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A framework for resource assignments in skill-based environments

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A Framework for Resource Assignments in Skill-Based Environments

by

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A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
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DEDICATION

I dedicate this dissertation to my family. I am extremely grateful to God for such an exceptional family. You guys are truly blessings in my life!

To my parents Angel L. Otero (Pa) and Lydia E. Rivera (Ma):

Thank you for always being there for me. Among the many great things that you taught me, today I thank you for teaching me to set high goals in life and to work hard to achieve these goals. Most importantly, I thank you for teaching me to have a strong faith in God and put Him first in every aspect of my life. This dissertation is mainly dedicated to you!

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As you know, you two are tremendous role models in my life. Your outstanding qualities as professionals and human beings motivate me to reach the highest possible goals. I know that you are as proud of me as I am of you two.

To my beautiful wife Aymara and my son Christian Daniel (and the others to come):

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

A Framework for Resource Assignments in Skill-Based Environments

Luis Daniel Otero

ABSTRACT

The development of effective personnel assignment methodologies has been the focus of research to academicians and practitioners for many years. The common theory among researchers is that improvements to the effectiveness of personnel assignment decisions are directly associated with favorable outcomes to organizations. Today, companies continue to struggle to develop high quality products in a timely fashion. This elevates the necessity to further explore and improve the decision-making science of personnel assignments.

The central goal of this research is to develop a novel framework for human resource assignments in skill-based environments. An extensive literature review resulted in the identification of the following three areas of the general personnel assignment problem as potential improvement opportunities: determining assignment criteria, properly evaluating personnel capabilities, and effectively assigning resources to tasks. Thus, developing new approaches to improve each of these areas constitute the objectives of this dissertation work.

The main contributions of this research are threefold. First, this research presents an effective two-stage methodology to determine assignment criteria based on data

envelopment analysis (DEA) and Tobit regression. Second, this research develops a novel fuzzy expert system for resource capability assessments in skill-based scenarios. The expert system properly evaluates the capabilities of resources in particular skills as a function of imprecise relationships that may exist between different skills. Third, this research develops an assignment model based on the fuzzy goal programming (FGP) technique. The model defines capabilities of resources, tasks requirements, and other important parameters as imprecise/fuzzy variables.

The novelty of the research presented in this dissertation stems from the fact that it advances the science of personnel assignments by combining concepts from the fields of statistics, economics, artificial intelligence, and mathematical programming to develop a solution approach with an expected high practical value.

CHAPTER 1

INTRODUCTION

The development of effective personnel assignment methodologies have been the focus of research to academicians and practitioners for many years. The common theory among researchers is that improvements to the effectiveness of personnel assignment decisions are directly associated with favorable outcomes to organizations [1]. These outcomes may include enhanced quality of products, increased employee productivity, lower turnover rates, increased market shares, and competitive advantage.

The continued struggle of companies to develop high quality products in a timely fashion elevates the necessity to further explore and improve the decision-making science of personnel assignments. For example, the U.S. Government recently spent nearly 8 billion dollars in the software development industry to rework software due to quality-related issues [2]. In the accounting field, audit quality problems are currently a major concern given "the cascade of audit failures in the concluding years of the last century and the first few years of the new century" [3]. In fact, "developing [quality] products faster has become critical to success in many industries, whether the product is an office building, software package, or computer chip" [1].

From a personnel assignment point of view, a common denominator in the types of industries mentioned above is the presence of highly imprecise parameters. For instance, expertise levels of personnel in various specialized areas are more adequately

described with imprecise parameters (e.g., high, average, low) rather than using precise values (e.g., 12 units per hour). These parameters are typically defined by decision makers. Some examples include describing the expertise of an auditor in a particular accounting software tool, the expertise of a programmer with a programming language, or the expertise of a statistician with stochastic processes. Similarly, tasks' requirements are more adequately defined with imprecise parameters.

The type of assignment problem characterized by imprecise personnel capabilities and tasks requirements is denoted in this research as the skill-based resource assignment problem (SBRAP). The focus of this research is to develop a new solution approach to the SBRAP. Although there is extensive literature related to personnel assignment approaches, most of these approaches deal with precise parameters. Moreover, relatively minor research has been conducted on the topic of competence-based assignment of employees to workplaces [4].

1.1   Motivation

The motivation for conducting this research grew from the particular industry experience of the author as a software engineer in major software projects for the defense industry. Experiencing first-hand the absence of proper processes for assigning software developers to software tasks provided the initial push to pursue this research. A thorough review of the current literature, as well as discussions with software managers regarding the problem statement, demonstrate an evident opportunity and confirm that this study has the potential to make significant contributions to the general personnel assignment literature.

2

1.2 Research Objectives

The central goal of this research is to develop a novel framework for human resource assignments in skill-based environments. To this end, a literature review was conducted to investigate current resource assignment methodologies applicable to skill-based environments in order to develop new approaches that address the major weaknesses found in current methods. Through the review of the literature, three areas of the general personnel assignment problem were identified as opportunities for improvement. They include: determining assignment criteria, properly evaluating personnel capabilities, and effectively assigning resources to tasks. Thus, developing new approaches to improve each of these areas constitute the objectives (or sub-problems) of this dissertation work.

1.3 Solution Approach and Contributions

The main contributions of this research are threefold. The first one focuses on the development of an effective two-stage methodology, based on data envelopment analysis (DEA) and Tobit regression, to determine assignment criteria. DEA analyzes data from previously completed tasks to determine relative efficiencies of personnel assignments. Then, Tobit regression analysis models DEA scores against factors believed to affect efficiency. The model incorporates capabilities of resources and task factors as independent variables. The capability of the methodology was demonstrated with data collected from a major software development organization. The results obtained were compared to results from existing approaches.

Secondly, this research presents a methodology for resource capability assessments in skill-based scenarios. This methodology is an extension to an exploratory approach developed by the author in [5]. The methodology suggests that capability levels in particular skills are influenced by resources' knowledge in other related skills. To properly evaluate the capabilities of resources in particular skills, the methodology employs concepts from fuzzy logic and fuzzy set theory to account for the imprecise relationships that may exist between different skills.

Thirdly, this research develops an assignment model based on the fuzzy goal programming (FGP) technique. The approach defines capabilities of resources, tasks requirements (i.e., goals), and other important parameters as imprecise variables. Thus, it develops fuzzy sets for these parameters, which are then meticulously manipulated to incorporate fuzzy priorities of goals and tasks. The resulting fuzzy values are then fed to the FGP model to develop a solution that maximizes the suitability of resources with tasks. An important aspect of the FGP approach is that the author developed a software application to determine the fuzzy suitability of resources with tasks. This lays the foundation for the future development of a complete software package to serve as a decision support system, including the solution methodologies to determine assignment criteria and assess resources' capabilities. This presents a significant opportunity to further extend this research, given that "the competence-based assignment of employees to workplaces is not supported by any commercially available software system" [4].

The novelty of the research presented in this dissertation stems from the fact that it advances the science of personnel assignments by combining concepts from the fields

of statistics, economics, artificial intelligence, and mathematical programming to develop a solution approach with an expected high practical value.

1.4   Organization of Dissertation

The rest of this dissertation is organized into five chapters. Chapter 2 through Chapter 4 are independent sections structured as journal articles to address each of the three major objectives of this dissertation. Chapter 2 focuses on the DEA-Tobit methodology to determine relative priorities for assignment criteria in skill-based environments. Chapter 3 presents a methodology for fuzzy resource capability assessments in skill-based scenarios. In Chapter 4, a fuzzy goal programming model for resource assignment in skill-based environments is presented. Finally, Chapter 5 concludes with a global summary of the contributions to the literature and recommendations for future research.

CHAPTER 2

A DEA-TOBIT ANALYSIS TO IDENTIFY KEY ASSIGNMENT CRITERIA IN SKILL-BASED ENVIRONMENTS

2.1   Abstract

This research presents a two-stage methodology to identify important assignment criteria in skill-based environments. These environments are characterized by the need to assess the ability of available resources to successfully complete a set of tasks. The first stage uses data envelopment analysis (DEA) to establish relative efficiencies of personnel assignments in previous tasks. Efficiency is defined as a ratio of weighted outputs (i.e., quality and productivity measures) over weighted inputs (i.e., effort and overall industry experience). The second stage uses Tobit regression analysis to model DEA scores against factors believed to affect efficiency. These factors include experience of resources on specific skills and particular characteristics of working environments.

A software development industrial setting is explored to validate the practical value of the methodology. Data related to tasks from a leading software development organization are analyzed and key assignment criteria are determined.

The contribution of this research to the literature is two-fold. First, it presents an innovative methodology to prioritize assignment criteria in skill-based environments. Second, it develops an efficiency model for personnel assignments using real industrial

software development data. To the best of our knowledge, an efficiency model of this type is non-existent in the literature regarding personnel assignments.

2.2   Introduction and Overview

Research regarding methodologies to identify and prioritize assignment criteria in human resource assignment problems is very limited. This is particularly true for skill-based resource assignment problems (SBRAPs), which are characterized by the need to assess the ability of candidates to successfully complete specific tasks. Examples of environments where decision-makers encounter SBRAPs are software engineering, healthcare, and research and development (R&D) organizations among others.

In SBRAPs, assignment criteria and their associated priorities are key parameters to determine the suitability of resources to execute certain tasks. Nevertheless, assignment criteria are usually determined subjectively [6], or based on the effect of particular factors to a single performance measure. Furthermore, priorities for assignment criteria are usually not included in personnel assignment approaches, and are mostly determined intuitively by project leaders or supervisors. Consequently, the effectiveness and practical value of current methodologies suffer significantly. According to Acuña et al. [6], this presents an open area for conducting research that incorporates a diversity of factors of individual employees in the assignment decision such as personal preferences and technical knowledge and skills.

