The box contained 13 rows of syringes which are approximately 7 columns wide and the accelerometer-syringe was placed on the 4th column and the 7th row, counting from the bottom. To start the drop-test ‘Run’ and ‘Record’ are clicked on the top bar of the SignalExpress screen. The box of syringes is raised to the test height of 10 in. from the bottom of the box to the impact surface. A metal crossbar marks the height to ensure consistency in drop height. The box is then released in a manner such that all four corners of the box impact as close to the same time as possible. Upon impact the data is immediately exported into an Excel file and saved. If the box does not impact evenly, then the data is deleted and a new test is run. After two to three drops it is necessary to correctly re-arrange the syringes back into the moderately nested configuration and verify that the modified syringe is still in the same position. A total of 10 drops are conducted in this orientation, which represents the preliminary testing. A second drop test is conducted while the syringes were placed in the Fully

Nested orientation from the same height of 10 in. and the same placement within the box. Using the same procedure as described for the first test, a total of 10 drops are completed and saved to worksheets within an Excel file.

Model Parameter Estimation Methodology

Contact Phase 1 Parameters

When a carton of product packages is dropped from a low height (e.g., 0.5 in), no 'collisions' occur between the enclosed products; i.e., the k_s and c_s parameters have no influence on the MSD model. Thus, drop tests from a low height are used to determine the k_p and c_p parameters for the packaging. In the experimental setup, a LDV is focused on reflective tape that is applied to a product package. The LDV records the velocity of an individual product on the n-1 row as the carton is dropped from a low height.

Figure 38 and Figure 39 present graphs of the velocity response of the n-1 row of product packages. Figure 38 shows theoretical MSD responses for various k_p values. The appropriate k_p value is chosen by matching the theoretical MSD response to the experimental velocity response data. Notice that increasing the packaging stiffness coefficient alters the magnitude and frequency of the system response. Figure 39 presents the same experimental data along with MSD responses for various c_p values. The c_p value is also chosen by comparisons to experimental data. Notice that the changing stiffness parameter primarily affects the magnitude of the response and also has an effect on the response frequency. Note that some noise has been removed from the experimental data at around 0.05 sec.

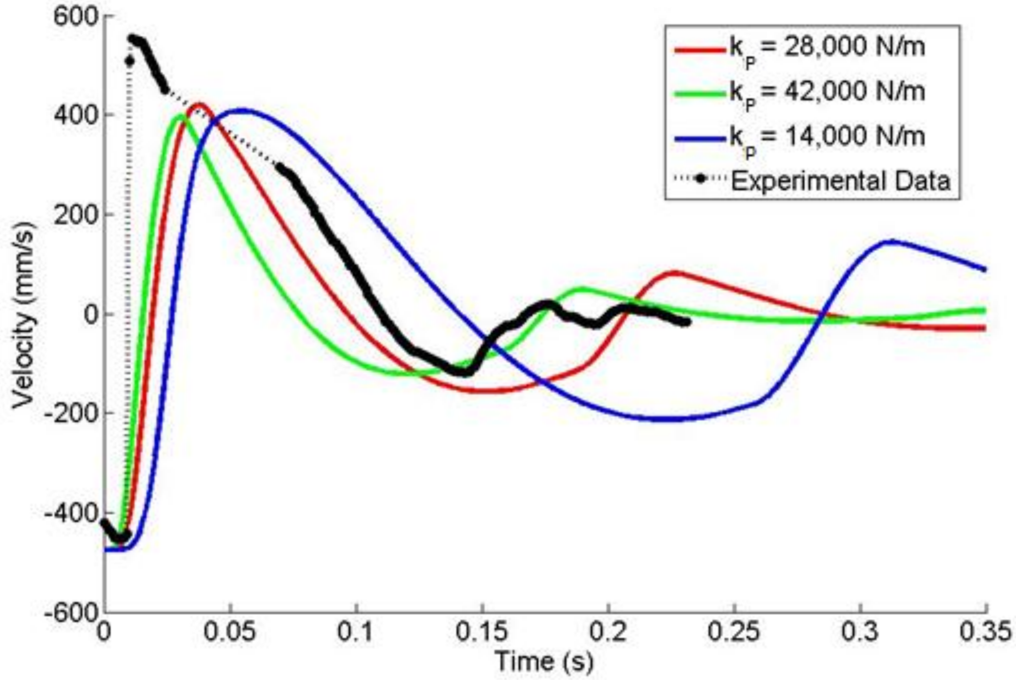


Figure 38. Velocity response of packaging subject to 0.5 in drop; data shown for *n*-1 row; c_p is held constant at 84.0 N-s/m

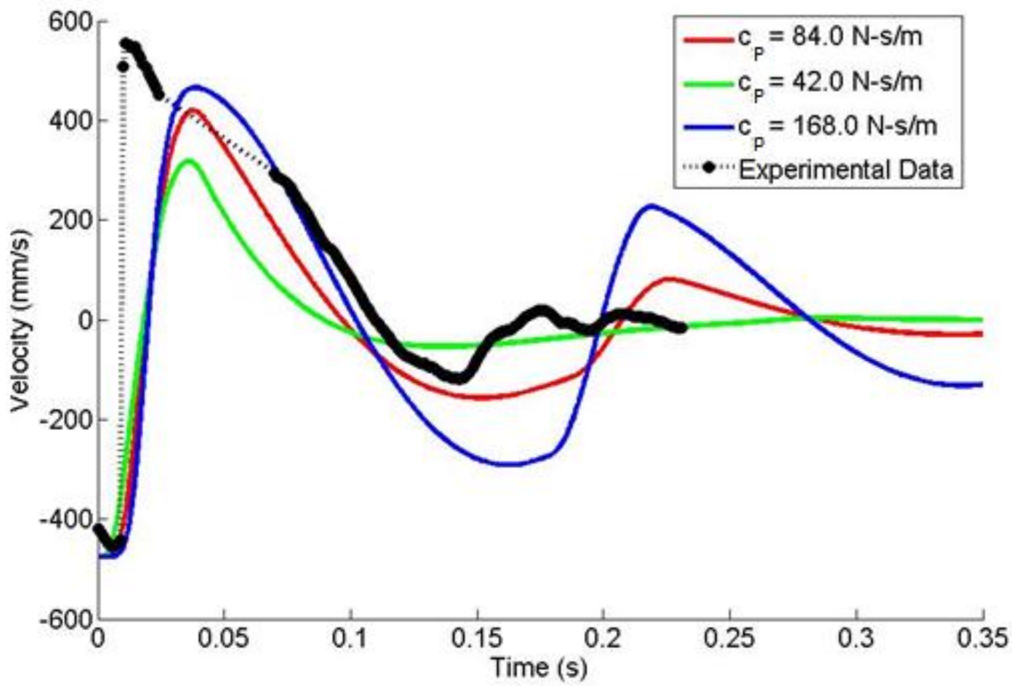


Figure 39. Velocity response of packaging subject to 0.5 in drop; data shown for *n*-1 row; k_p is held constant at 28,000. N/m

Contact Phase 2 Parameters

When a carton of product packages is dropped a large height, the contact phase 2 parameters are required—k_s and c_s. These parameters correspond to the 'collision' of the products, which calls for the inclusion of elastic stops in the MSD model. The experimental setup using the LDV is not sufficient to record data for high drop tests. Thus, an accelerometer is attached to individual packaged products within the carton. The row of the measured packaged product is recorded.

Figure 40 presents the experimental response of measured rows of product packages, along with responses calculated using the three MSD system models. Of particular interest is the maximum acceleration of the package, and the impulse time. Also, note that variations in the accelerometer reading after impact (0.014 sec) are caused by the vibration of the accelerometer components, and do not reflect the actual response of the packaging. Contact phase 2 model parameters are modified such that the theoretical MSD response matches the experimental acceleration data. The data in Figure 40 supports the claim that each of the contact force models can be used to accurately model the actual system. However, the data also shows that contact phase 2 may need to be divided into a loading phase and an unloading phase, since the model and theoretical data exhibit different trends in the unloading phase. Fortunately, the loading phase and maximum acceleration are the key features when considering impact analysis.

Table 4. Parameter estimations

	k_p (N/m)	c_p (N-s/m)	k_s	c_s
Model 1	28000.	84	1130.	81
Model 2	28000.	84	35000.	2835
Model 3	28000.	84	1400. $1.12\text{x}10^9$	1260. $1.12\text{x}10^8$

The estimated model parameters are presented in Table 4. The same contact phase 1 model was used for all three system models. Thus, the associate parameter values are the same throughout. Model 3 has four unknown parameters: $k_{s,1}$, $k_{s,2}$, $c_{s,1}$, and $c_{s,2}$. The units of the spring and damper coefficients are different for each model.

Preliminary Contact Force Results

The composition of the contact force—spring force, damping force, and total force—experienced by the bottom of an individual package on row 2 is shown in Figure 41. The damping force is the primary contributor to the maximum contact force. Model 1 is used to produce this data; other models show the same trend.

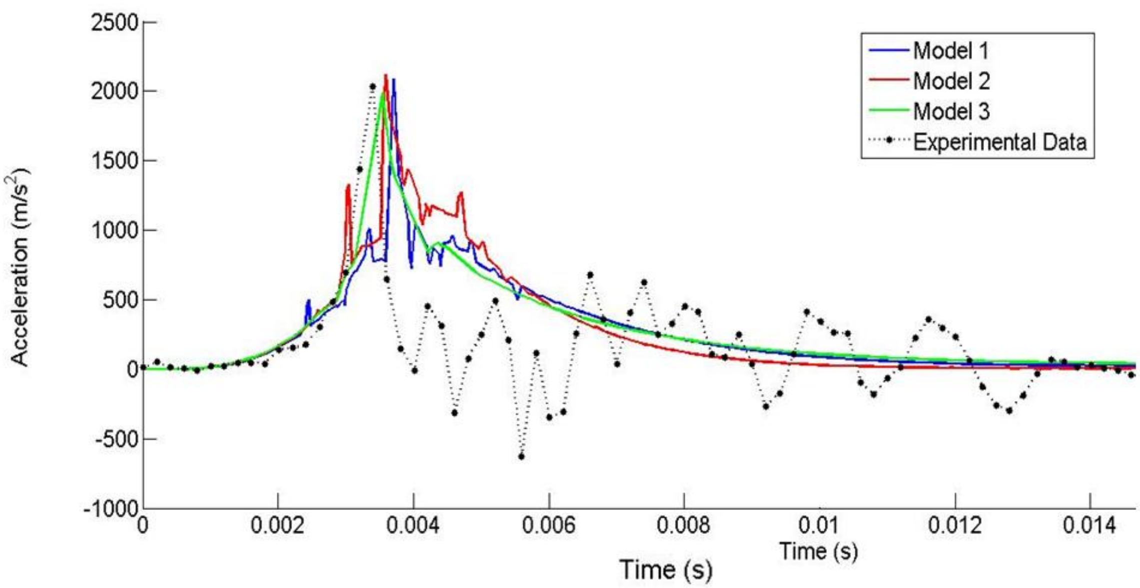


Figure 40. Acceleration response of MSD system subject to 30 in drop; data for 7th product package row shown

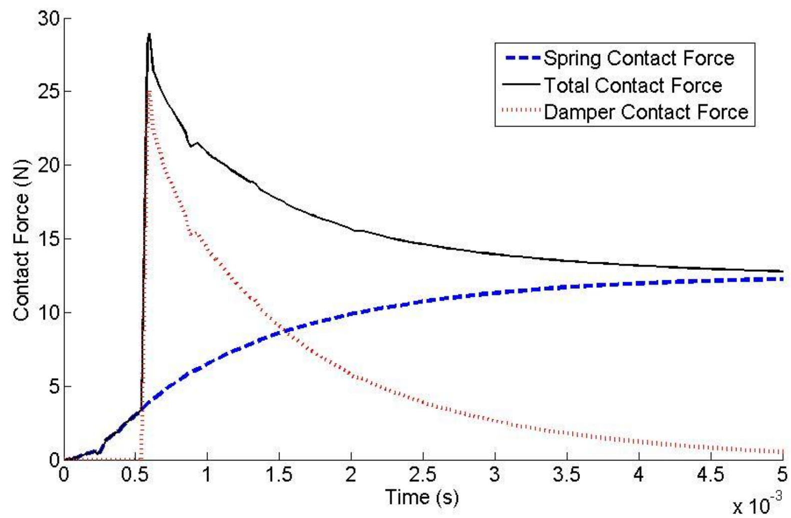


Figure 41. Theoretical contact force response components for Model 1; data for 2nd product package row shown

The contact force for individual product packages on various rows is shown in Figure 42. Notice that the packages on the bottom row experience a significantly higher contact force than the other products. Thus, it is important for understanding the interaction of the packaging carton and product packages. Even though the contact force is highest on the bottom, an increased surface area may actually contribute to a lower rate of failure for packages on the bottom row.

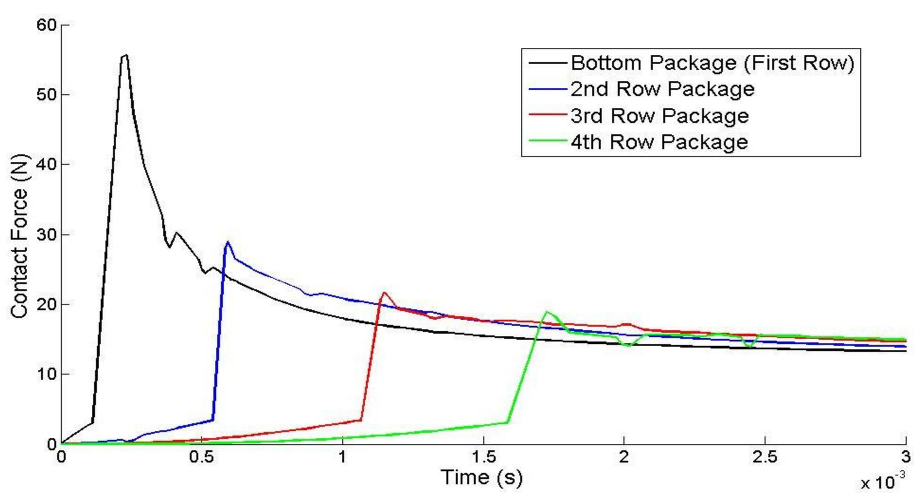


Figure 42. Theoretical contact force response for Model 1; data for first four product package rows shown; contact force is on bottom side of packages

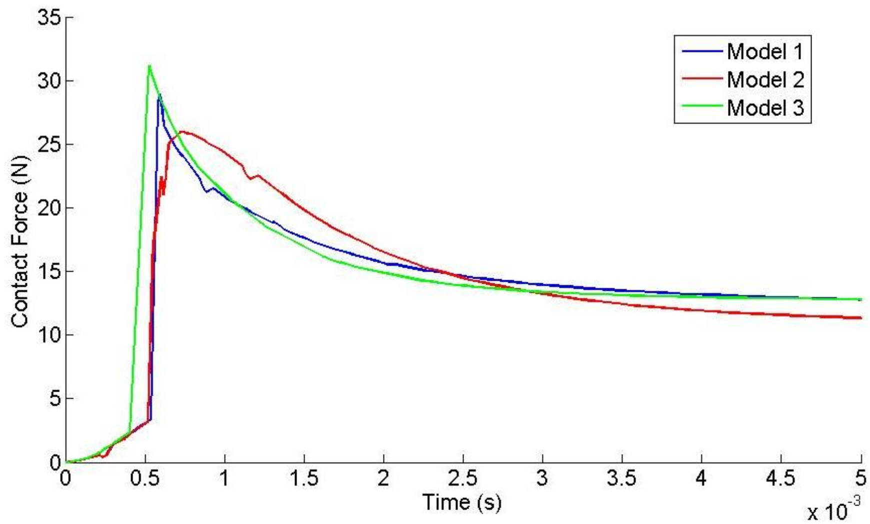


Figure 43. Theoretical contact force response for three models; data for 2nd product package row shown; contact force is experienced on bottom side of packages

The results of the 3 proposed models are presented in Figure 43. The transient contact force experienced by the bottom of a product package on the second row is shown. All three models show similar trends, and the maximum contact force for the second row does not vary from the corresponding average contact force by more than 10%. Table 5 includes data for the second row of packages, as well as the bottom row of packages. The bottom row of packages experiences a significantly higher contact force, and shows more variation between models. However, further investigation is required in order to interpret bottom row contact force. As aforementioned, an increased surface area may contribute to lower rate of failure for packages on the bottom row.

Table 5. Theoretical maximum contact force values

	Max Contact Force, F_c (N)		Variation of Max F_c from Average F_c (%)	
	Bottom Row	Second Row	Bottom Row	Second Row
Model 1	55.6	29.0	-10.8	0.928
Model 2	57.5	26.0	-7.71	-9.51
Model 3	73.9	31.2	18.5	8.58

Results show that all three models produce similar results. Variation in the maximum contact force for the second row is less that 10%, relative to the average value. The bottom row contact force values have more variation—up to 18.5%. Thus, the interaction of the bottom row of syringes with the carton may require a more complex spring/damper model. Since all three system models exhibit comparable performance, the simple Kelvin-Voigt model—Model 1—is chosen in order to minimize the number of model parameters required, while maintaining sufficient model accuracy, for this particular packaging design. The increased number of unknowns in Model 3 does not significantly improve the ability to match the system model to experimental data. For verification and validation, pressure sensors are used to measure actual contact pressure values; whereby, contact force measurements are be derived. If desired, the implemented MSD model can be integrated into a conventional design process, such as the reliability-based design optimization. However, this thesis considers deterministic design optimization.

3.2 Proposed Framework for Model Development Decisions

Figure 45 depicts the key steps of the proposed framework for facilitating model development under uncertainty. Specifically, CA is utilized to make decisions on model development with the consideration of decision outcome attributes. Uncertainty in the decision outcome is considered by propagating experimentation uncertainties through the framework. All of the framework steps are described in this section.

Step 1: *Create preliminary models* – A system can be described by virtually an unlimited number of models and model variations, each with different numbers of features and parameters. The DM has freedom to choose any level of abstraction by varying the number of degrees of freedom, model features, solution method (numerical vs. analytical), etc. For the proposed framework, the DM creates multiple, distinct preliminary models for comparison. The quality of preliminary models depends heavily on the DM's understanding of the system, and is based on limited, initial observations. Poor preliminary models will eventually be eliminated, but not before preliminary experimentation costs are spent.

Step 2: *Conduct preliminary tests* – The DM conducts a limited number of tests in order to define the preliminary models created in Step 1. Types of model parameters vary by application—e.g., drag coefficients for aerodynamic models, elastic modulus for material models, wall roughness for fluid flow models, etc. Note that one or more tests may be required to define each model parameter. For a model that requires two types of tests (e.g., Test A and Test B), the DM will acquire the results,

$$\{x_{A,i}\}_{i=1}^{n_A}, \{x_{B,j}\}_{j=1}^{n_B} \tag{19}$$

where n_A and n_B are the number of Test A results and Test B results, respectively, $x_{A,i}$ is the i^{th} Test A result, and $x_{B,j}$ is the j^{th} Test B result.

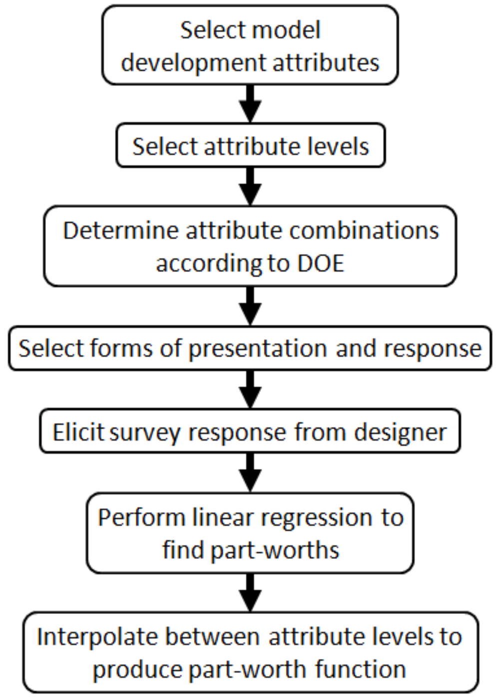


Figure 44. Conjoint analysis flowchart

Step 3: *Determine decision attributes and perform conjoint analysis* – Conjoint analysis (CA) serves as a method for evaluating the preference of DMs. When applied to model selection, the best model development decision according to CA is the one that has the optimal, feasible combination of attribute levels. And the optimal combination of attribute levels is the combination that has the highest part-worth. For example, the best decision may result in 'high' accuracy and 'low' experimentation cost. Figure 44 illustrates the CA process applied to model development.

Step 4: *Represent imprecision in test results via interval* – Oftentimes, there exists an inherent variability in test results. The 'grayed' boxes in Figure 45 depict PDFs that are not perfectly known by the DM. Further experimentation can lead to better approximations of the true PDFs; however, of primary concern in the proposed framework are the mean values of the test results—not the variability. If the model was intended to be used in a reliability-based design problem, the variability of the test results would need to be considered. But, in this thesis, the model parameters are defined based on the mean values of test results, such that the model can ultimately be used in deterministic design optimization.

However, the mean value of the preliminary test results (sample mean) is only an estimate of the true mean of the actual test results. The fact that the true mean is not known represents imprecision. To re-iterate, imprecision results from a lack of knowledge and can be reduced by gathering more information (i.e., conducting more tests). Further experimentation will consume irrevocable resources, so a decision should be made based on the preliminary (prior) test results. The imprecision can be estimated using an interval which describes the possible values of the actual mean test result. Based on the sample mean derived from the preliminary test results, $\hat{\mu}$, the upper and lower bounds of the mean are constructed, $[\underline{\mu}, \bar{\mu}]$,where $\underline{\mu}$ and $\bar{\mu}$ are the lower and upper bounds, respectively. A particular method for evaluating these interval bounds is presented in later sections. The construction of this interval represents an attempt to account for the imprecision in test results that are primarily caused by systematic errors—which tend to 'shift' all of the results in an unknown direction. The true mean is assumed to lie within the interval, $[\underline{\mu}, \bar{\mu}]$. Note that one value in the interval is not considered more probable than any other value—as opposed to descriptions of variability (i.e., PDF).

Step 5: *Evaluate uncertain attributes over intervals* – Most model decision attributes are not considered to be uncertain, e.g., modeling difficulty and computation time. Basic modifications to the proposed framework could be implemented in order to handle any number of uncertain attributes; however, this work focuses on the uncertainty in the accuracy attribute alone. In the early stages of model development, the accuracy of the model is uncertain because limited testing has been completed. The goal of Step 5 is to use the bounds of mean test results (Step 4) to find the bounds on the model accuracy.