The objective of this research is to develop an approach to effectively select assignment criteria in skill-based resource allocation scenarios. The result is a two-stage methodology composed of data envelopment analysis (DEA) and Tobit regression. The

first stage applies DEA to analyze data from completed tasks to determine efficiencies of personnel assignments based on quality and productivity measures. DEA first constructs an empirical production frontier composed of the most efficient assignments, which are the ones that produced the most outputs with the least amount of inputs. DEA determines the efficiencies of the assignments that are not in the production frontier based on the distance to their closest point (i.e., assignment) in the production frontier [7].

There are several benefits from using DEA over other methods. One of these benefits is that DEA considers multiple outputs simultaneously. This produces more thorough efficiency evaluations. Another benefit is that DEA enables the comparison of personnel assignments with best performers (i.e., assignments in the efficient production frontier), which results in more rigorous efficiency assessments.

The second stage employs Tobit regression analysis to model DEA scores against parameters assumed to affect efficiency. These parameters include capabilities of resources and task factors. Tobit regression was selected over ordinary least squares methods because the dependent variable (i.e., DEA score) always falls between two corner solutions (i.e., zero and one), and Tobit regression is more robust in such situations [8], [9].

To demonstrate its practical value, the methodology was used to identify key assignment criteria with data from a leading software development organization. The company specializes in the development of software applications for the defense industry and is rated a capability maturity model integration (CMMI) level 5 organization. A level 5 ranking means that the company has the highest standards for quantitative process monitoring and improvement. The organization provided data under nondisclosure

agreements, as has been the case in prior studies [10], [11]. The data provided information about software tasks such as the number and types of software defects, the size in terms of number of software lines of code (SLOC), and programming language and domain experience of resources.

This paper is organized into five sections of which this introduction is the first one. Section 2.2 describes literature related to methodologies for identifying assignment criteria in skill-based environments. Section 2.3 explains the proposed DEA-Tobit regression solution approach. Section 2.4 describes the application of the proposed methodology with data from a software development company. Finally, Section 2.5 concludes with contributions to the literature and recommendations for future research.

2.3   Related Literature

The literature in SBRAPs shows a limited number of methods used to determine and prioritize assignment criteria. Holness [12] mentions the lack of analyses to explain the selection of factors included in personnel assignment models. That is, most studies incorporate assignment criteria without explaining the rationale behind the selection of such criteria. Other studies determine assignment criteria using methods such as standard personality tests, interviews and surveys, the analytical hierarchy process (AHP), regression analysis, and case studies. Relevant literature associated with these methods is discussed next.

Standard personality tests are commonly used to determine assignment criteria. These tests usually rely on the Myers-Briggs scale to determine personality characteristics of available candidates, and classify candidates in four personality areas:

extrovert versus introvert (E/I), sensing versus intuitive (S/N), thinking versus feeling (T/F), and judgment versus perception (J/P) [13]. These personality characteristics are used as criteria in assignment processes to create heterogeneous teams. Examples of studies that used the Myers-Briggs scale for assignment criteria are [13], [14], and [15]. Other studies such as [6] and [16] used the 16 personality factors (16PF) and the "assessment center method" standard tests to determine assignment criteria.

Interviews and survey analyses are also used to determine assignment criteria. For example, Ng and Skitmore [17] conducted a survey and analyzed responses with a discriminant analysis to identify similarities and differences between responses. Peslak [18] conducted a survey among university students and included personality factors using the Myers-Briggs scale. The author used principal component analysis and multiple linear regression to analyze survey responses and determine assignment criteria. Wong et al. [19] statistically analyzed survey responses with the Spearman rank correlation test and a two-way analysis of variance (ANOVA). Hauschildt et al. [20] presented an interview and survey study that asked respondents to rate employees based on a list of traits, and conducted a factor analysis to reduce the list. Banaitiene and Banaitis [21], Zhang and Pham [22], and Cheney et al. [23] also conducted interviews and surveys to determine assignment criteria.

The literature on assignment criteria also shows studies that used AHP. Most recently, El-Sawalhi [24] presented a model that prioritizes assignment criteria using AHP. The authors used a three-step screening process to determine assignment criteria. First, they conducted a literature review to create a general criteria list. Second, they refined the list by including only criteria that were recommended by more than three

authors in the literature. Third, they conducted an e-mail questionnaire to refine the list one more time, and establish a final criteria set. Al-Harbi [25] also presented a method that uses AHP to establish priorities for assignment criteria. In the study by Cheung et al. [26], the authors developed a multi-criteria approach to describe subjective judgment in a structured manner. The authors gathered data using a questionnaire survey, and applied AHP as a second stage analysis.

Empirical tests that include regression analysis as a tool to determine assignment criteria are common in the literature regarding team formation and team performance analysis. Agrawal and Chari [10] developed a regression model to determine criteria that affects quality and performance. Other similar studies that use regression analyses are [11], [27], [28], and [29].

Case study analyses and the Delphi technique have also been used to determine assignment criteria. Pieterse et al. [30] conducted a case study analysis using students as subjects, and analyzed data with the non-parametric Spearman rank correlation test. Karn and Cowling [31] used a similar approach. Wynekoop and Walz [32] used the Delphi method to determine characteristics of top performers, and conducted a case study to support the results obtained from the Delphi method. The Delphi method involves several rounds of data gathering from experts in the field until a consensus is reached [33]. Patanakul et al. [34], Patanakul and Milosevic [35], and Milosevic and Patanakul [36] also used case studies in conjunction with the Delphi method to determine assignment criteria.

The literature shows two interesting insights related to the use of priorities for assignment criteria. First, most personnel assignment methodologies do not consider

relative priorities of criteria (e.g., [4], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], and [47]). Second, the methodologies that incorporate priorities do not explain their rationale for determining the priorities. That is, there is no process to help decision-makers establish these priorities. Examples of such methodologies are found in [48], [49], [50], [51], [52], and [53]. This research assumes that prioritizing assignment criteria helps to develop more accurate assessments of the suitability of candidates with tasks, hence leading to assignments that are more efficient.

In summary, the current literature shows that there are opportunities to improve areas regarding assignment criteria in SBRAPs. The following list highlights the major gaps found in the literature:

- Most assignment methodologies incorporate assignment criteria without explaining the rationale behind the selection of such criteria.

- Methods to determine assignment criteria are based on the effect of parameters to a single performance measure. There is a lack of methodologies to select assignment criteria based on data analysis that consider multiple performance measures.

- Priorities for assignment criteria are seldom included in personnel assignment approaches, and are mostly determined subjectively.

2.4 Solution Approach and Methodology

A conceptual diagram of the solution approach is shown in Figure 2.1. The goal is to develop a generalized approach that can be easily transferred and customized to various industrial settings. The following subsections provide a detailed explanation of

the two-stage methodology proposed to identify key assignment criteria in skill based environments. The methodology will be further explained in Section 2.4 through an example.
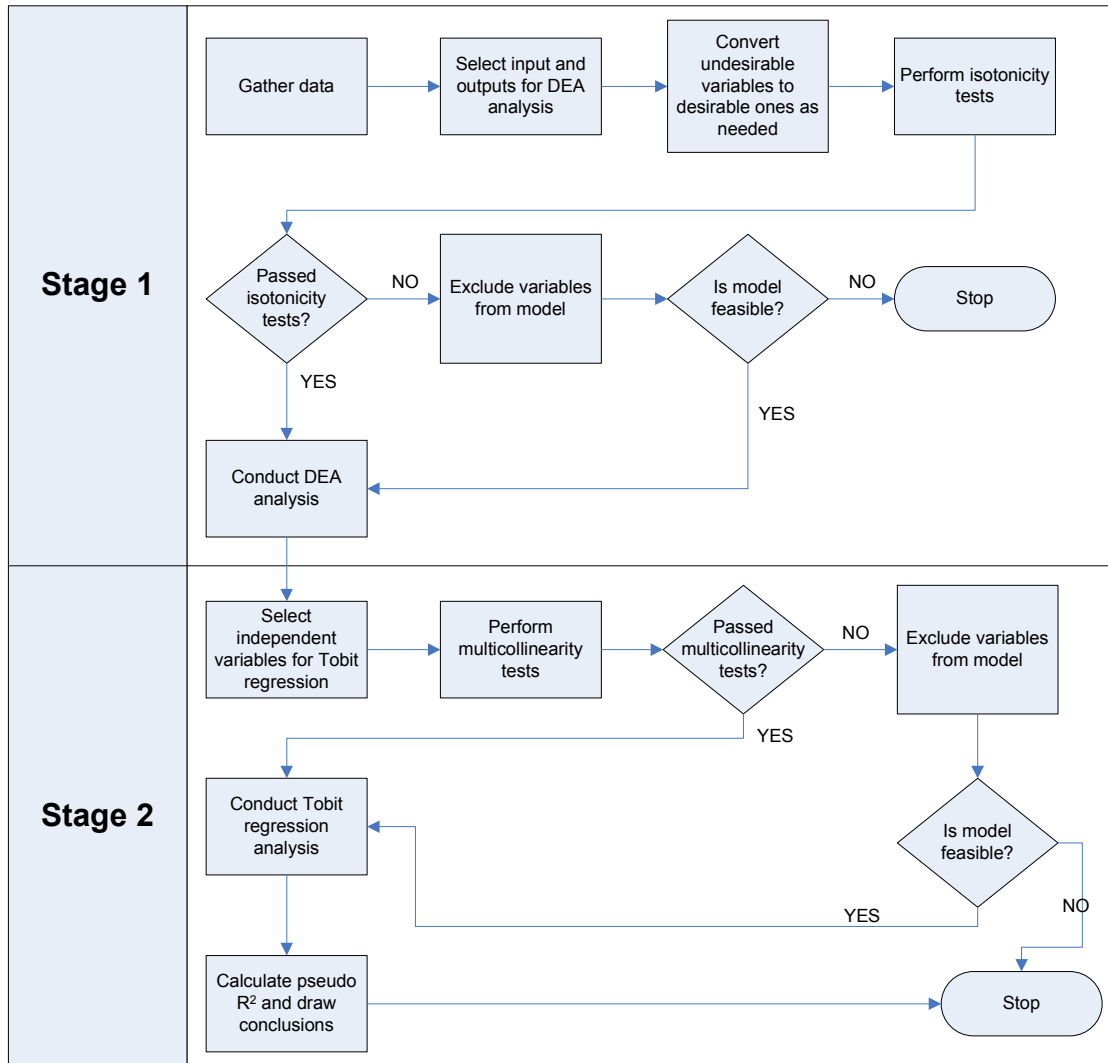
Figure 2.1 - Conceptual Diagram of Solution Approach

2.4.1   First Stage – DEA Analysis

DEA is a non-parametric methodology based on linear programming to evaluate the relative efficiencies of a group of entities called decision making units (DMUs).

DMUs "must complete similar types of activities, produce similar types of products and service, consume similar types of resources, and perform under similar environmental constraints" [54]. The DMUs in this research are personnel assignments to tasks. These are basically assignments of expertise (i.e., years of experience) to tasks, which result in significant impact to quality and productivity measures. This way, expertise is treated as a discretionary variable since decision-makers may control the amount of expertise assigned to tasks.

DEA estimates an empirical production frontier composed of the most efficient DMUs (i.e. those DMUs that are 100% efficient). The efficiency/inefficiency of a DMU not in the production frontier is calculated as the distance from the DMU to its corresponding reference point on the frontier.

DMUs are classified as efficient/inefficient based on the "Pareto improvement" and "Pareto efficient" concepts. A Pareto improvement is an allocation that results in an improvement of at least one entity without worsening other entities. For example, a Pareto improvement occurs if reallocation of an employee from project X to project Y improves the productivity of project X and does not affect the productivity of project Y. A Pareto efficient allocation (a.k.a. Pareto optimum) occurs when there is no possibility for a Pareto improvement. Therefore, DMUs considered efficient cannot improve their position without worsening the position of other DMUs.

2.4.1.1 DEA Characteristics

There are several characteristics of DEA that are relevant and appealing to this study. First, DEA allows multiple outputs to be simultaneously considered, whereas

other tools such as stochastic production frontier are limited to one output. This is very important in studies where multiple output parameters are necessary to properly determine efficiencies of DMUs. Second, being a non-parametric approach, DEA does not assume functional relationships between parameters nor assumes the distribution of efficiency scores. Third, DEA evaluates the efficiency of a DMU relative to the efficiencies of other DMUs. This way, a DMU is always compared to the best performer instead of being compared with an average performance as in regression analyses. Fourth, DEA assumes the responsibility of assigning weights to parameters. This characteristic makes DEA very suitable in situations where differences in the production practices of DMUs are difficult to comprehend and the level of importance of parameters may not be the same across DMUs. DEA assigns weights in order to show a DMU in its "best possible way", and then compares the efficiency of the DMUs considered. If the "best possible way" scenario results in another DMU being more efficient than the DMU in question, then there is strong evidence for inefficiency of the DMU. As such, DEA can focus on finding evidence of inefficiency for a DMU compared to a set of DMUs. Furthermore, DEA gives important insights into ways to increase the efficiency of DMUs by determining which input and output parameters need to be improved.

There are some limitations to DEA when using it to evaluate efficiencies. First, being a non-parametric approach, outliers and statistical noise may significantly affect efficiency calculations. Therefore, decision-makers must try to eliminate outliers from data samples. Second, a relatively small number of DMUs may lead to underestimated efficiency calculations. This can be overcome by selecting a small number of relevant inputs and outputs.

2.4.1.2   Undesirable Variables and Isotonicity

In DEA, an efficient DMU is one that can produce the most outputs consuming the least amount of inputs. There are two fundamental rules about input/output parameters that must be followed to properly determine efficiency scores. First, DEA expects increases in output values and decreases in input values to be beneficial. Therefore, output parameters such as project duration and inputs parameters such as workload per employee must be transformed so that they become beneficial. Input and output variables that require transformation to comply with this rule are called undesirable parameters.

There are several methods discussed in the DEA literature to model undesirable variables. One of the most common methods is called the [TRβ] transformation. In the [TRβ] transformation, an undesirable output is subtracted from a larger scalar value such that all transformed values are positive and increasing values are desirable. "The large scalar value is usually selected as a value just slightly larger than the maximum value of the undesirable output observed in the data set, since choosing a value that is much greater than this maximum value can distort model results" [54].

The second fundamental DEA rule is that an increase in an input variable must improve each of the outputs. This is called the isotonicity property of DEA parameters. Correlation analyses must be conducted to ensure positive relations between inputs and outputs. Negative correlation results indicate that one or more parameters may need to be excluded from the model. Testing for isotonicity of parameters is essential to validate DEA models.

2.4.1.3 DEA Input/Output Parameters and Number of DMUs

The minimum number of DMUs for a DEA analysis needs to be carefully selected, given that DEA could identify a large portion, if not all, of the DMUs as efficient. This can occur due to an inadequate number of degrees of freedom. Dyson et al. [55] recommends having at least twice as many DMUs as the total number of inputs and outputs. However, as a rule of thumb stated by one of the creators of the DEA technique in [7], the number of DMUs should be at least equal to $\max(m * s, \quad 3 * (m + s))$ where m and s are the number of inputs and outputs respectively.

Obtaining data for analysis in skill-based environments is often very difficult [10], which results in limited number of DMUs to conduct DEA studies. Since the minimum required number of DMUs is a function of the number of inputs and outputs, it is advisable to keep the number of inputs and outputs as small as possible. This helps to improve the efficiency estimation capability of DEA. One way to minimize the number of parameters is to include those that serve as proxies to other parameters. For example, overall years of experience of an employee can be used to represent salary, organizational experience, and exposure to company processes. Other types of parameters, such as specific knowledge in particular skills, will be included in the Tobit regression analysis during the second stage.

The generalized DEA model consists of two inputs and two outputs. These parameters are shown in Table 2.1, as well as their definition in particular disciplines. Overall experience is defined as the number of years of experience of resources that were assigned to a task. Effort, quality, and performance are application-specific measures that must be determined by decision-makers. Correlation tests need to be performed to

17

ensure that the parameters adhere to the isotonicity property of DEA. Again, negative correlation between parameters may cause the exclusion of a parameter from the model.

Table 2.1 - Inputs/Outputs for DEA Model

Parameter	Input/ Output	Examples	
		Software Engineering	R&D Projects
Overall experience	Input	Years of industry experience	Years of experience of a resource as a Ph.D.
Effort	Input	Number of engineers assigned per KSLOC	Hours per Project
Quality	Output	KSLOC per software defect	Number of publications per project
Performance	Output	Cycle time density (i.e., number of SLOC per hour)	Adherence to Schedule

2.4.1.4 Orientation of DEA Model

DEA provides two basic model orientations: output maximizing and input minimizing. The selection of model orientation depends on the objectives of the study. An output maximizing oriented model determines the maximum proportional increase in outputs relative to the actual input values, which is adequate to establish a set of target output values. Output maximizing models are also used when output levels are discretionary but input levels are relatively fixed (i.e. non-discretionary) [54]. An input minimizing oriented model determines the amount by which the input values can be decreased while still producing the same outputs, which is adequate to evaluate the efficiencies of internal processes. For this research, an input-oriented model is used

given that the main objective is to allocate resources more efficiently based on input parameters rather than to improve the outputs.

2.4.1.5 DEA Model Selection

Returns to scale is an important concept in the field of Economics that needs to be well understood since it is used by DEA models to form efficient frontiers. There are three types of returns to scale: increasing, decreasing, and constant. Constant returns to scale describe the case where an increase of input by a constant amount results in an increase in output by the same constant amount. If the output increases by more than the constant amount, then it is called increasing returns to scale, or economies of scale. If the output increases by less than the constant amount, then it is called decreasing returns to scale or diseconomies of scale [56].

Employees in skill-based environments are more likely to operate under both economies and diseconomies of scale. Skirbekk [57] mentions that "job experience improves productivity for several years, but there does come a point at which further experience no longer has an effect." That is, more experience does not necessarily equate to increased productivity. Therefore, it will be appropriate to select a DEA model that allows resources in the efficient frontier to operate under diseconomies of scale.

The DEA model selected is the input-oriented BCC model, named after its inventors Banker, Charnes, and Cooper in 1984 [7]. The model assumes variable returns to scale frontiers, which means that efficient DMUs may operate under increasing, decreasing, or constant returns to scale. Hence, the model allows DMUs operating under diseconomies of scale to be classified as efficient (i.e. be part of the efficient frontier).

19

Complexity of tasks must be considered when determining efficiencies of past personnel assignments. Decision-makers have two options to deal with complexity. The first option is to compare performances of personnel assignments in tasks with similar complexity levels. That is, in the case of low and high-complexity tasks, develop an input-oriented BCC model for low-complexity tasks and another for high-complexity tasks. The second option is to compare performances among tasks with different complexity levels. More specifically, performances of personnel assignments to lower level complexity tasks may be compared to those with higher level complexity tasks, but not vice versa. This option requires a hierarchical categorical model, which is easily incorporated into the BCC model. Cooper et al. [7] call this model the categorical variable DEA model.

2.4.2 Second Stage - Tobit Regression Analysis

The DEA analysis from the first stage provides efficiency scores for personnel assignments. After focusing on the level of efficiency of the assignments, the main challenge is to understand the impact of personnel skills on efficiency scores. This can be achieved through regression analysis.

Efficiency scores are considered censored variables because they are continuous and distributed over a limited interval, in this case between 0-1. The common regression analysis using the ordinary least squares approach provides bias results in the presence of censored variables [58]. The preferred choice among researchers is Tobit regression, which is based on maximum likelihood procedures. A recent study comparing

approaches for modeling DEA scores indicates that Tobit regression is an effective tool that provides reliable results [8].