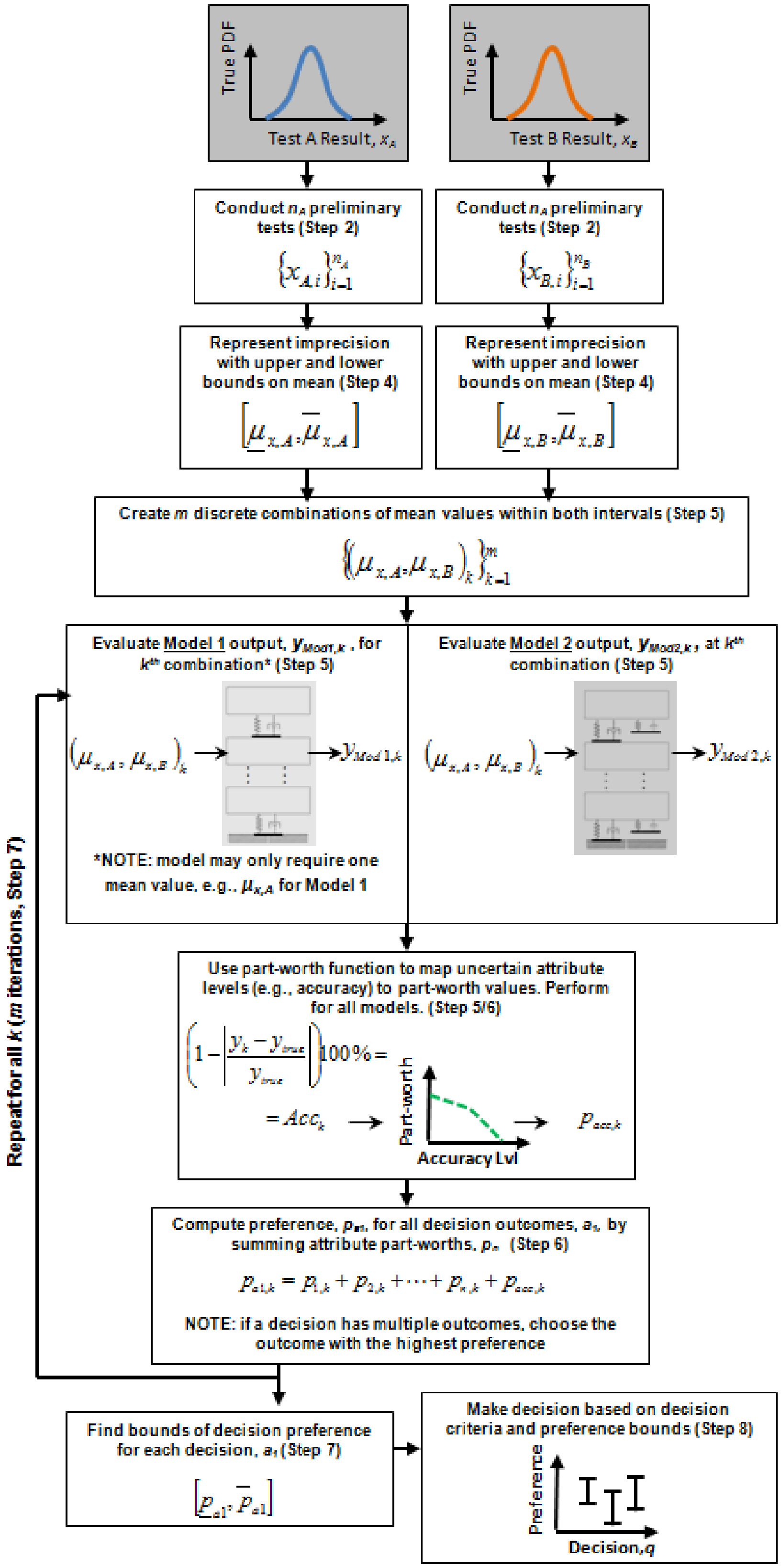


Figure 45. Key steps of model development framework

The possible mean values of each set of test results are described by intervals, $\left[\underline{\mu}_{x,A}, \overline{\mu}_{x,A}\right]$ and $\left[\underline{\mu}_{x,B}, \overline{\mu}_{x,B}\right]$, for Test A and Test B, respectively. The discrete values within the intervals are combined such that all possible pairs of mean values are created. Every value in the Test A interval, $\left[\underline{\mu}_{x,A}, \overline{\mu}_{x,A}\right]$, is paired with every value in the Test B interval, $\left[\underline{\mu}_{x,B}, \overline{\mu}_{x,B}\right]$.

$$\left\{\left(\mu_{X,A}, \mu_{X,B}\right)_k\right\}_{k=1}^{m} \tag{20}$$

where m is the total number of mean value pairs, and k denotes a particular pair of mean values. The pairs are then used to define the model parameters, and a model output, y_k, is evaluated for each combination. In most model design scenarios, the DM is interested in the accuracy of the model. The true model output, y_{rue}, is compared to the output of the model to find the accuracy.

$$\left(1-\left|\frac{y_k - y_{true}}{y_{true}}\right|\right)\times 100\% = Acc_k \tag{21}$$

where Acc_k is the model accuracy for a particular set of test results. This simple computation of the model accuracy is made possible only if the true model output, y_{rue}, is known. This value may be found through experimentation, or it may be known via past experience. Note more complex accuracy metrics can be implemented if deemed necessary.

Step 6: *Map decision outcomes to preference values* – Step 6 involves finding the preference for each modeling decision outcome. This preference is represented by a summation of the part-worths for each attribute, which quantifies the DM's preference for a particular decision outcome. Higher values represent more-preferred outcomes than outcomes with lower values. Equation (22) shows the summation of part-worths.

$$p = p_1 + p_2 + \cdots + p_n \tag{22}$$

where p_n is the part-worth associated with the n^{th} attribute, and p is the total preference for the outcome of the decision.

At times, a decision may include the option to choose between multiple models after the final experimentation has been completed (as shown in Figure 46). Thus, there would be two preference values for each iteration, m (see Figure 45). After obtaining the final test results, the DM will always choose the model decision with the highest preference. Therefore, the lower preference value should be discarded for that particular iteration, m, signifying that the corresponding model was not chosen. This sub-step accounts for the dependence between the two decisions. Not considering this sub-stop can result in gross errors.

Step 7: *Repeat Steps 4-6 to find preference interval for decision outcome*– In order to determine the interval of possible preference values, Steps 4 through 6 are conducted for all possible combinations of $\mu_{X,A}$ and $\mu_{X,B}$—m iterations. The minimum and maximum preference values for each decision form the preference intervals for each modeling decision, $\left[\underline{p}_{a1}, \overline{p}_{a1}\right]$, where $\underline{p}_{a1}$ and $\overline{p}_{a1}$ are the lower and upper bounds on the preference of outcome of the decision a_1, respectively.

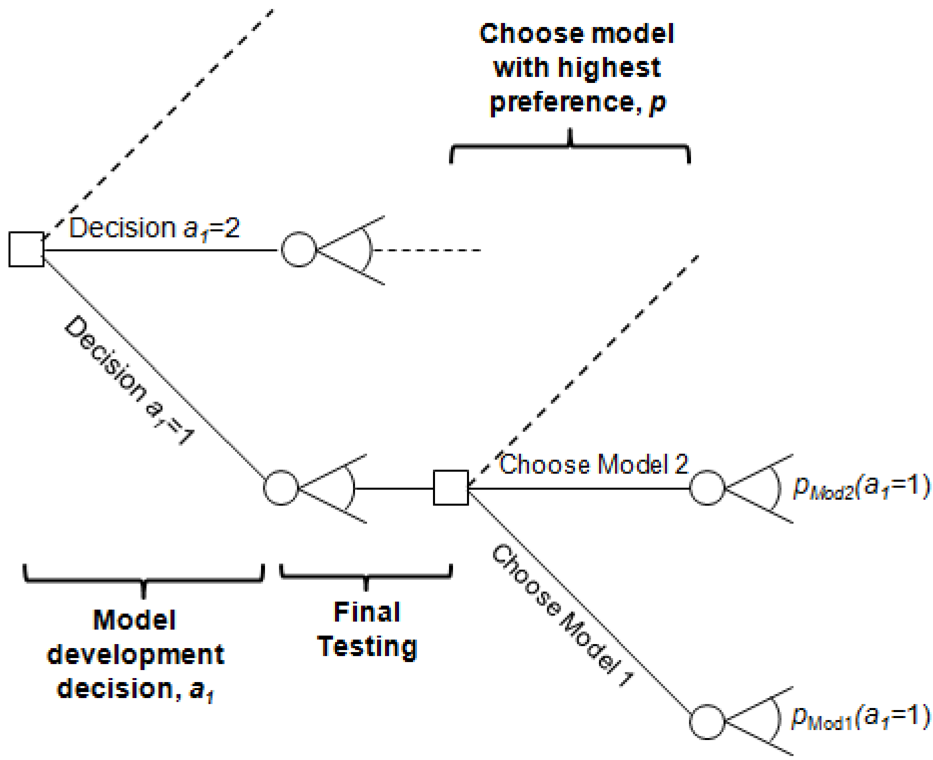


Figure 46. Portion of example decision tree

Step 8: *Choose modeling decision based on decision criteria* – There are many criterion for making a decision under uncertainty. If interval dominance does not exist, the DM can consider a decision policy of maximin, maximax, etc.

CHAPTER 4

ENGINEERING APPLICATION

Packaging design and development for a disposable medical device is a complex and challenging task. The reason for complexity is because of involvement of multiple overlapping dimensions including (a) device, (b) sterilization, and (c) package. According to ISO standards [3], the goal of medical packaging is to allow sterilization, provide physical protection, maintain sterility up to the point of use, and allow aseptic presentation. The chosen model will be used to optimize the packaging design such that these goals are met.

Drop tests are conducted to gather performance information simulating shipping and handling. Poor packaging reliability can have a direct impact on cost of goods and the bottom line for medical product manufacturers. However, increasing the reliability without bounds results in overdesign which can lead to higher costs. The particular product in question is a disposable medical product. Each product is packaged in a thermoformed polymer film which is heat-sealed to a paper-plastic backing. These individual packages are then placed in a standard cardboard shipping carton. Even this simple packaging design can result in high packaging costs. Thus, the DM seeks to implement low-cost improvements to increase the reliability of the packaging.

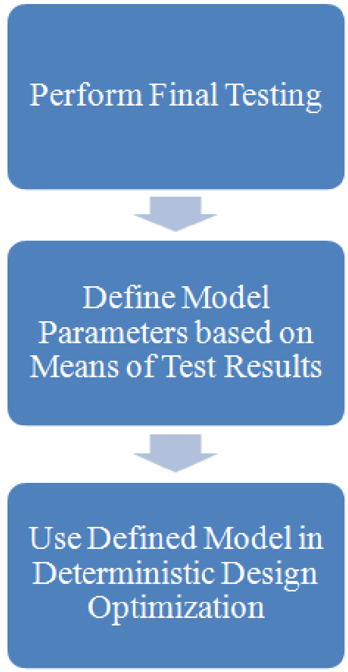


Figure 47. Outline of design problem in conceptual design phase

The DM has the following low-cost packaging design parameters to work with: carton dimensions (length and height), number of individual packages in each carton, and orientation of individual packages. Implementing a full Design of Experiments (DOE) to understand the impact of each design variable would require creation of various carton sizes and extensive manual labor to conduct numerous physical drop tests. In order to avoid these costs, a simulation model is developed to obtain an initial assessment of design variables and explore the design space. This model can predict the contact forces between the packages for any carton size. After final testing, the mean of the final test results are used to define the decision model. Then the model is used to optimize the package design. The goal of this thesis is to make the best model development decisions—optimizing the outcome of the decision and resource allocation.

4.1 Model Development Problem

Preliminary Models

For the demonstration of the proposed framework, two model variations are evaluated: a Simple Model and Medium Model (Figure 49). The Simple Model includes only one set of springs/dampers to describe each contact force. The Medium Model includes an extra spring/damper set that is expected to refine the contact force predicted by the model. In the Simple and Medium Models, the rows of packages are assumed to move in unison. Further details on the modeling can be found in Ref. [40]. For the sake of simplicity, the framework demonstration only considers the Simple and Medium Models. There also exists Complex Model which includes the extra spring/damper set, and also adds degrees of freedom to the movement of the rows of masses. The added degrees of freedom allow the interaction between columns of packages to be considered. However, the Complex Model is not considered in this thesis demonstration.