Although Tobit regression analysis has been previously used to model DEA efficiency scores, a DEA-Tobit regression approach for personnel assignments in skill-based settings has not been addressed in the literature. Equation (2.1) shows the Tobit model specification, where θ_i^* is the DEA efficiency score for personnel assignment i, x_{ij} are independent variables (j = 1 to k) for personnel assignment i, and ε_i is the disturbance term. Standard linear regression assumptions for the disturbance term must be met [59]. That is, appropriate tests for normal distribution and constant variances of the error terms must be conducted.

$$\theta_i^* = \beta_0 + \sum_{j=1}^{k} \beta_i x_{ij} + \varepsilon_i \qquad (2.1)$$

2.4.2.1 Independent Variables

The most important independent variables to consider are skills/expertise of personnel. However, other factors (e.g., task factors or team factors) can be included if necessary to improve the performance of the model.

Table 2.2 shows examples of parameters that can be used to develop Tobit models for particular disciplines. These parameters can be modeled using either quantitative or categorical variables.

Table 2.2 - Examples of Parameters for Tobit Models in Particular Disciplines

Type of Factor	Examples of Independent Variables	
	Software Engineering	R&D Projects
Personnel	Programming language experience	Domain expertise
	Domain expertise	Statistical software experience
	Application expertise	Expertise in non-parametric approaches
Task	Size (i.e., number of SLOC)	Scope

2.5   Example – Software Development Setting

Data from a software development organization was used to test the capability of the solution approach.   Task assignment in software development environments is considered one of the most critical decisions since it influences the performance and quality of projects [6].   Quality, as evidenced in the U.S. General Accounting Office Report in [2], continues to be a major struggle to software companies.   This report states that in 2004 the U.S. Department of Defense spent nearly 8 billion dollars to rework software because of quality-related issues.   Even more important than huge monetary costs is the fact that software failures in safety-critical systems may result in life-threatening situations.   Tsai et al. [43] stated that "evidence reveals that the failure of software development projects is often a result of inadequate human resource project planning".

Despite its importance, the literature reveals major gaps related to the assignment criteria and methodology in software development projects.   To close these gaps, it is necessary to determine factors that significantly affect the efficiency of assignments of software developers to software tasks. Efficiency is measured in terms of how the overall

experience of developers, considering different levels of task complexities, affect the number of software defects and cycle time (i.e., the time it takes to complete tasks) simultaneously. The research questions addressed through this example are the following:

- What are the relative impacts of various personnel and task factors on the technical efficiency of software tasks?
- How do these relative impacts compare with the conclusions of studies in the literature regarding factors affecting the quality at the project level?

These questions are of importance from both the practical and theoretical perspective.

The purpose of applying the DEA-Tobit methodology in a software development setting is two-fold. First, this example serves to demonstrate the capability of the methodology using real industry data. Second, the results significantly contribute to the software engineering literature by identifying and prioritizing assignment criteria based on the effects of particular factors to the quality and duration of tasks. This type of analysis, which considers multiple performance measures simultaneously, has not been conducted in the software engineering field.

2.5.1 Previous Studies

The software development literature shows that software defects increase repair costs [60]. The common peer review technique for defect-detection catches from 31 to 93 percent defects, with a median of approximately 60 percent [61]. However, "very few research efforts have been conducted with respect to factors influencing defect injection" [60]. Figure 2.2 shows defect introduction and removal pipes similar to [60]. A

percentage of residual defects from the earlier phases of software development will continue into subsequent phases, increasing the probability of more costly defects at the later phases, and eventually becoming field defects. Despite the fact that minimizing faults in code is the responsibility of individual programmers, most methods ignore causal effects of programmers [62].
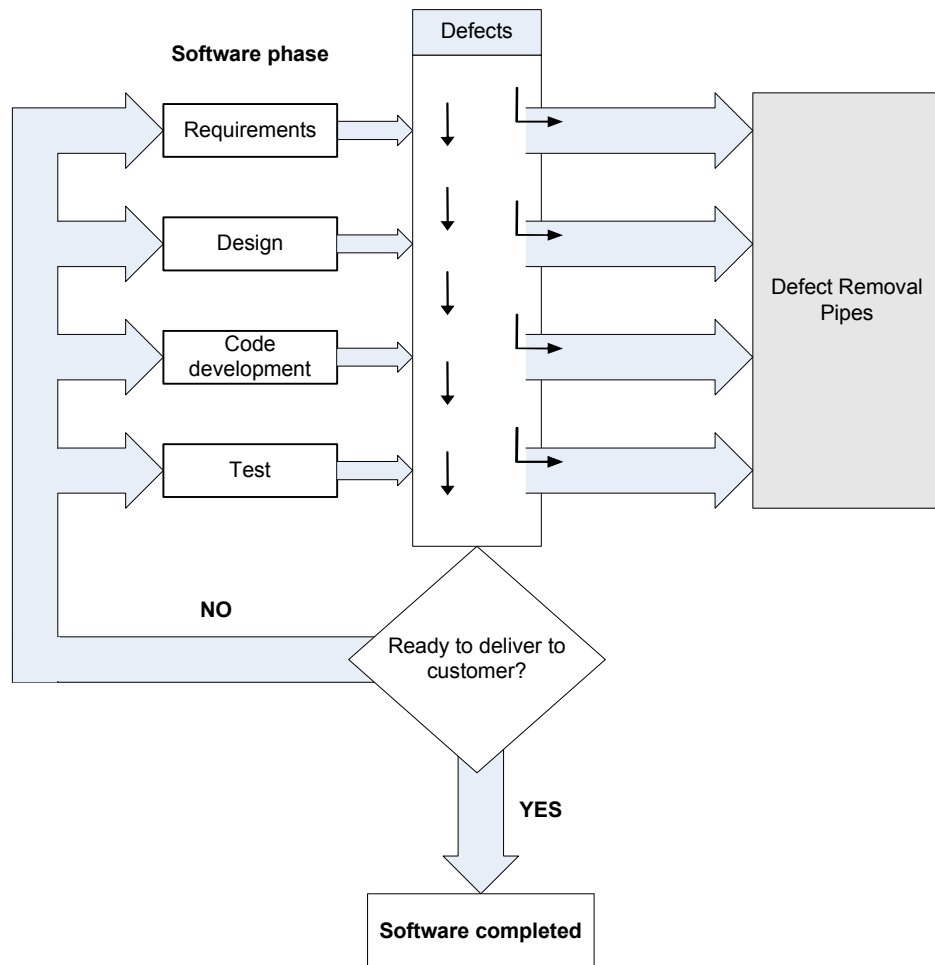
Figure 2.2 - Software Defect Introduction and Removal Process

Table 2.3 shows a selection of studies on team factors affecting the quality and productivity of software projects. Factors such as project size, team capabilities, team average domain experience, communication among team members, and task complexity

have been found to influence the quality and productivity of software projects. Other studies provided contradictory results, concluding that project size and complexity [63], and professional experience [64] do not affect the outcome of projects.   These contradictions elevate the necessity to conduct a more detailed investigation regarding the factors affecting important performance measures of software tasks.

Table 2.3 - Selected Literature on Team Factors Affecting Quality and/or Productivity

Study	Selected Dependent Variables	Selected Independent Variables	Industry	Findings
Agrawal and Chari (2007) [10]	Effort, Quality, Cycle Time	Product size, Complexity, Team size, Team capability	CMMI level 5 organization (mainly business applications)	• Product size was the only significant driver of effort, cycle time, and quality.
Jacobs et al. (2007) [60]	N/A	N/A	Various	• This was a literature survey to determine factors that affect defect injection. • Capability, domain knowledge, team parameters, complexity, process maturity, and communication affect quality.
Tiwana (2004) [65]	Design effectiveness and efficiency, and design density	Knowledge integration (business domain and technical knowledge)	Unknown	• Knowledge integration affects development effectiveness and defect density.
Nan et al. (2003) [66]	Effort, Quality, Cycle Time	Schedule pressure	Unknown	• Schedule pressure may reduce effort and cycle time without impacting quality.

Table 2.3 (Continued)

Krishnan et al. (2000) [11]	Productivity, Quality	Product size, Team capability, Usage of tools, Process factors, Proportion of front-end investments	Commercial software systems applications	• Product size, team capability, front-end investment, and software process affect quality. • The usage of tools was not a significant factor affecting the quality.
Faraj (2000) [64]	Team performance (based on expert judgment of quality, goals met, and team operations)	Technical expertise (subjective average of technical, design, and domain expertise), Professional expertise (years of experience), Administration measures (number of status meetings, etc.)	Large software company developing software for commercial clients	• Technical expertise coordination affects team performance more than the actual presence of team expertise and administrative coordination. • Professional experience had no impact on team effectiveness. • Social integration contributes to performance more than technical integration.
Fenton and Ohlsson (2000) [63]	Quality	Product size, Complexity	Ericsson Telecom AB	• Quality is not affected by product size or complexity.
Krishnan and Kellner (1999) [28]	Quality	CMMI software process practices, Product size, Team capability	Commercial software systems applications	• Consistent adoption of CMMI practices reduces field defects. • Team capability affects the number of field defects.
Krishnan (1998) [29]	Quality, Cost	Product size, Team capability, Programming language experience, Domain experience	Commercial packaged software projects	• Team capability, domain experience, and product size affect the quality. • Team capability and product size affect the development cost. • Domain experience has no effect on the development costs. • Programming language experience has no effect on either quality or development costs.
Gaffney (1984) [67]	Quality	Product size	Unknown	• Product size is a good estimator of quality.