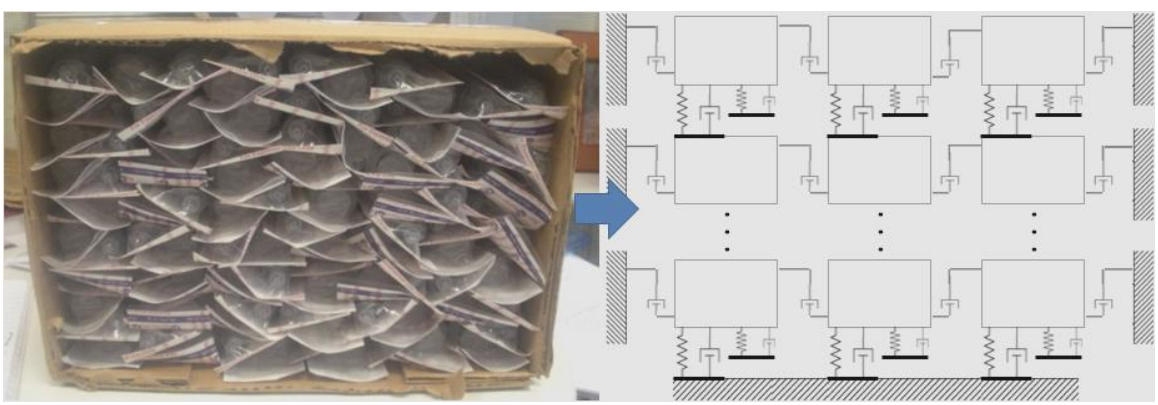
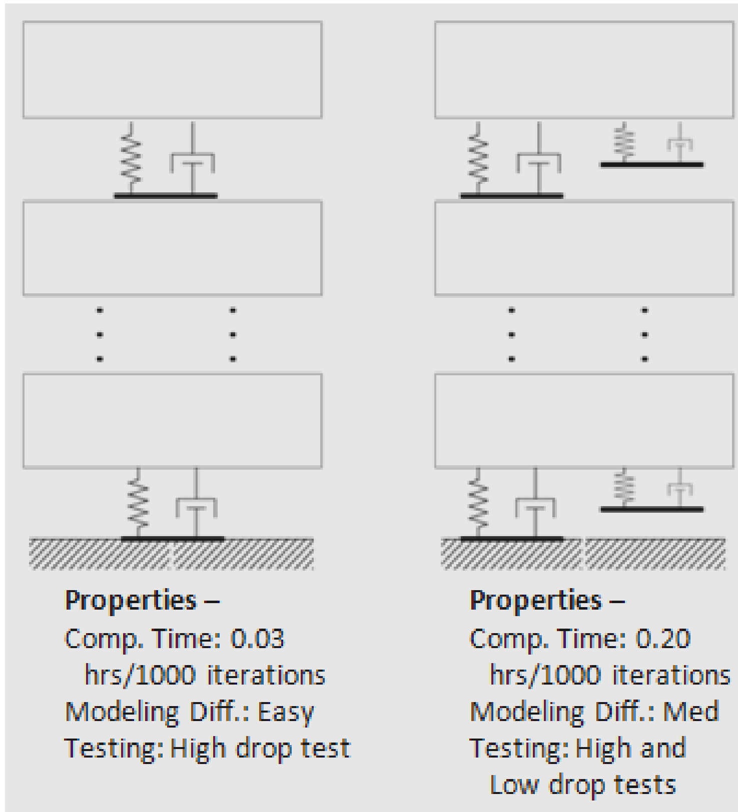


Figure 48. Actual system and Complex Model



(a) (b)

Figure 49. MSD model representations of packaging; (a) Simple and (b) Complex Models

Required Experimentation

Each model requires different sets of experiments in order to define its parameters (e.g., spring constant, damping coefficient, etc.). The Simple Model requires only a high drop test to fully define all of its parameters. In the high drop test, an accelerometer measures the acceleration time-response of an individual package, and the model parameters are adjusted such that the model acceleration output matches the experimental acceleration. For the Medium Model, two tests are required—the high drop test and a low drop test must be conducted in order to define all of the parameters. The low drop test records a velocity measurement for an individual package. The model's velocity output is matched to the actual velocity to define the parameters associated with the second set of springs/dampers. Details are explained in previous sections.

Problem Statement

The model development decision presents the DM with two options for final testing: conduct both high and low drop tests (a_1=1), or conduct only high drop tests (a_1=2). It is assumed that preliminary testing has already been conducted. For this example, preliminary testing includes the results for 10 of each high and low drop tests. All of the test results will be used to define the model parameters after final experimentation. The best model will be utilized in packaging design optimization—in particular, for determining the optimal carton size and number of primary packages. In the framework demonstration, the DM can choose to conduct only high drop tests during the final experimentation phase, or he/she can conduct both high and low drop tests (as shown in Figure 50). The choice depends on the DM's preference of the outcomes, which is determined in the CA. The decision tree is shown in Figure 50. It is assumed that conducting only low drop tests would not be preferable, because the Simple Model is indifferent to low drop test results and the Medium Model requires both high and low drop test results. Conducting no further tests is not provided as a decision alternative; it is assumed that the preliminary test results alone are not sufficient to adequately define the model parameters. For demonstration purposes, the cost of the final experimentation is assumed to be \$10,000 for high drop tests and \$6,250 for low drop tests. The DM must choose which tests to conduct in final experimentation (i.e., model development decision), and then choose which model to use in packaging design optimization.

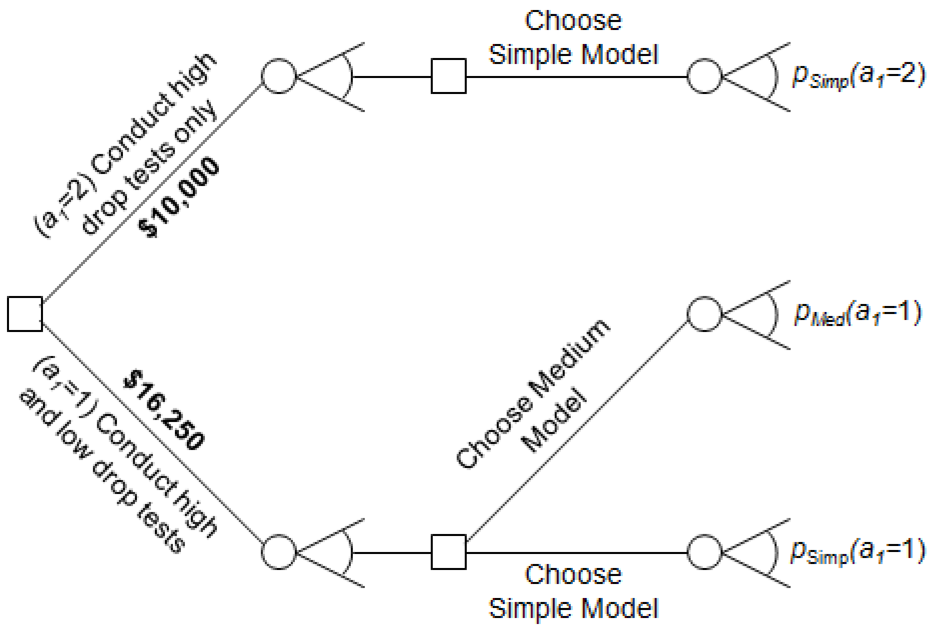


Figure 50. Decision tree for model development

4.2 Framework Demonstration

Step 1: *Create preliminary models* – A system can be described by a virtually an unlimited number of model vatiations. The DM has freedom to choose the number of degrees of freedom, model features, solution method (numerical vs. analytical), etc. For the sake of simplicity, this framework demonstration only considers the Simple Model and the Medium Model. i.e., for Step 1, the DM has created two preliminary models. Details on the models are provided in previous sections, and Figure 51 and Figure 52 show the relationship between the mean value of the experimentation results and the output of the model. The model output is the maximum contact force, F_c, experienced by a product package during impact. Note that the relationship between the experimentation results and the model output for the Medium Model is relatively complex. A surrogate model is used in further analysis.

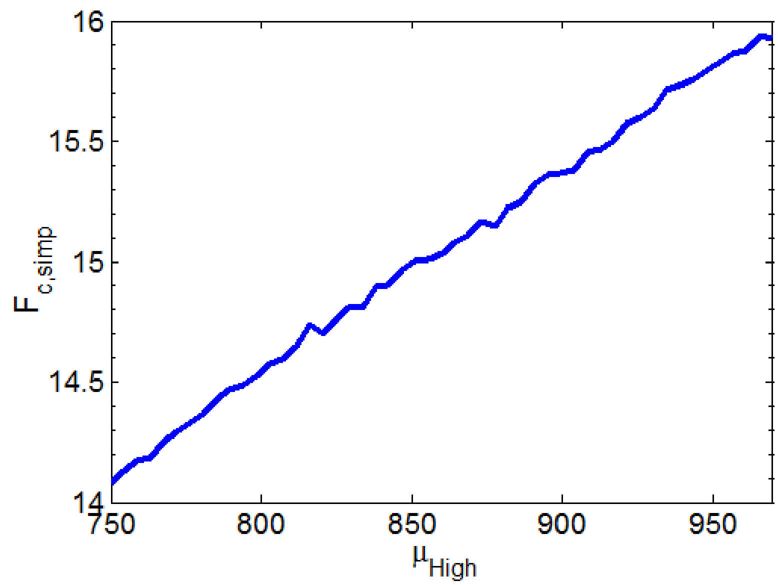


Figure 51. Output of Simple Model versus mean of test result

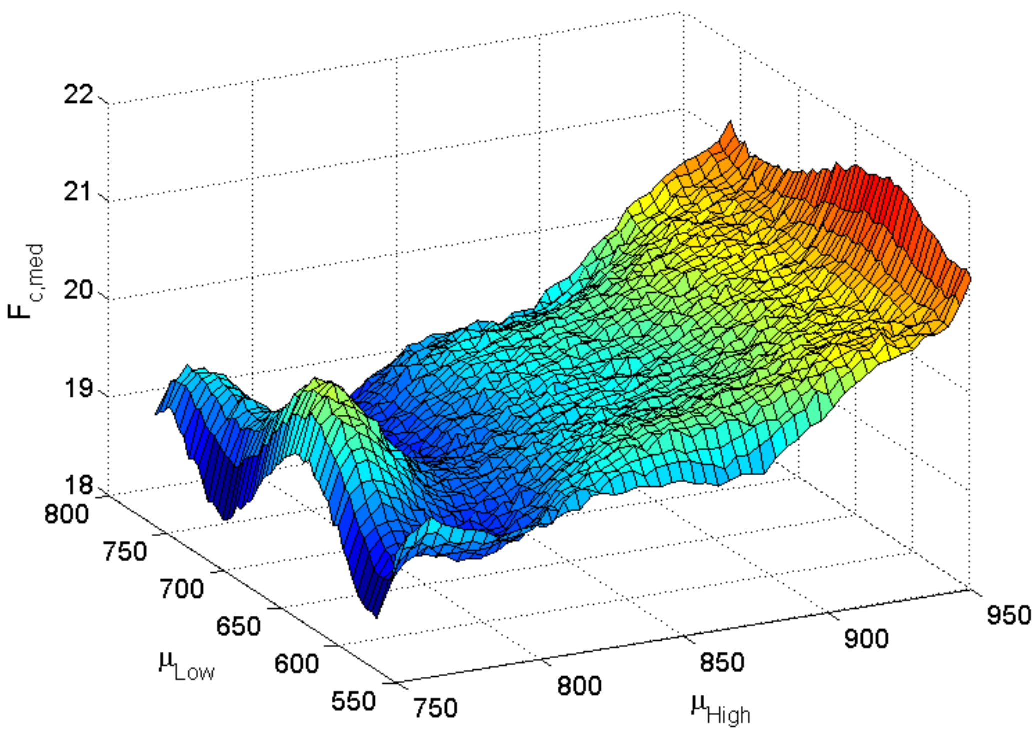


Figure 52. Output of Medium Model as a function of means of test results

Step 2: *Conduct preliminary tests* – A limited number of tests are conducted to define the proposed model concepts. As aforementioned, there are two tests: high drop test and low drop test. The results of the tests are maximum velocity for the low drop test, x_{Low}, and maximum acceleration for the high drop test, x_{High}, respectively. It is assumed that the preliminary results can be characterized by a normal distribution. For example, the preliminary output of 10 low drop tests can be used to describe the probability

$$x_{Low} \sim N(\hat{\mu}_{Low}, s_{Low}) \tag{23}$$

where $\hat{\mu}_{Low}$ is the mean of the preliminary test results, and s_{Low} is the standard deviation of the preliminary test results. The sample means and sample standard deviations acquired from preliminary test results are shown in Table 6.