A major drawback from previous studies is that data samples, most of the time, come from students and not professional employees [29]. The reason for this is that obtaining software development data from corporations is very complicated in the best of circumstances [10]. Therefore, it is necessary to conduct more research studies with industry data in order to significantly contribute to the literature on software quality.

Another limitation of previous studies is that most are based on multiple-input-single-output analyses (e.g., [10], [68], and [69]). To the best of our knowledge, a study that considers the multiple-input and multiple-output case has not been addressed in the literature regarding software quality and productivity.

The literature also shows studies that investigate important factors of individual team members. In [70], the authors conducted a controlled experiment and found that years of experience in specific software domains was a significant factor affecting the time it took programmers to find planted bugs. Acuña et al. [6] described capabilities of individuals based on standard tests for behavioral assessments. Other studies such as [14], [15], and [71] examined individual characteristics for software development team success with different standard personality tests. Examples of additional studies that have considered personality traits of top performing software developers can be found in [72], [73], [74], and [75]. Personal characteristics that have been identified as common traits of top performing engineers include creative problem solving skills, leadership skills, and communication skills, among others. Researchers have also looked at technical skills of top performing developers by collecting data from interviews and surveys and using subjective performance measures [22], [23]. In [76], the authors studied the ability of teams to work together based on the working style of individual

members. A methodology to add personnel to the team with the objective of reducing conflict was developed.

2.5.2 Data for Analysis

Data for this research was collected from a leading CMMI level 5 organization specializing in the development of software applications for the defense industry. The data included information from two projects. Each project was divided into smaller software components called computer software configuration items (CSCIs), where each CSCI was divided into computer software components (CSCs). Figure 2.3 shows this modular project structure which is necessary to improve the management of software products. On average, four engineers were assigned to each CSC. The data collected contained information on 76 CSCs. For simplicity, the rest of this paper uses the term "task" instead of CSC. Therefore, as mentioned in Section 0, the DMUs in this research are personnel assignments to tasks.
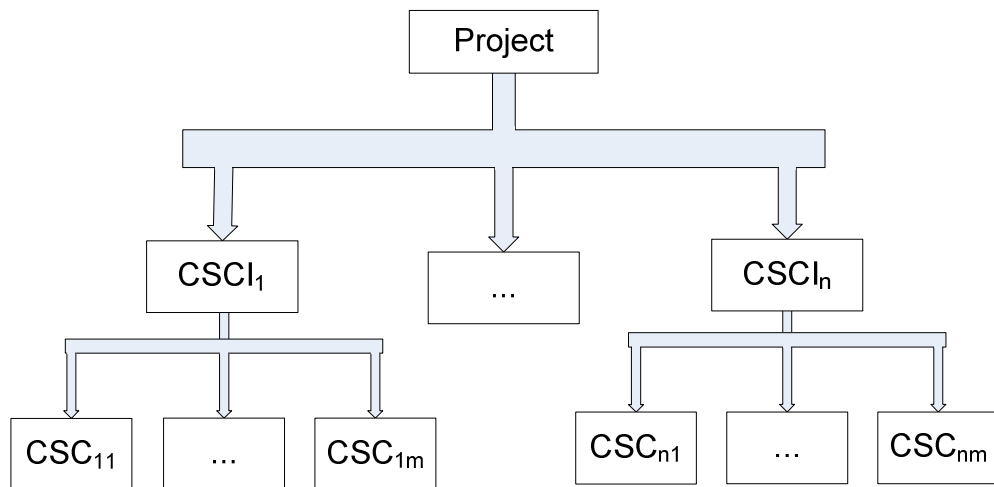
Figure 2.3 - Modular Project Structure

The data provided a categorical parameter to describe the complexity of each task: high and average-complexity. Levels of complexity were assigned based on types of applications. For example, creating operating systems or real-time embedded software applications were considered of high complexity. Developing graphical user interface applications or client-server applications were considered of average complexity. In addition, meetings with software analysts were conducted to ensure the validity of the data.

There were 36 average-complexity tasks and 40 of high complexity. According to [10], a sample size of 30 or higher is an adequate size for the analysis. It is also comparable with related studies [77]. Moreover, this sample size is especially significant for this study since there are only 141 CMMI level 5 organizations worldwide [78].

The input parameters considered for the DEA model are overall experience and effort. For each task, overall experience is defined as the average number of years of industry experience of its resources working with software architectures, specifications, and requirements. This input serves as a proxy to parameters such as salary, leadership, and organizational experience. On the other hand, effort is defined as the number of engineers assigned for a thousand software lines of code (KSLOC). That is, effort is normalized by the size of software tasks to allow fair comparisons between assignments. For example, two engineers that completed two KSLOC and one engineer that completed one KSLOC results in the same effort value (i.e., one engineer per KSLOC). Effort may also be explained in terms of workload (i.e., KSLOC per engineer). As effort values increase, workloads per engineer decrease. Less workload per engineer should result in better performance since debugging software applications becomes more complex as the

number of SLOC increases. These inputs are good indicators of the overall knowledge and costs invested to complete software tasks.

The output parameters considered are quality and productivity. In [10], the authors define quality as the "total number of defects that escaped to the customer". Studies such as [28] and [29] also define quality as number of defects. Instead of defect counts, this research defines quality as the number of KSLOC per post-release defects. This measure of quality has been used in previous studies such as [11] and [68]. KSLOC per defect is selected over defect counts because it controls the effect of varying SLOC sizes among tasks.

The measurement for productivity is cycle time density which is the number of SLOC written per hour. This allows cycle time to be modeled as a desired output variable since higher values of this parameter are preferred. This definition is slightly different than the usual one found throughout the literature, which is the number of days that elapsed from starting the requirements or design phases to completing the development phase [10], [66].

2.5.3   First Stage – DEA Analysis

The goal of this stage was to develop DEA models to determine relative efficiencies of personnel assignments to average and high-complexity tasks. First, correlation analyses were conducted to verify the presence of isotonicity between inputs and outputs. Table 2.4 and Table 2.5 show the correlation results.

Table 2.4 - Correlation Analysis for DEA Parameters (Average-Complexity Tasks)

	KSLOC per Defect	Productivity
Experience	0.85	0.73
Effort (Staff per KSLOC)	-0.61	-0.42

Table 2.5 - Correlation Analysis for DEA Parameters (High-Complexity Tasks)

	KSLOC per Defect	Productivity
Experience	0.63	0.59
Effort (Staff per KSLOC)	-0.63	0.10

The results from the correlation analyses showed a strong positive correlation between experience and both output parameters. However, there was negative correlation between effort and KSLOC per defect in both analyses, and between effort and productivity in one of the analyses. Therefore, the effort parameter was removed from the DEA analyses due to lack of isotonicity.

Increasing the effort assigned to tasks was expected to improve both KSLOC per defect and productivity. The rationale was that increasing the number of staff per KSLOC would have decreased workloads per staff, therefore resulting in improvement of outputs. Correlation results clearly showed that this was not the case. A possible explanation for this behavior is that increasing the number of staff may have also increased communication overhead. As in [79], increased communication overhead could have led to non-productive results.

Other input parameters such as average cost per KSLOC or average cost per staff would have been adequate if data were available. However, research data was limited in

this regards.   As mentioned before, experience encompasses different important parameters such as salary, leadership, and organizational experience; therefore, experience is the only input parameter considered in the DEA analyses.

Z-tests were conducted to determine if the means of the output parameters, normalized by years of experience, from average complexity tasks were statistically equal to those from high complexity tasks. In other words, the goal of these tests was to determine if productivity (and quality) per years of experience was different between the high and average tasks. The results from the z-tests provided evidence, at an alpha of 0.05, that the normalized means were statistically different between both types of tasks. This justifies conducting separate DEA analyses for high and average complexity tasks to allow fair comparisons between DMUs.

Table 2.6 shows the results of the DEA analyses. Recall that input-oriented BCC models were used.

Table 2.6 - DEA Results - Efficiency of Personnel Assignments

Complexity			
High		**Average**	
DMU	DEA Score	DMU	DEA Score
Hi_1	1.000	Nom_1	1.000
Hi_2	1.000	Nom_2	1.000
Hi_3	1.000	Nom_3	1.000
Hi_4	0.975	Nom_4	0.714
Hi_5	0.941	Nom_5	0.500
Hi_6	1.000	Nom_6	0.667
Hi_7	1.000	Nom_7	0.500
Hi_8	1.000	Nom_8	0.621
Hi_9	0.662	Nom_9	1.000
Hi_10	0.500	Nom_10	1.000
Hi_11	1.000	Nom_11	0.555
Hi_12	1.000	Nom_12	1.000
Hi_13	1.000	Nom_13	0.625
Hi_14	1.000	Nom_14	0.759
Hi_15	0.500	Nom_15	0.640
Hi_16	0.730	Nom_16	0.526
Hi_17	0.668	Nom_17	0.624
Hi_18	0.659	Nom_18	1.000
Hi_19	0.802	Nom_19	0.564
Hi_20	0.668	Nom_20	1.000
Hi_21	0.629	Nom_21	0.742
Hi_22	0.602	Nom_22	0.705
Hi_23	0.500	Nom_23	0.785
Hi_24	0.823	Nom_24	0.735
Hi_25	0.629	Nom_25	0.756
Hi_26	0.250	Nom_26	0.960
Hi_27	0.530	Nom_27	0.750
Hi_28	0.618	Nom_28	0.480
Hi_29	0.333	Nom_29	1.000
Hi_30	0.382	Nom_30	1.000
Hi_31	0.795	Nom_31	0.703
Hi_32	0.375	Nom_32	0.667
Hi_33	0.566	Nom_33	0.882
Hi_34	0.558	Nom_34	0.782
Hi_35	0.987	Nom_35	0.587
Hi_36	0.475	Nom_36	0.882
Hi_37	0.301		
Hi_38	1.000		
Hi_39	0.389		
Hi_40	0.916		
Avg. = 0.719		**Avg. = 0.770**	

2.5.4   Second Stage - Tobit Regression Model

Tobit regression analyses were conducted to investigate the factors that significantly affect the efficiency of personnel assignments to average and high

complexity tasks. The idea is to identify potential assignment criteria based on the factors that significantly increase efficiency. The dependent variable in the Tobit models is the DEA score. Independent variables include the personnel and task factors shown in Table 2.7.