Table 6. Preliminary testing results

	Preliminary Tests	Sample Mean	Sample Standard Deviation
High Drop Test, x_{High}	10	856 m/s^2	39 m/s^2
Low Drop Test, x_{Low}	10	668 m/s	38 m/s

Step 3: *Determine decision attributes and perform conjoint analysis* – Conjoint analysis (CA) serves as a method for evaluating the preference of DMs. When applied to model selection, the best model decision according to CA is the one that has the highest preference value.

Attribute selection – A reasonable number of attributes are chosen to represent the model development decisions. In traditional CA techniques, more than five or six attributes can overload the CA respondent [38], which is the DM in this case. The chosen attributes should adequately represent the design without causing respondent fatigue—if too many options are provided, the respondent may be overwhelmed and provide inaccurate information. The attributes can be qualitative as well as quantitative. For this framework demonstration, the chosen attributes are accuracy, modeling difficulty (qualitative), experimentation cost, and computation time.

Table 7. Survey design and response for CA

Decision Outcome	Acc. (%)	Comp. Time (hrs/1000 iterations)	Diff.	Exper. Cost ($)	Rank
1	95	0.03	Easy	10,000	9
2	95	0.20	Medium	15,000	8
3	95	1.00	Hard	25,000	5
4	90	0.03	Medium	25,000	4
5	90	0.20	Hard	10,000	7
6	90	1.00	Easy	15,000	6
7	85	0.03	Hard	15,000	2
8	85	0.20	Easy	25,000	1
9	85	1.00	Medium	10,000	3

Select attribute levels – Appropriate levels must be chosen for each attribute. The levels should be within reasonable upper and lower bounds—typically within a feasible design range. For example, the accuracy will not have a level of over 100%. Also, the number of levels is important to consider carefully. The number of levels per attribute affects the length of the survey, and thus, respondent fatigue. For example, four attributes with two levels each results in $2^4=16$ combinations for the respondent to rank. The number of combinations can be reduced by implementing a fractional factorial design, rather than a full factorial design.

Present attribute combinations to respondents – There are various survey formats for CA. Conjoint Value Analysis (CVA), also known as full profile CA, is the traditional format. In CVA, all attributes are presented to the respondents in the form of stimulus cards. A stimulus card simply presents the attribute levels of a particular decision outcome to the respondent. The respondent then ranks the cards. As aforementioned, implementing fractional factorial design for the survey allows fewer judgments to be made by each respondent by decreasing the number of cards. CVA can be easily implemented via Excel or simple hand calculations; thus, it is used for the framework demonstration. The proposed attribute levels, and survey responses (ranks) are shown in

Table 7—higher 'Rank' is better. The survey also includes attribute levels that correspond to the Complex Model, so all three of the models could be included in a future, more comprehensive decision analysis.

Calculate part-worth values – The method of determining the part-worth values associated with each attribute level differs according to the type of CA survey that is employed. For CVA, details on the calculation procedures are readily available in literature [19,26]. In short, the ranking data is fit to a regression model of the general form,

$$y = b_0 + b_1 x_1 + b_2 x_2 + \cdots + b_r x_r + e \tag{24}$$

where y is the preference value, $b_1, b_2, \ldots, b_r$ are the part-worth values associated with the r^{th} attribute level, b_0 is an intercept term, and e is an error term associated with linear regression. In Equation (24), $x_1, x_2, \ldots, x_r$ take values of 1 or 0 to indicate that an attribute level is 'present' or 'absent,' respectively. Table 8 shows the part-worths for each attribute level (except accuracy).

Table 8. Attribute levels and part-worths

Attribute	Level	Part-worth
Computation Time (hrs/1,000 iterations)	0.03	0.12
	0.2	0
	1	-0.16
Difficulty	Easy	0
	Medium	-0.045
	Hard	-0.089
Experimentation Cost ($)	10,000	1.5
	15,000	0.73
	25,000	0

Create part-worth function – The values in Table 8 only provide part-worths at three discrete attribute levels. This is acceptable for the attributes displayed in Table 3, but the accuracy part-worth needs to be defined at more than just three points. i.e., the accuracy part-worth needs to be evaluated at levels other than 95%, 90%, and 85%. The final CA step is to create part-worth functions from the individual part-worth values. Linear interpolation and extrapolation are employed, and the resulting accuracy part-worth function is shown in Figure 53. Note that it is best to choose attribute levels that are close to the actual attribute levels of modeling decisions, since this reduces the uncertainty introduced by interpolation/extrapolation. The uncertainty in the linear regression (Eq. 6) and interpolation are not within the scope of this thesis.

Figure 54 shows the part-worth functions for all of the attributes. The accuracy and experimentation cost attributes are the most influential on overall preference according to the survey respondent. Computation time and difficulty do not have a significant influence for the range of attribute levels selected.

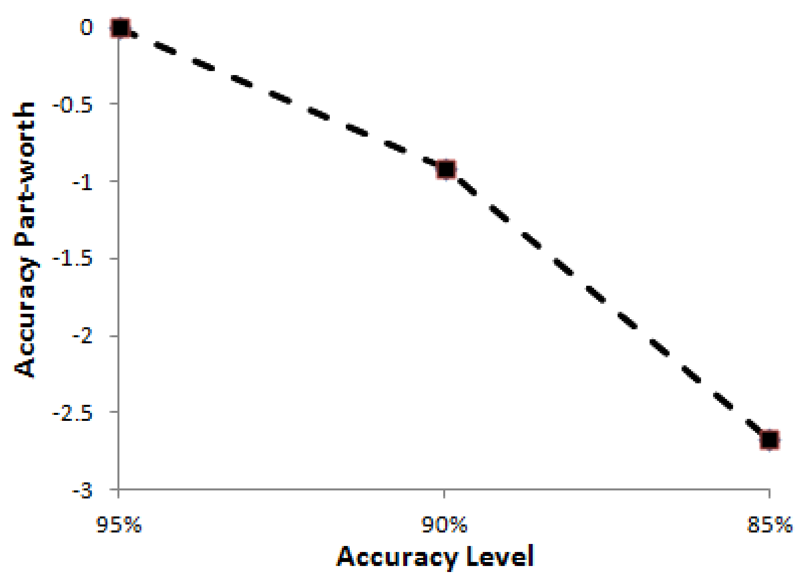


Figure 53. Accuracy part-worth function

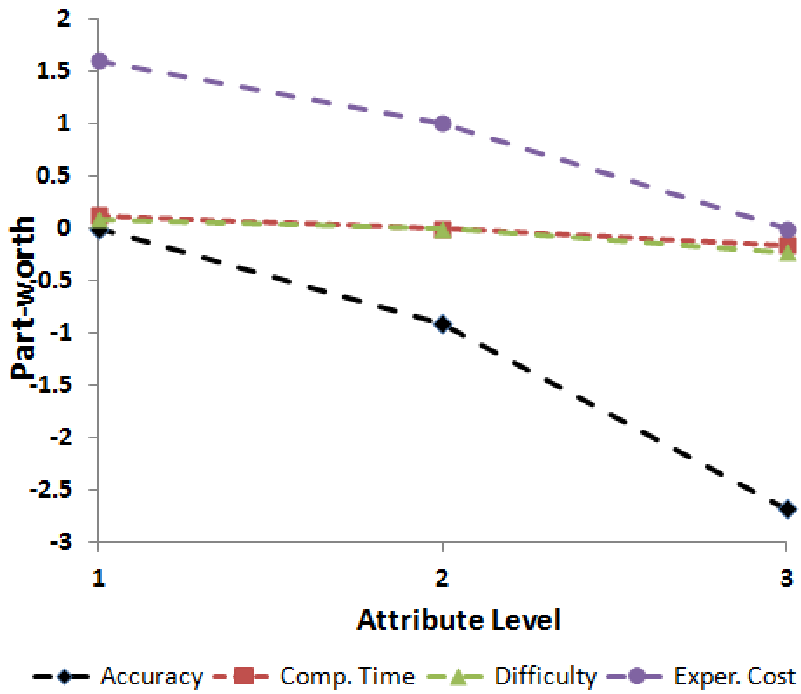


Figure 54. Part-worth functions for all attributes

Step 4: *Represent imprecision in test results via interval* – A major focus of this thesis is considering the uncertainty that exists in early model development phases. The model in the framework demonstration will be used for deterministic design optimization, so the parameters of the model will be defined based on the expected value (mean) of test results. However, imprecision in testing leads to tests results that can be 'shifted' to one extreme or the other. This imprecision is modeled using an interval which describes the possible values of the mean test result. Based on the preliminary sample mean, $\hat{\mu}$, the upper and lower bounds on the actual mean are constructed such that

$$\left[\underline{\mu}_{\alpha}, \overline{\mu}_{\alpha}\right] = \left[\hat{\mu} - t_{\alpha/2,n-1}\frac{s}{\sqrt{n}}, \hat{\mu} + t_{\alpha/2,n-1}\frac{s}{\sqrt{n}}\right] \tag{25}$$

where $\underline{\mu}_{\alpha}$ and $\overline{\mu}_{\alpha}$ are the lower and upper bounds on the mean corresponding to a significance level, α, respectively. t is the t-statistic with n – 1 degrees of freedom, and s is the sample standard deviation. n is equal to the number of data (i.e., test results) acquired in preliminary testing for a particular type of test. The interval in Equation (25) represents an attempt to account for the imprecision in test results that can result from systematic errors that can bias the results. The bounds for α=0.05 and α=0.2 are shown in Table 9, and visual representation is shown in Figure 55. Higher values of α indicate a greater confidence that the sample mean is close to the true mean, and thus result in a smaller interval. The interval represents a sort of confidence interval in which the DM expects the true mean to lie. Note that one value in the interval is not considered more probable than any other value (as in probabilistic descriptions). Also, note that the aleatory uncertainty would need to be considered for models that are used in reliability-based design optimizations.

Table 9. Bounds of test result means

	$\underline{\mu}_{95\%}$ (α=0.05)	$\overline{\mu}_{95\%}$ (α=0.05)	$\underline{\mu}_{80\%}$ (α=0.2)	$\overline{\mu}_{80\%}$ (α=0.2)
High drop test (m/s^2)	828	884	839	874
Low drop test (m/s)	641	695	651	684

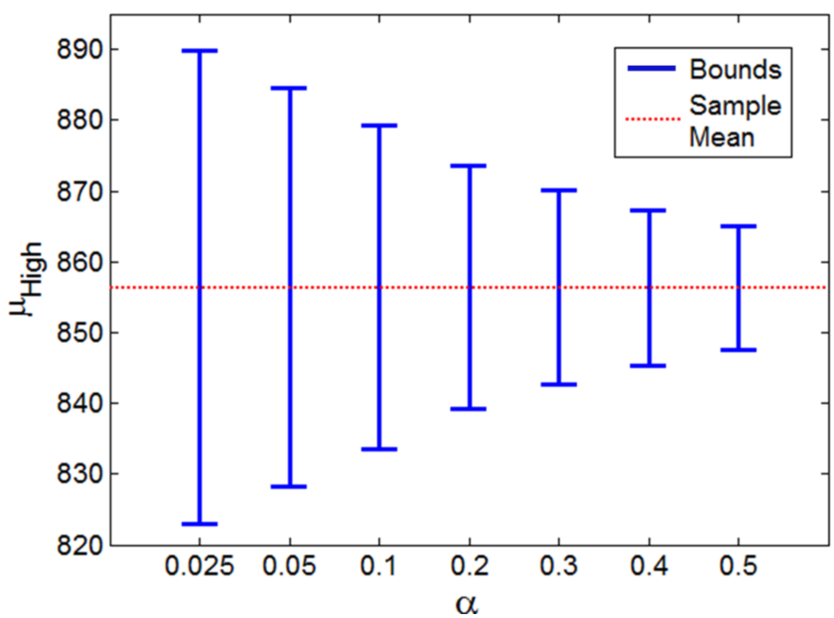


Figure 55. Bounds on mean test result based on various α values

Step 5: *Evaluate uncertain attributes over intervals* – The uncertainty in test results leads to an uncertainty in attribute levels. For the proposed framework, the only attribute that is affected by the uncertainty is accuracy. An interval of possible test result values leads to an interval of possible model parameter values and model output. Since the model accuracy depends on the model output, the accuracy can also be expressed as an interval—a function of the test result mean interval.

The mean value intervals are discretized and combined such that all possible pairs of mean values are created, $(\mu_{High}, \mu_{Low})_k$,where μ_{High} is the high drop test mean and μ_{Low} is the low drop test mean in the k^{th} pair of mean values. The mean value pairs are then used to define the model parameters. A numerical method is employed for defining model parameters. Then, the defined models are utilized in a drop test simulation in order to produce a model output (contact force, F_c) for each mean value pair.

$$F_{c,Simp} = f_{Simp}(\mu_{High}) \tag{26}$$

$$F_{c,Med} = f_{Med}(\mu_{High}, \mu_{Low}) \tag{27}$$

where f_{Simp} represents the numerical analysis for the Simple Model, and f_{Med} represents the numerical analysis for the Medium Model.

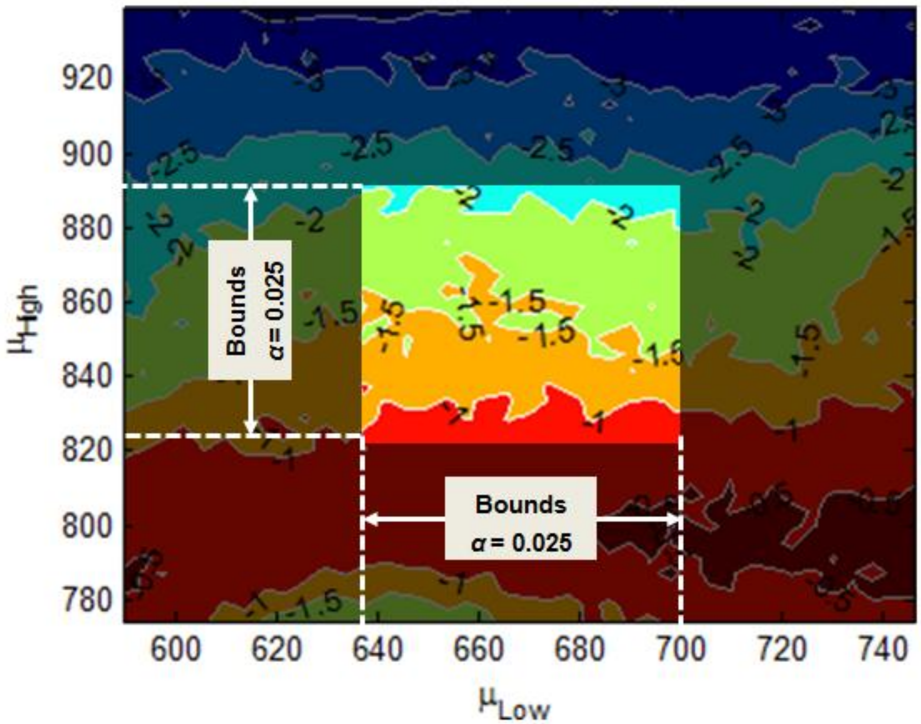


Figure 56. Contour plot showing preference values for the Medium Model a_1=1

The functional relationship of the test results to the contact force values are relatively complex, so a surrogate model is used to increase the computation speed. Even more complexity would be introduced to this framework demonstration if environmental conditions and design parameters were included, e.g., drop height, box dimensions, and package weight. For the accuracy evaluation, the models are evaluated for only one set of environmental conditions and design parameters. This decreases the complexity of this particular framework demonstration, as it allows for the accuracy to be determined in a simple manner.

The true contact force, F_{true}, is compared to the output of the model to find the accuracy.

$$\left(1-\left|\frac{F_c - F_{true}}{F_{true}}\right|\right)\times 100\% = Acc \tag{28}$$

where *Acc* is the model accuracy, which is evaluated for each iteration, *k*. A specialized experiment is conducted in order to find F_{true}. This experiment includes a pressure sensor that is used to determine the true contact force experienced during the drop. The particular results and methods for the pressure sensor test are proprietary—the F_{true} value for this particular framework demonstration is 17.65 N. This represents the actual maximum contact force experienced during the prescribed drop test.

Step 6: *Map decision outcomes to preference values* – Step 6 involves finding the preference for each modeling decision outcome. In general, the preference value, *p*, is simply the sum of all of the part-worths associated with a set of attribute levels.

$$\begin{aligned} & p = p_{acc} + p_{diff} + p_{\exp er} + p_{comp} \\ & ,where \qquad p_{acc} = f(\mu_{High}, \mu_{Low}, a_2) \\ & \qquad\qquad\quad p_{diff} = f(a_2) \\ & \qquad\qquad\quad p_{\exp er} = f(a_1) \\ & \qquad\qquad\quad p_{comp} = f(a_2) \end{aligned} \tag{29}$$

where p_{acc}, p_{diff}, p_{exper}, and p_{comp} are the part-worths associated with the accuracy, difficulty, experimentation cost, and computation time of the decision outcome, respectively. Note that p_{diff}, p_{exper}, and p_{comp} do not depend on the test results; whereas, p_{acc} changes with respect to the test result mean value. Therefore, p_{acc} needs to be evaluated for all combinations of μ_{High} and μ_{Low}, and the other part-worths only need to evaluated once for each combination of model development and model selection decisions. Figure 57 and Figure 58 show samples of the relationship between mean test results, model output, and accuracy part-worth.

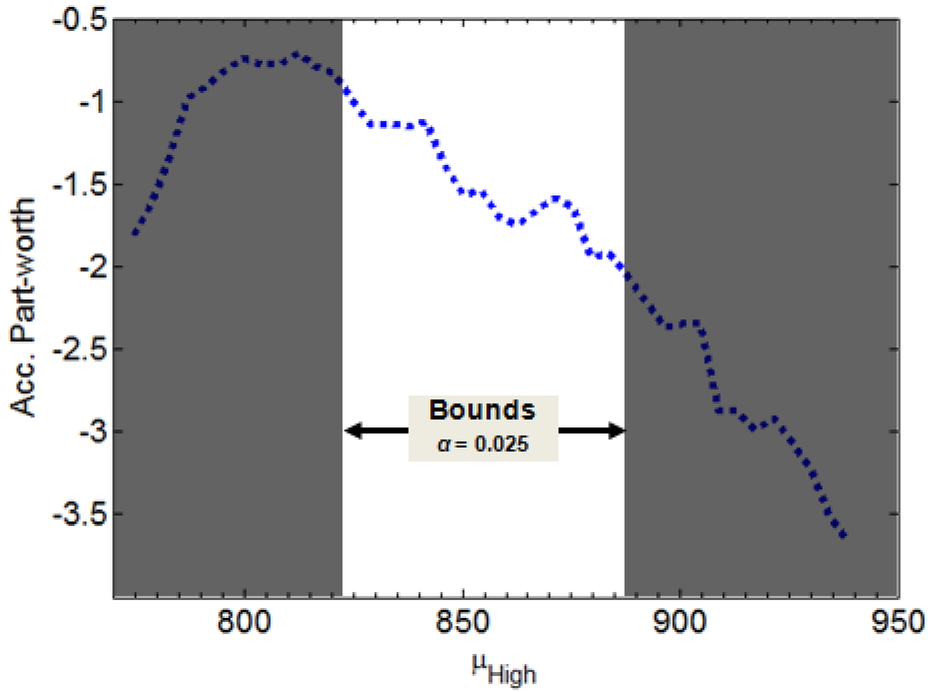


Figure 57. Bounds on accuracy part-worth (Medium Model, μ_{Low} = 636 m/s)

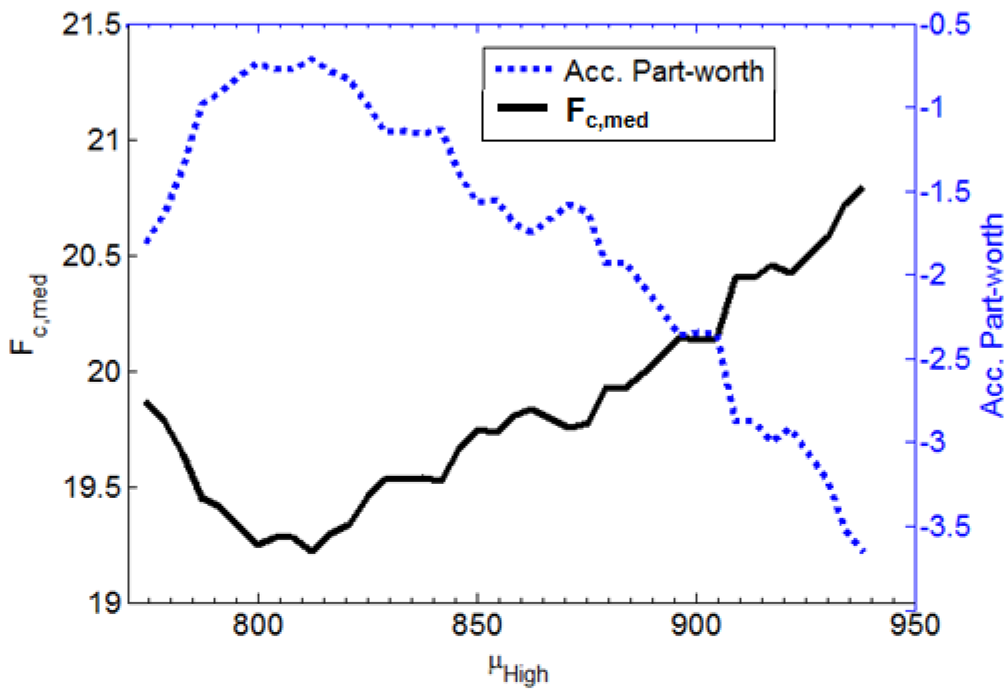


Figure 58. Output and accuracy part-worth (Medium Model, μ_{Low} = 636 m/s)

One of the decisions (to conduct both high and low drop tests) includes the option to choose between each of the models after the final experimentation has been completed. Thus, there are two *p* values for each iteration, *k*, in this case. After obtaining final test results, the DM will always choose the model with the highest preference, *p*. Therefore, the other *p* value is discarded for that particular iteration, since only one model is implemented in packaging design optimization. This sub-step accounts for the dependence between the two models and information sources, and it is important for finding the correct preference interval in Step 7. Figure 59 exhibits how the inclusion of both models as potential options can minimize the downside of a model development decision. If the μ_{High} value is significantly lower than the sample mean, the Medium Model is chosen, and if the μ_{High} value is significantly higher than the sample mean, the Simple Model is chosen.