Table 2.7 - Independent Variables

Type of Factor	Factor Name	Variable (abbreviation)	Description	Measurement Type
Personnel Factors	Programming language experience	PL	Experience with the programming language required by the task	Categorical variable with two levels: High = 1 Low = 0
	Development system experience	DSE	Experience with the software and hardware tools to complete the task	Categorical variable with two levels: High = 1 Low = 0
	Practices and methods experience	PME	Experience with the software processes and methods particular to the task, such as design reviews and other QA activities	Categorical variable with two levels: High = 1 Low = 0
	Programmer Capabilities	PC	Subjective measure of ability, including motivation and communication skills	Categorical variable with two levels: High = 1 Low = 0
Task Factors	Size	SIZE	SLOC count	Quantitative
	Requirements volatility	REQ	Frequency and scope of requirement changes after being approved.	Categorical variable with two levels: High = 1 Low = 0

Personnel factors are modeled as dichotomous categorical variables with high and low levels. High levels of experience are defined as more than two years of experience. It is important to not confuse years of experience with programmer capabilities (PC). Instead, capability subjectively measures the abilities of resources based on their perceived potential, including motivation and communication skills.

The size of tasks (SIZE) is measured using number of functional SLOC. The number of SLOC has been shown in the literature to affect both the quality and cycle time of software tasks [10], [29], [28]. Requirements volatility (REQ) captures the frequency and scope of requirement changes. These changes may be caused by the inability of the customers to define requirements during the initial stages of projects, inability to properly characterize and document requirements, and other unexpected constraints imposed by software/hardware tools.

Correlation analyses between independent variables were conducted to test for multicollinearity. Correlation between dichotomous variables is usually computed with the phi-coefficient or point biserial methods. Comrey and Lee [80] explained that the Pearson correlation coefficient yields the same results if dichotomous variables are scored 1 for the higher category and 0 for the lower one. Therefore, the Pearson coefficient method was used to calculate the correlation coefficients (see Table 2.8 and Table 2.9).

Table 2.8 - Correlation of Independent Variables in Tobit (Average-Complexity)

	PL	DSE	PME	PC
PL	1			
DSE	0.478	1		
PME	0.181	0.076	1	
PC	0.331	0.277	-0.021	1

Table 2.9 - Correlation of Independent Variables in Tobit (High-Complexity)

	PL	DSE	PME	PC
PL	1			
DSE	0.498	1		
PME	-0.020	-0.108	1	
PC	0.332	0.175	0.233	1

The results show mostly weak correlations between parameters. However, there is a weak-to-moderate correlation between programming language and development system experience in both cases, which is expected. The lack of strong correlations between the parameters satisfies the multicollinearity assumption in multiple regression analysis.

Equation (2.2) specifies the empirical model for the DEA efficiency scores. Equation (2.3) shows the Tobit regression model, where θ^* is the vector of DEA efficiency scores.

$$\text{Efficiency} = \text{Function (PL, DSE, PME, PC, SIZE, REQ)} \tag{2.2}$$

$$\theta^* = \beta_0 + \beta_1(PL) + \beta_2(DSE) + \beta_3(PME) + \beta_4(PC) + \beta_5(SLOC) + \beta_6(REQ) \tag{2.3}$$

The Tobit regression analyses were developed using the R statistical software tool. Residual analyses and normal probability plots showed that the assumptions of constant variance and normal distribution of the error terms were met.

Table 2.10 shows the results of the Tobit regressions. The goodness-of-fit measure for the models was the square of the correlations between actual and expected DEA scores [9]. This measure, denoted pseudo-R^2, represents the variability of the DEA scores that is explained by the independent variables. The Wald Chi-Square statistic

result rejects the null hypothesis that the regression coefficients, except for the intercept term, are not significantly different from zero [81].

Table 2.10 - Tobit Regression Results

Explanatory variable	Personnel assignments	
	Average-complexity _____ Estimated β coefficient	High-complexity _____ Estimated β coefficient
INTERCEPT	0.434*	0.968**
Personnel Factors		
PL	0.239	0.095
DSE	0.178	0.992**
PME	0.082	0.140
PC	0.302**	-0.013
Task Factors		
SIZE	-2.789E-06	-1.851E-05**
REQ	-0.135	-0.201*
Pseudo-R^2	0.400	0.530
Wald Chi-Square statistic	16.06 on 6 DF (p = 0.0134)	27.54 on 6 DF (p = 0.0001)

* = significant at 5%
** = significant at 1%

2.5.5   Discussion

The results from the Tobit analyses show important differences between high and average-complexity tasks. For personnel assignments to high-complexity tasks, the results show that both task factors are statistically significant and negatively affect the efficiency scores. These results are compatible with other studies in the literature which

concluded that the number of SLOC and changes in requirements significantly affect the quality and productivity of software projects [10], [11]. However, both tasks factors were not significant in average complexity tasks, which suggests that resources working these tasks are able recuperate from requirement changes without a significant effect to quality and productivity. This also suggests that increased values of SLOC and changes in requirements result in additional complications that significantly affect the outcome of high-complexity tasks. Regarding high SLOC values, managers must ensure that object-oriented (i.e., software modularity) standards are strictly followed by developers. Regarding changes in requirements, there is a vast amount of literature on methods for creating and managing software requirements [82], [83], [84].

The effect of programming language experience on efficiency was not statistically significant for either average or high-complexity tasks. These results are compatible with the study of Krishnan [29], where it was concluded that programming language experience had no effect on software quality. This is a critical finding since often programming language is used as the main criteria for resource assignments [5].

The experience of resources in software practices and methods was not a significant contributor to efficiency for both types of tasks. Studies such as [11] and [28] analyzed the effects of implementing consistent software practices and processes and concluded that they significantly affect quality. However, the literature lacks a study that incorporates the knowledge of resources in software practices as a potential driver for quality and productivity. To the best of the authors' knowledge, this study is the first one to incorporate and analyze the effect of such factor.

Of the four personnel factors in the model, development system experience was found to be the only significant contributor to efficiency in high-complexity tasks. In average-complexity tasks, only programmer capability was found to be significant. This suggests that in-depth knowledge of software techniques and hardware tools are drivers of efficiency in challenging tasks, whereas motivation and communication skills are the efficiency drivers for the less challenging ones. Consequently, development system experience should be given higher priority as an assignment criterion for high-complexity tasks, and programmer capability for average-complexity ones.

2.6   Summary and Contributions

This study presented a methodology based on DEA and Tobit regression to analyze the impact of factors believed to affect the efficiency of personnel assignments in skill-based tasks. The methodology was used to analyze data regarding software tasks from a leading software development company. The data were divided into two categories: average and high-complexity tasks. Using DEA, efficiency scores were computed for each of the two categories. Input and output parameters for the DEA analyses were validated by conducting correlation tests to verify that the models followed the isotonicity assumption of DEA.

Tobit regression models were developed to regress the DEA scores against personnel and task factors believed to affect efficiency. Task factors included number of SLOC and frequency of changes in requirements. Personnel factors included programmer capability, programming language experience, practices and methods experience, and development system experience. The results showed that both task

factors were significant in high-complexity tasks only. Furthermore, programming language experience was not a significant factor affecting efficiency. The results indicated that development system experience was the only significant personnel factor for high-complexity tasks, and programmer capability for average-complexity tasks.

This work contributes to personnel assignment research by presenting an analytical approach that considers multiple outputs simultaneously and eliminates subjectivity when determining relative priorities for assignment criteria in skill-based environments. This is of significant use and relevance to decision makers since most personnel assignment decisions in industry settings involve the evaluation of several performance measures and a struggle for decision makers to subjectively determine important parameters.

The methodology presented in this research provides a new mechanism for decision makers to objectively identify assignment criteria based on the factors that significantly affect efficiency. The methodology reduces subjectivity in two ways. First, it eliminates the need for decision makers to establish subjective weights for parameters when determining efficiencies, as the best possible weights for each parameter are determined by DEA. Second, assignment criteria are identified as a result of regression analyses from actual data.

An important aspect of the methodology is that it determines efficiencies of previous personnel assignments as a function of the efficiency of best performers. This results in more rigorous evaluation of relative efficiencies than other methodologies which determine efficiencies as a function of average performances.

Demonstrating the capability of the methodology using software development data from a major corporation resulted in the identification of drivers of efficiency (i.e., assignment criteria) of personnel assignments per task complexity. The resulting assignment criteria are readily available for decision makers in software development settings, which is another key contribution of this research.

To further confirm the capability of the research presented, future work is needed to apply the methodology in different industrial settings. Furthermore, it is necessary to determine the acceptance of the results by decision-makers from other environments. Doing so will help to further establish the real practical value of the solution approach.

Another future research opportunity for software engineering researchers is to confirm and expand the results of this study. That is, the data provided for this study were limited to four personnel factors. It will be beneficial to conduct research with additional personnel and task factors to increase our understanding of drivers of efficiency of software applications.

This research was motivated by a notable gap in the literature regarding a lack of adequate methodologies to assign resources to tasks in skill-based scenarios. The outcome of this research fills this gap by providing a process that can be measured and improved, therefore promoting a mentality of continuous improvement.