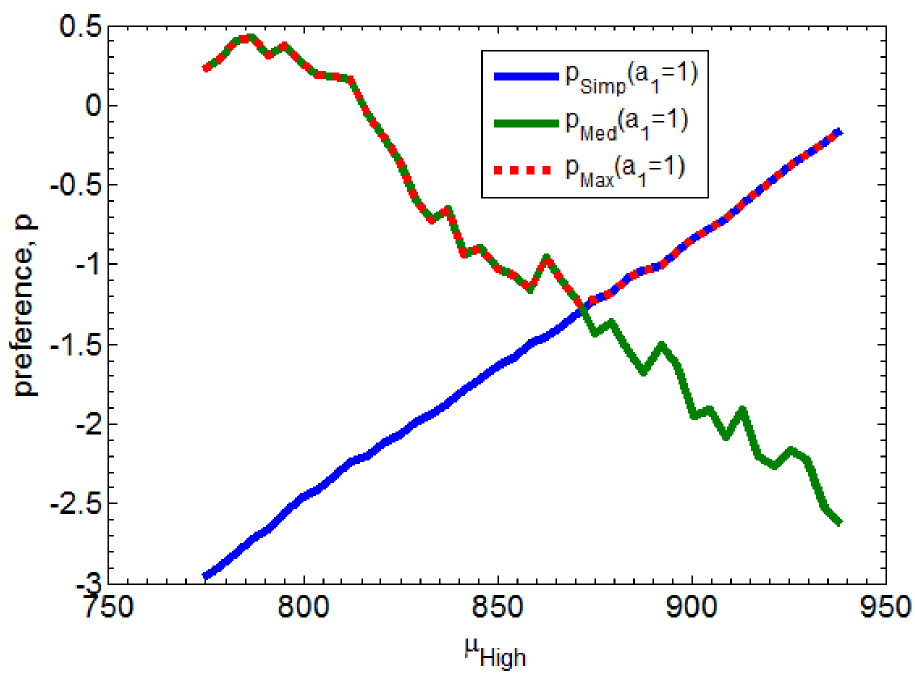


Figure 59. Dependence of model development decision (*a₁*=1); μ_{Low}= 589.6 m/s

Step 7: *Repeat Steps 4-6 to find preference interval for decision outcome* – In order to determine the interval of possible preference values, Steps 4 through 6 are conducted for all possible combinations of μ_{High} and μ_{Low}—*m* iterations. The minimum and maximum preference values for each decision form the bounds of the preference intervals, $\left[\underline{p}_{a1=1}, \overline{p}_{a1=1}\right]$ and $\left[\underline{p}_{a1=2}, \overline{p}_{a1=2}\right]$.

Step 8: *Choose modeling decision based on decision criteria* – There are many criterion for making a decision under uncertainty such as interval dominance, maximin, and maximax. Figure 60 shows that neither decision dominates the other—for α=0.05 or α=0.20. Thus, for this framework demonstration, interval dominance criterion is not useful.

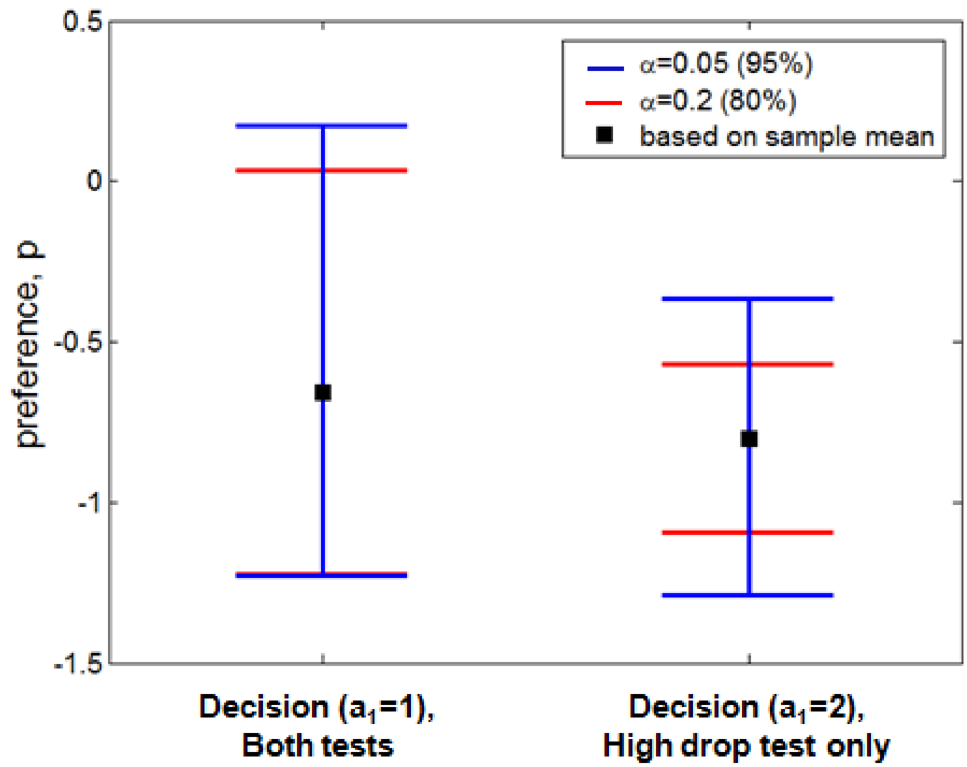


Figure 60. Preference intervals for decisions

However, for α=0.05, Decision a_1=1 is the preferred decision according to both the maximax and maximin decision policies. Decision a_1=1 exhibits the highest maximum preference and the highest minimum preference. Having the highest maximum preference (maximax) indicates that the decision outcome has the potential to be most-preferable.

An optimistic DM would follow this decision policy. Having the highest minimum preference (maximin) indicates that the decision mitigates against having a low preference, i.e., the decision has a relatively preferable worst-case outcome. A pessimistic DM would follow this decision policy. Thus, if the DM is satisfied with the imprecision description (i.e., α=0.05), the DM would choose to conduct both the high and low drop tests (a_1=1), and then select the best model after the tests are completed. This decision costs more in terms of experimentation cost, but the possible increase in accuracy of the Medium Model (derived from the low drop tests) is determined to be an appropriate trade-off. Choosing Decision a_1=1 would also be appropriate if uncertainty was not considered—i.e., if the preference was calculated based on the sample mean, $\hat{\mu}$, values from preliminary experimentation.

However, if the DM chooses a different description of the imprecision in the test results (e.g., α=0.20), the framework evaluation may dictate a different conclusion. Changing α to be 0.20 represents the belief that the imprecision in the preliminary results is less (relative to α=0.05). i.e., the DM believes that the sample mean is a better estimate of the true mean of the test results. For this case, the DM would choose Decision a_1=2 according to the maximin decision policy, but he/she would choose Decision a_1=1 according to the maximax policy. Following the maximin policy may be favorable in this circumstance because it ensures that the model decision will not be 'too bad'. i.e., it mitigates against a very low preference by maximizing the minimum preference of the outcome. This is different than the conclusion drawn the preference evaluation based on sample means, $\hat{\mu}$—thus, demonstrating a benefit of incorporating uncertainty information into the framework. Choosing Decision a_1=2 would effectively eliminate the Medium Model and devote all final experimentation resources to the Simple Model, since Decision a_1=2 does not incorporate the low drop tests that are required for the Medium Model. Even though the Simple Model tends to be less accurate, the savings in experimentation cost, computation time, and modeling difficulty is determined to be an acceptable trade-off per the maximin decision policy.

Notice in both cases (α=0.05 or α=0.20) that Decision a_1=1 has the largest preference range—indicating more uncertainty. This is partially due to the fact that the Medium Model is a function of two tests, both of which are imprecise—as opposed to one test for the Simple Model. Also, the range of possible accuracy values is larger for the Medium Model, indicating that the model is more sensitive to variation in the experimentation results.

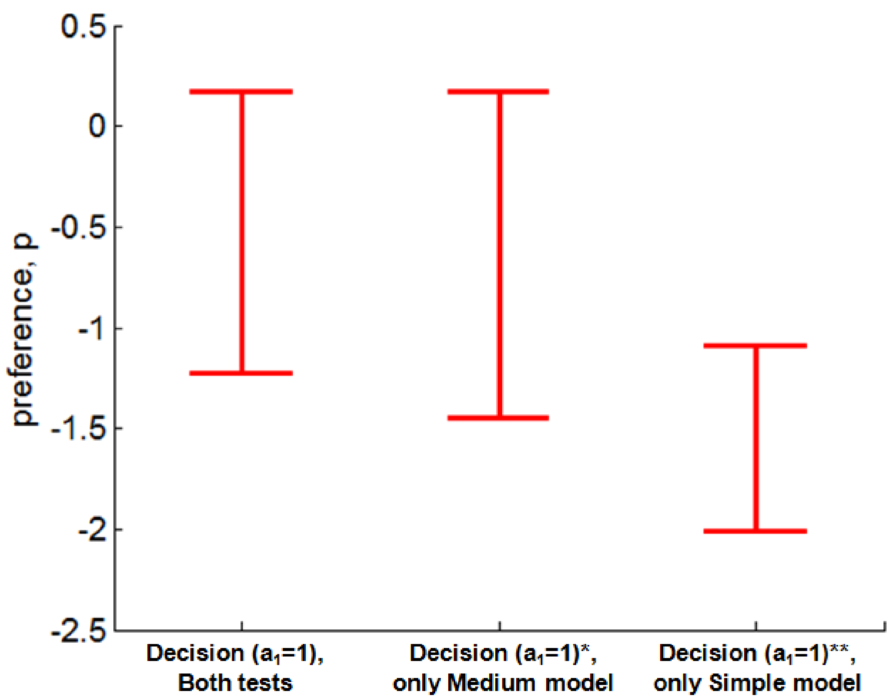


Figure 61. Bounds of decision (a_1=1) with Medium and Simple Model components shown

Figure 61 demonstrates how considering the dependency between the models is important. For decision a_1=1, the lower bound of the preference, p, is -1.22. However, if only the Medium Model was considered in the model selection decision, then the lower bound would be misleadingly low. Even though the Simple Model is generally not the preferable model to select (when performing tests for both models), it still mitigates against some of the *unlucky* outcomes of the Medium Model. Therefore, the framework shows that it is important to appropriately consider the dependency between the models—i.e., the common source of information (μ_{Low}).

CHAPTER 5

CONCLUSIONS AND FUTURE WORK

The proposed framework is demonstrated to provide direction in choosing model development decisions. Upon completion of the preliminary experimentation phase, the DM uses the framework to make decisions with respect to the final experimentation phase. Thus, the DM can appropriately allocate irrevocable resources by observing the preference intervals of the decision outcomes. Also, the MSD model along with novel experimentation techniques proved to be capable of predicting the contact forces experienced by medical product packages.

5.1 Research Question 1 and Hypothesis

Question: How can the DM choose a model development decision in the conceptual design phase, where there is significant model uncertainty and objective uncertainty?

Hypothesis: Conjoint analysis is used to elicit the DMs preferences during the conceptual design phase, and the uncertainty in model parameters is represented with intervals such that imprecision is appropriately considered.

A design problem was considered that did not have a clear overall objective—thus, it represents a typical conceptual design problem. Instead of using an objective function from embodiment design, the preferences of the DM were solicited via conjoint analysis. This allowed a quasi-objective function to be created that best represented the goals of the DM and his current state of information about the design goals.

The large amount of imprecision that exists early in the design process was accounted for via imprecision—represented as intervals. The intervals do not ascribe any probability information to the test results. Instead, the interval simply suggests that the true mean of the test results lies somewhere within the interval. Thus, the possible bias in the sample mean of the preliminary test results is handled appropriately. Moreover, the part-worth function allowed for the uncertainty in the accuracy attribute to be propagated through the model development framework.

5.2 Research Question 2 and Hypothesis

Question: How can a DM choose correct model development decision when there are multiple models with common information sources?

Hypothesis: A model development decision with multiple models is appropriately evaluated with decision-based-design techniques that account for the dependencies that exist between the models—perhaps, due to common sources of information

A decision tree was used to accommodate the multiple model options, and the dependence between models was addressed by recognizing the common source of uncertainty in the decision tree. The output of both models depends on the mean of the high drop test results; hence, the models outputs are dependent. For Decision a_1=1, the mean value for the high drop test is applied to both models (at a branch in the decision tree), and the model with the highest preference is chosen on each iteration. Also, the framework is shown to appropriately handle dependencies between the models. The common source of information is considered in the decision tree, and the framework demonstration shows that the multiple model options mitigates against *unlucky* outcomes for one of the models.

5.3 Research Question 3 and Hypothesis

Question: How can the proposed decision framework be applied to a practical model develoment problem?

Hypothesis: The proposed decision framework can be used to choose model development decisions in a packaging design problem with complex interactions and experimentation/measurements.

Novel testing techniques were used to acquire data from the packaging system. A non-contact sensor—laser doppler vibrometer—was used to measure the velocity of individual product packages during impact. And a light-weight accelerometer was imbedded in a medical product to record acceleration. Weight was removed from the product such that the final weight of the modified product and the accelerometer was the same as that of the original product. The MSD model was able to predict the contact forces acting on the individual packages during a drop test, and the results were similar to pressure sensor results (the pressure sensor results are not presented because they are proprietary).

5.4 Limitations

Selecting Bounds based on Preliminary Experimentation Results

The model development decision determined by the framework depends on the selection of the parameter α. A low value of alpha indicates that the DM is not confident that the sample mean of the preliminary test results is near to the actually mean of the experimentation output. On the other hand, a high value of alpha indicates that the sample is a better approximation of the true mean. On one hand, this contributes to subjectivity in the framework. On the other hand, it allows for adjustments based on the DM’s experience. For example, if a particular type of testing is known to be relatively reliable, then the DM can ascribe a high α value. Also, multiple sources of information can each be ascribed different α values, which lends to the robustness of the framework.

Development of Objective Function

The framework is only as accurate as the assumptions that underlie the objective function. Essentially, conjoint analysis is used to develop part-worth functions for each attribute. The objective is then to maximize the total preference, which is a sum of the part-worths. The objective functions represent the DM's preferences which are based on his overall understanding of the design goals. As aforementioned, the design goals can be unclear during the conceptual design phase. Also, the attribute levels must be selected such that the feasible decision attributes are close to the selected attribute levels. A part-worth value that is ascribed via extensive interpolation/extrapolation may not accurately express the DMs true preference.

5.5 Potential Future Work

Variability and Comprehensive Accuracy Metric

The accuracy metric used in the framework demonstration is relatively simplistic. A more comprehensive accuracy metric would take into account the accuracy of the model over the entire design space. Also, the model is assumed to be used in a deterministic design problem, when in fact, the model parameters are highly variable. Considering variability in the optimization of the medical packaging—e.g., reliability-based design—would call for a more comprehensive accuracy metric.

Embodiment Design

Even though the focus of this paper was on model development in conceptual design, the framework could be applied to an embodiment design problem. In future work, the framework could be applied with a more rigid problem statement. i,e., the objective will be to maximize payoff (a dollar amount). With modifications and a clear objective statement, the framework could provide more robust guidance for Design of Experiments challenges, such as ‘how many experiments should be performed?’ However, this challenge has already been addressed by other works.

5.6 Closing Remarks

The proposed challenges were addressed by the framework. (1) Model development decisions were considered under significant uncertainty during the conceptual design phase. CA was employed to create an objective function in the absence of clear design goals. Trade-offs were made between experimentation cost, accuracy, computation time, and modeling difficulty. Imprecision in preliminary test results was handled by the model development framework. (2) The framework assessed multiple models with multiple sources of information. Moreover, dependencies between the models-- in the form of commons sources of information—were accommodated. (3) A MSD model was developed to model the impacts experienced during shipping and handling. The model can predict contact forces (output) for various packaging design parameters (input): carton length/height, drop height, etc. Proprietary test techniques showed that the MSD model was valid for predicting contact forces between primary packages. Overall, this thesis contributes to the fields of model development and decision-based design—particularly addressing three research gaps (1) conceptual design and unclear objective functions, (2) handling imprecise information , and (3) model dependencies between multiple models.

REFERENCES

[1] Liang, C.-C. and Chiang, C.-F., 2006, "A study on biodynamic models of seated human subjects exposed to vertical vibration," International Journal of Industrial Ergonomics, 36(10), pp. 869-890.

[2] Pahl, G. and W. Beitz, 1996, “Engineering Design: A Systematic Approach.” London, Springer Publishing.

[3] ISO 11607-1, 2006, “Packaging for terminally sterilized medical devices - Part 1: Requirements for materials, sterile barrier systems and packaging systems”," International Organization for Standardization, Geneva, Switzerland.

[4] ASTM D7386–08, 2006, “Standard Practice for Performance Testing of Packages for Single Parcel Delivery Systems,” ASTM International, West Conshohocken, PA.

[5] Muthukumar, S. and DesRoches, R., 2006, "A Hertz contact model with non-linear damping for pounding simulation," Earthquake Engineering & Structural Dynamics, 35(7), pp. 811-828.

[6] Hunt, K. H. and Crossley, F. R. E., 1975, "Coefficient of Restitution Interpreted as Damping in Vibroimpact," Journal of Applied Mechanics, 42(2), pp. 440-445.

[7] Natsiavas, S., 1993, “Dynamics of multiple-degree-of-freedom oscillators with colliding components,” J. Sound Vib., 165, pp. 439–453.

[8] Van Zeebroeck, M., 2005, “The discrete element method (DEM) to simulate fruit impact damage during transport and handling,” PhD no. 643, Faculty of Bio-engineering, Catholic University Leuven.

[9] Van Zeebroeck, M., Tijskens, E., Dintwa, E., Loodts J., DeBaerdemaeker, J. and Ramon, H., 2006, “The Discrete Element Method (DEM) to simulate fruit impact damage during transport and handling: model building and validation of DEM to predict bruise damage of apples,” Postharvest Biol Technol, 41, pp. 85–91.

[10] Van Zeebroeck, M., Tijskens, E., Van Liedekerke, P., Deli, V., DeBaerdemaeker J. and Ramon, H., 2003, “Determination of the dynamical behaviour of biological materials using a pendulum device,” J Sound Vib, 266, pp. 465–480.

[11] Cochran, A. J., 2002, "Development and use of one-dimensional models of a golf ball," Journal of Sports Sciences, pp. 635-641.

[12] Yang, M. and Qiao, P., 2005, "Nonlinear impact analysis of fully backed composite sandwich structures," Composites Science and Technology, 65(3-4), pp. 551-562.

[13] Zhou, C. Y. and Yu, T. X., 2009, “Analytical models for shock isolation of typical components in portable electronics,” International Journal of Impact Engineering, 36, pp. 1377-1384.

[14] Poh, K. L. and Horzitz, Eric J., “Reasoning about the Value of Decision-Model Refinements: Methods and Applications,” in Proceedings of the Ninth Conference on Uncertainty on Uncertainty in Artificial Intelligence (UAI-93), pp. 174–182.

[15] Oberkampf, W. L., S. M. DeLand, B. M. Rutherford, K. V. Diegert and K. F. Alvin, 2002, “Error and Uncertainty in Modeling and Simulation,” Reliability Engineering and Safety Systems, 75(3), pp. 333-357.

[16] Nikolaidis, E., D. M. Ghiocel and S. Singhal, 2005, “Engineering Design Reliability Handbook, Boca Raton, Florida, CRC Press.

[17] Ling, J. M., Aughenbaugh, J. M., and Paredis, C. J. J., 2006, “Managing the Collection of Information Under Uncertainty Using Information Economics,” ASME J. Mech. Des., 128(4), pp. 980–990.

[18] Li, H. and Azarm, S., 2000, “Product design selection under uncertainty and with competitive advantage,” ASME J. Mech. Des., 122(4), pp. 411-418.

[19] Li, H. and Azarm, S., 2002, “An approach for product line design selection under uncertainty and competition,” ASME J. Mech. Des., 124(3), pp. 385-392.

[20] Rekuc, S., Aughenbaugh, J. M., Bruns, M. and Paredis, C. J. J., 2007, "Eliminating Design Alternatives Based on Imprecise Information," Society of Automotive Engineering Transactions, Detroit, MI.

[21] Ling, J., and Paredis, C. J. J., 2006, “An Information Economic Approach for Model Selection in Engineering Design,” 2006 ASME International Mechanical Engineering Conference RD&D Exp, Paper No. IMECE2006-14535.

[22] Radhakrishnan, R., and McAdams, D. A., 2005, “A Methodology for Model Selection in Engineering Design,” ASME J. Mech. Des., 127, pp. 378–387.

[23] Thompson, S. C., and Paredis, C. J. J., 2010, "An Investigation Into the Decision Analysis of Design Process Decisions," Journal of Mechanical Design, 132(Dec), pp. 980-990.

[24] Fernández, M. G., Seepersad, C. C., Rosen, D., Allen, J. K. and Mistree, F., 2005, “Decision support in concurrent engineering – the utility-based selection decision support problem. Concurrent engineering research applications,“ 13(1), pp. 13–28.

[25] Bradley S. R. and Agogino A. M., 1994, “An Intelligent Real Time Design Methodology for Component Selection: An Approach to Managing Uncertainty,” J. Math. Biol., 116, pp. 980– 988.

[26] Panchal, J., Paredis, C. J. J., Allen, J. K. and Mistree, F., 2008, “A Value-of Information Based Approach to Simulation Model Refinement,” Eng. Optimiz., 40(3), pp. 223–251.

[27] Lewis, K., Chen, W. and Schmidt, L. C., 2006, Decision Making in Engineering Design, ASME, New York.

[28] Amarchinta, H. and Grandhi, R. V., 2008, “Multi-Attribute Structural Optimization Based on Conjoint Analysis,” AIAA J., 46(4), pp. 884–893.

[29] Hazelrigg, G. A., 1998, “A Framework for Decision-Based Engineering Design,” ASME J. Mech. Des., 120(4), pp. 653–658.

[30] Messac, A., 1996, “Physical Programming: Effective Optimization for Computational Design,” AIAA J., 34(1), pp. 149–158.

[31] Orme, B. K., 2006, Getting Started With Conjoint Analysis: Strategies for Product Design and Pricing Research, Research, Madison, WI.

[32] Ruderman, A. M., Choi, SK,, Patel, J., Kumar, A. and Allen, J. K., 2010, “Simulation-Based Robust Design of Multiscale Products,” ASME J. Mech. Des., 132(10), pp. 1-12.

[33] Kulok, M. and Lewis, K., 2007, “A Method to Ensure Preference Consistency in Multi-Attribute Selection Decisions,” Journal of Mechanical Design, Transactions of the ASME, 129(10), pp. 1002-1011.

[34] See, TK. and Lewis, K., 2004, “A formal approach to handling conflicts in multi-attribute group decision making,” Proceedings of the ASME Design Technical Conferences, Salt Lake City, USA.

[35] Ruderman, A. M., Choi, SK and Jiao, R. J., 2011, “Simulation-based conjoint ranking for optimal decision support process under aleatory uncertainty,” J. Intell. Manuf., paper no. DOI 10.1007/s10845-011-0610-9. See also URL www.springerlink.com.prx.library.

[36] Akao, Y., Mizuno, S. and Ishihara, K., 1994, Quality Function Deployment: The Customer-Driven Approach to Quality Planning and Deployment, Asian Productivity Organization, Tokyo, Japan.

[37] Hayes, B. E., 1997, Measuring Customer Satisfaction: Survey Design, Use, and Statistical Analysis Methods, American Society for Quality, Milwaukee, WI.

[38] Green, P., Carroll, J., and Goldberg, S., 1981, “A General Approach to Product Design Optimization via Conjoint Analysis,” J. Marketing, 43(Summer), pp. 17–35.

[39] Reutterer, T., and Kotzab, H. W., 2000, “The Use of Conjoint Analysis for Measuring Preferences in Supply Chain Design,” Ind. Mark. Manage., 29(1), pp. 27–35.

[40] Stone, T. M., Choi, SK and Amarchinta, H., 2011, “Dynamic Modeling and Parameter Estimation for Impact Analysis of Packaging Designs,” Proceedings of the ASME Early Career Technical Conference, Atlanta, GA.

[41] Kuwabara, G. and Kono, K., 1987, "Restitution Coefficient in a Collision between Two Spheres," Japanese Journal of Applied Physics, 26, p. 1230.

[42] Tsuji, Y., Tanaka, T., and Ishida, T., 1992, "Lagrangian numerical simulation of plug flow of cohesionless particles in a horizontal pipe," Powder Technology, 71(3), pp. 239-250.

[43] Zhu, S. J., Zheng, Y. F., and Fu, Y. M., 2004, "Analysis of non-linear dynamics of a two-degree-of-freedom vibration system with non-linear damping and non-linear spring," Journal of Sound and Vibration, 271(1-2), pp. 15-24.