CHAPTER 3

A FUZZY EXPERT SYSTEM ARCHITECTURE FOR CAPABILITY ASSESSMENTS IN SKILL-BASED ENVIRONMENTS

3.1   Abstract

The fast pace at which new technologies and techniques are being developed to improve the design and development of products increases the demand for specialized individual skills in the workforce. As a result of higher demands, candidates with exact required skills to work tasks are usually unavailable. Due to the lack of proper methods to assess personnel capabilities, decision makers are forced to assign resources to tasks based on shallow assessments. To tackle this issue, this research presents a layered expert architecture where subcomponents can be customized to specific industrial settings. A fuzzy logic scheme is described to model personnel capabilities as imprecise parameters, and to consider complete skill sets of resources when evaluating their levels of expertise in a skill. The proposed approach leads to thorough capability assessments, as well as an increased number of capable candidates.

42

3.2   Introduction

Despite all the research and advances in the project management field, managing human resources remains a very complicated endeavor. A major contributor to this complexity is the increased demand for specialized individual skills in the workforce, which results from high turnover rates and the fast pace at which new technologies and techniques are being developed. As a result of higher demands, candidates with exact required skills to work tasks are usually unavailable. Due to the lack of proper methods to evaluate personnel capabilities, decision makers struggle to efficiently assign resources to tasks. This results in excess training times that significantly affect the cycle time for product development, as well as overall quality measures. Therefore, further studies of processes and techniques for personnel capability assessments are necessary to provide better solutions in terms of quality, cost, and schedule.

This research proposes a fuzzy expert system architecture as a solution to the personnel capability assessment problem. The proposed architecture is divided into four layers: user interface, fuzzy logic system, data repository, and global layers. The scope of this research is to provide a detailed description of the fuzzy logic inference system (a.k.a. approximate reasoning), and briefly describe the rest of the layers to give a clear idea of the expected flow of data throughout the system. As such, this research lays out the foundation for the development of fuzzy expert systems for personnel capability assessments in industrial environments.

The fuzzy logic scheme described in this research is an extension to an exploratory approach developed by Otero et al. [5]. Their methodology, denoted by the

authors as the best-fitted resource (BFR) methodology, suggests that capability levels in particular skills are influenced by resources' knowledge in related skills. That is, resources without proper experience in required skills perhaps are proficient in similar skills which can accelerate the learning process. For example, knowledge in the C++ programming language can decrease, to some extent, the training time of a programmer to become proficient in the C# programming language because they are both object-oriented languages and have a somewhat similar syntax. This approach of considering relationships between skills leads to more thorough capability assessments and increases the set of possible candidates to work tasks that require specific skills.

This research extends the BFR methodology in two ways based on the assumption that capability ratings and skill relationships are essentially imprecise factors. First, this study employs fuzzy set theory to describe the capability ratings of resources in particular skills as degrees of membership in various fuzzy sets. The BFR methodology, on the other hand, describes capability ratings as crisp values based on classical set theory. Second, this research describes skill-relationships using fuzzy rules, whereas the BFR method uses crisp values for the development of their skill-relationship tables. Although fuzzy expert systems for personnel assignments have already been introduced to the literature (e.g., [41] and [49]) to the best of our knowledge the use of a fuzzy logic approach to determine personnel capabilities is a new contribution to the literature.

This chapter is organized as follows. Section 3.2 describes the proposed fuzzy expert system architecture. It provides a review of important fuzzy logic concepts that are necessary for understanding the functionality of the expert system. The section concludes with a description of the step-by-step flow of data throughout the expert

system. Section 3.3 formulates a personnel capability assessment problem in a software development setting to demonstrate the implementation of the solution approach. The last section provides conclusion remarks, contributions to the literature, and ideas for future research.

3.3 Fuzzy Expert System Architecture

An expert system is a "computer-based system that emulates the reasoning process of human experts within a specific domain of knowledge" [85]. An expert system generally consists of three components: a user interface, usually a graphical user interface (GUI), that receives user inputs and shows final results; a logic system to make inferences about data; and a data repository used to store/receive information. Figure 3.1 shows the general components of an expert system and the bidirectional relationship that often exists among them.
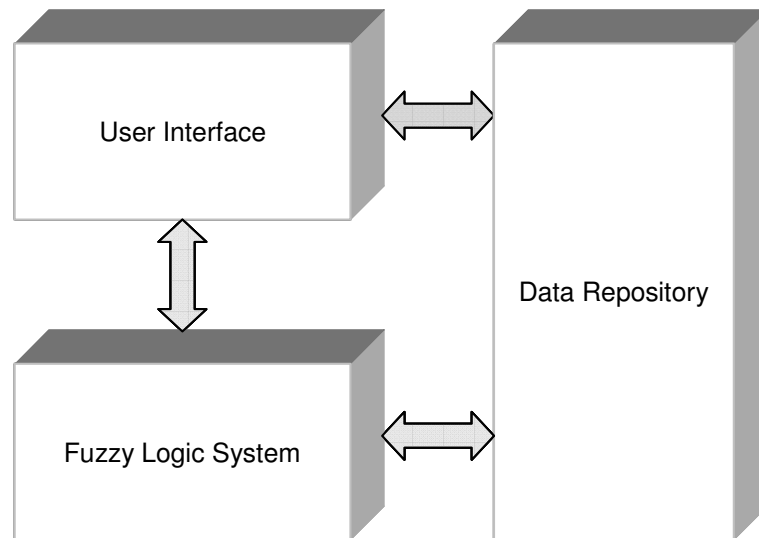
Figure 3.1 - Conceptual Fuzzy Expert System

Figure 3.2 shows the proposed high-level software architecture developed from the conceptual expert system shown in Figure 3.1. It corresponds to a layered architecture that minimizes dependencies between components. This type of architecture allows the system to be flexible to accommodate future expansions such as different subcomponents in the data layer (e.g., data files, Oracle database), or various types of presentation subcomponents (e.g., command line, Java GUI, C# GUI). The following subsections describe each of the architecture layers in mode detail.
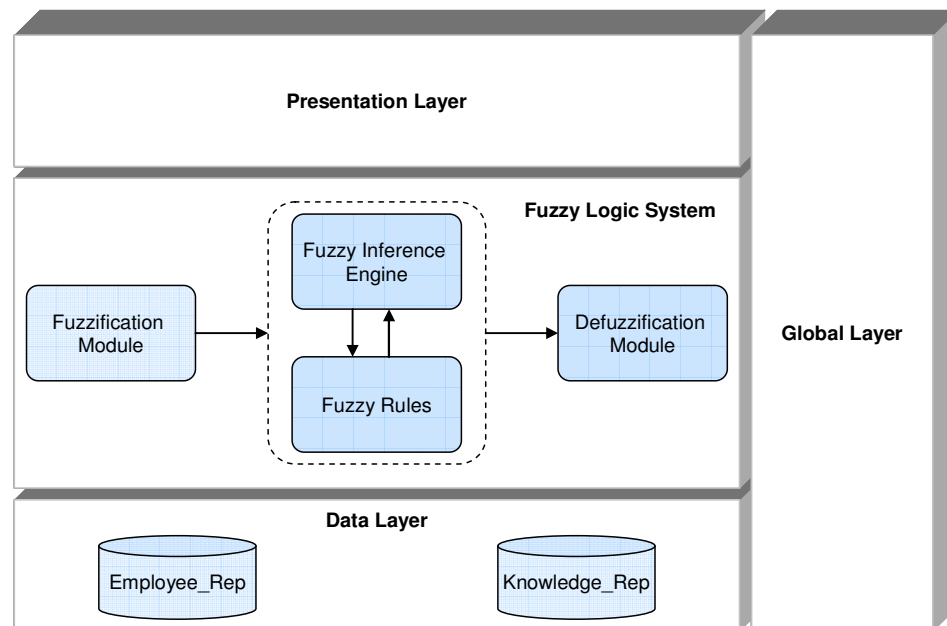
Figure 3.2 - Layered Software Architecture

3.3.1   Presentation, Data, and Global Layers

The presentation layer corresponds to any type of interface used to gather inputs and show information to users. The two commonly used interfaces are command lines and GUIs. Usually GUIs are preferred due to their user-friendly interfaces that facilitate the data retrieving/displaying activities.

The data layer is composed of two repositories: Knowledge_Rep and Employee_Rep. The Knowledge_Rep repository contains a set of fuzzy rules to be used by the logic system to make inferences. In addition, this repository manages the set of membership functions used to model levels of expertise of employees in various skills, and those that are used to establish fuzzy implications between skill levels.

The Employee_Rep respository manages crisp rating values representing the capabilities of resources in various skills. For example, consider a rating scale from 0-5 and let $\{s, rt\}$ denote the crisp rating rt of a resource in skill s, where the number of skills in the resource's skill set is three. Then, values like $\{1, 2.5\}$, $\{2, 4\}$, and $\{3, 1\}$ would indicate that the crisp capability rating of the resource in the first skill is 2.5, in the second skill is 4, and in the third skill is 1.

The global layer acts as a mediator for the rest of the layers to communicate with each other. This is possible because the global layer is equipped with information regarding the subcomponents responsible for any request. For instance, whenever the presentation layer wants to retrieve information from the data layer, the presentation layer makes a request using an interface provided by the global layer. This interface guarantees that the request is forwarded to the appropriate subcomponent in the data layer. This means that the presentation layer requests information without worrying about the type of data repository subcomponent used in the data layer to hold such information. When the required information is gathered, the data layer provides the desired information to the presentation layer through the global layer. This type of architecture minimizes dependencies between layers by making them communicate with each other only through the global layer. Therefore, new subcomponents added to the

data layer to handle requests from the presentation layer, for example, will not require any modifications to the presentation layer. This type of architecture follows the object-oriented paradigm by being reusable, robust, and easy to maintain.

3.3.2 Fuzzy Logic System

Logic is the study of methods for reasoning [85]. Classical logic relies on the assumption that propositions are either true or false. Fuzzy logic, on the other hand, relies on the assumption that propositions are true to some degree. This way, fuzzy logic allows logical reasoning with partially true imprecise statements.

The following subsections describe the type of fuzzy reasoning employed in the proposed expert system. First, a description of fuzzy sets, fuzzy propositions, and fuzzy logical operators are presented. The understanding of these concepts is fundamental to comprehend the description of the fuzzy logic system.

3.3.2.1 Fuzzy Sets

Fuzzy set theory allows parameters to be represented with simple linguistic terms. The functions used to develop fuzzy sets are called membership functions, and their job is to map elements from any universal set into real numbers within the range 0-1. The resulting values represent the degrees of membership of elements to particular fuzzy sets, where values closer to 1 represent higher degrees of membership. Figure 3.3 shows an example of a triangular fuzzy set to denote LOW_CAPABILITY of employees in a particular skill as a function of years of experience. Here, a resource with one year of experience fully belongs to the fuzzy set; therefore the degree of membership is 1.0. Employees with one and a half years of experience have a 0.5 degree of membership to

the fuzzy set, and any employee with more than two years of experience does not belong

to the fuzzy set at all.
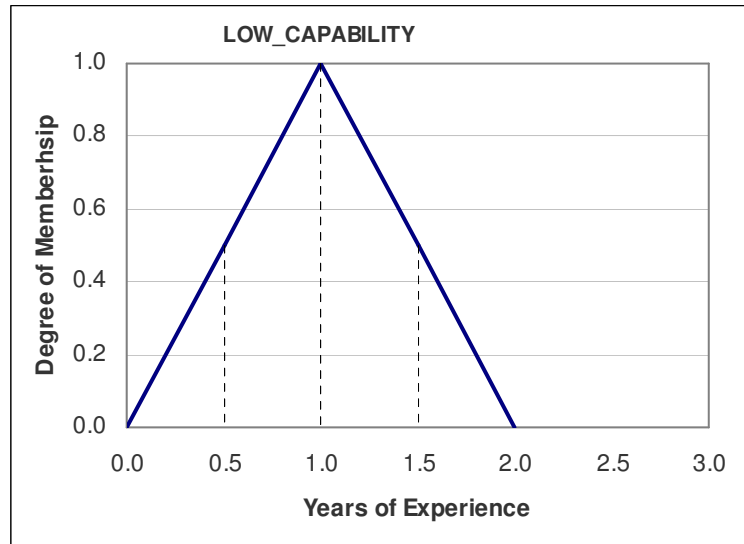
Figure 3.3 - Example of Triangular Fuzzy Set

Fuzzy set theory provides various forms of membership functions. The capability

to determine appropriate membership functions in the context of each particular

application is crucial for making fuzzy set theory practically useful [85]. Triangular,

trapezoidal, and linear shapes of membership functions are most commonly used to

represent fuzzy numbers. Triangular membership functions are usually preferred due to

their combination of solid theoretical basis and simplicity [86]. However, there are

situations that require more complex functions to more accurately represent the degrees

of membership of elements to fuzzy sets.

There are several methods for constructing membership functions. Klir and Yuan

[85] discussed direct and indirect methods that involve single or multiple experts. These

49

methods involve gathering and processing responses from experts in particular fields or from extensive literature reviews.

3.3.2.2 Fuzzy Propositions

A fuzzy proposition is a statement that has a truth value associated with it. For example, the statement "element x belongs to set A" has a truth value in the range of [0,1]. A truth value of zero means that x does not belong to set A. Similarly, a truth value of one means that x completely belongs to set A. Truth values between zero and one, also known as partial truth, imply that x belongs to set A to some degree. The partial truth of a fuzzy proposition is represented by a degree of truth similar to degrees of membership of elements to fuzzy sets.

A common type of proposition used in fuzzy logic is the conditional and unqualified proposition. The objective of this proposition is to denote a relationship between elements from either similar or different sets. This type of proposition is expressed with an "if-then" statement such as "if x belongs to set A, then y belongs to set B". The first part of the proposition (i.e., the "if" part), is called the antecedent; the second part is called the consequence. Unconditional and unqualified propositions are used for imprecise reasoning to describe the decision process that human beings undergo to express cause and effect relationships.

A proposition with an antecedent composed of only one statement is called a singleton. When the antecedent contains more than one statement (i.e., non-singleton proposition), fuzzy logical operators are used to resolve the antecedent into a single truth

value. An example of a non-singleton proposition is "if x belongs to set A AND x belongs to set B, then x belongs to set C".

3.3.2.3 Fuzzy Logical Operators

Similar to classical set theory, there are three logical operators that are commonly used with fuzzy sets. These are the intersection, union, and complement, which correspond to AND, OR, and NOT operators, respectively. For fuzzy sets A and B, the intersection corresponds to all the elements that are included simultaneously in both sets, and is represented as $A \cap B$. Equations (3.1) and (3.2) show the commonly used formulas for calculating the intersection between two fuzzy sets. The union of both sets, represented as $A \cup B$, corresponds to elements that are in either set. Equations (3.3) and (3.4) show the commonly used formulas to determine the union between two sets. The complement of a set, denoted as $\overline{A}$ for set A, corresponds to all elements that are not in the set. Equation (3.5) shows the formula for calculating the complement of a set.

$$\mu_{A \cap B}(x) = \min[\mu_A(x), \mu_B(x)] \tag{3.1}$$

$$\mu_{A \cap B}(x) = \mu_A(x)\,\mu_B(x) \tag{3.2}$$

$$\mu_{A \cup B}(x) = \max[\mu_A(x), \mu_B(x)] \tag{3.3}$$

$$\mu_{A \cup B}(x) = \mu_A(x) + \mu_B(x) - \mu_A(x)\,\mu_B(x) \tag{3.4}$$

$$\mu_{\overline{A}}(x) = 1 - \mu_A(x) \tag{3.5}$$

3.3.2.4 Fuzzy Reasoning

Fuzzy reasoning is the process of developing logical inferences from imprecise premises. One way to develop fuzzy inferences is via the compositional rule of inference, which was introduced by Zadeh in 1975 [87]. This inference rule has been the foundation for various fuzzy reasoning methods presented in the literature [88]. One of such methods, namely the Mamdani Max-Min approach [89], is the selected inference method in this research. The following subsections provide a description of the compositional rule of inference and the Mamdani Max-Min approach.

3.3.2.4.1 Generalized Modus Ponens and the Compositional Rule of Inference

A widely used inference rule in classical logic is the modus ponens, also known as forward chaining. It states that a conclusion can be inferred given a conditional proposition and a fact. For example, a modus ponens type of inference using the relationship between the levels of expertise of an employee in two skills can be expressed as shown in Table 3.1.

Table 3.1 - Classical Modus Ponens Form

Type of Statement	Statement
Proposition	$Knowledge\_Skill\_1 = x$
Proposition	$Knowledge\_Skill\_1 \Rightarrow Knowledge\_Skill\_2$
Conclusion	$Knowledge\_Skill\_2 = x$

This simply says that if an employee has expertise x in Skill_1, and knowledge in Skill_1 implies expertise in Skill_2, then it can be inferred that the employee has expertise x in Skill_2. Notice that this type of inference structure deals with binary-valued

propositions. That is, the solution set to describe the expertise of an employee in a skill is {0,1} when using the classical modus ponens.

To be used for fuzzy reasoning purposes, the classical modus ponens is customized through a process called the generalized modus ponens. Generalization of the classical modus ponens is achieved in three ways. First, the generalized version considers degrees of membership of elements to fuzzy sets. From the previous example, this means that the solution set to describe the expertise of an employee in a skill is expanded from {0,1} to [0,1]. Second, propositions showing completely true implications via the '$\Rightarrow$' symbol are replaced with fuzzy rules. Recall that a fuzzy rule is basically a conditional and unqualified proposition that implies a fuzzy relationship between an antecedent and a consequence. This relationship, also known as a fuzzy implication, is not explicit but rather embedded within the proposition and determined for all values of antecedents and consequences [90]. The literature presents various approaches to determine fuzzy implications (see [85]).

The third way to generalize the classical modus ponens is by using the compositional rule of inference shown in equation (3.6) for reasoning. Assuming that R is a fuzzy relation on $X \, x \, Y$, and A and B are fuzzy sets on X and Y respectively, equation (3.6) can obtain degree of membership $\mu_B(y)$ for all $y \in Y$ given a fuzzy implication R and a degree of membership $\mu_A(x)$ [85].

$$\mu_B(y) = \sup_{x \in X} \min[\mu_A(x), R(x, y)] \tag{3.6}$$

This means that using the compositional rule of inference, a fuzzy conclusion can be obtained given a fuzzy rule and a fuzzy fact. This generalized modus ponens form of inference is shown in Table 3.2.

Table 3.2 - Generalized Modus Ponens Form

Type of Statement	Statement
Fuzzy Rule	If x is A, Then y is B
Fact	$\mu_A(x)$
Fuzzy Conclusion	$\mu_B(y)$

3.3.2.5   Mamdani Max-Min Inference Approach

The inference approach used in this research is the Mamdani Max-Min method, which employs the generalized modus ponens process for each fuzzy rule in the system. This approach follows the multiconditional reasoning structure shown in Table 3.3.

Table 3.3 - Multiconditional Reasoning Structure

Type of Statement	Statement
Rule 1	If x is A_1, then y is B_1
Rule 2	If x is A_2, then y is B_2
Rule 3	If x is A_3, then y is B_3
....	....
Rule n	If x is A_n, then y is B_n
Fact	$\mu_A(x)$
Conclusion	$\mu_B(y)$

The Mamdani method specifies that the fuzzy implication *R* for each rule, which is required by the compositional rule of inference, equals the truth value of the antecedent. More specifically, the fuzzy relation *R* for singleton fuzzy rules (i.e., antecedents composed of only one statement) equals the degree of membership of the only statement in the antecedent (see Figure 3.4a). For non-singleton fuzzy rules (see Figure 3.4b), the relation *R* is computed as the intersection of the statements in the antecedent via the minimum logical operation using equation (3.1).
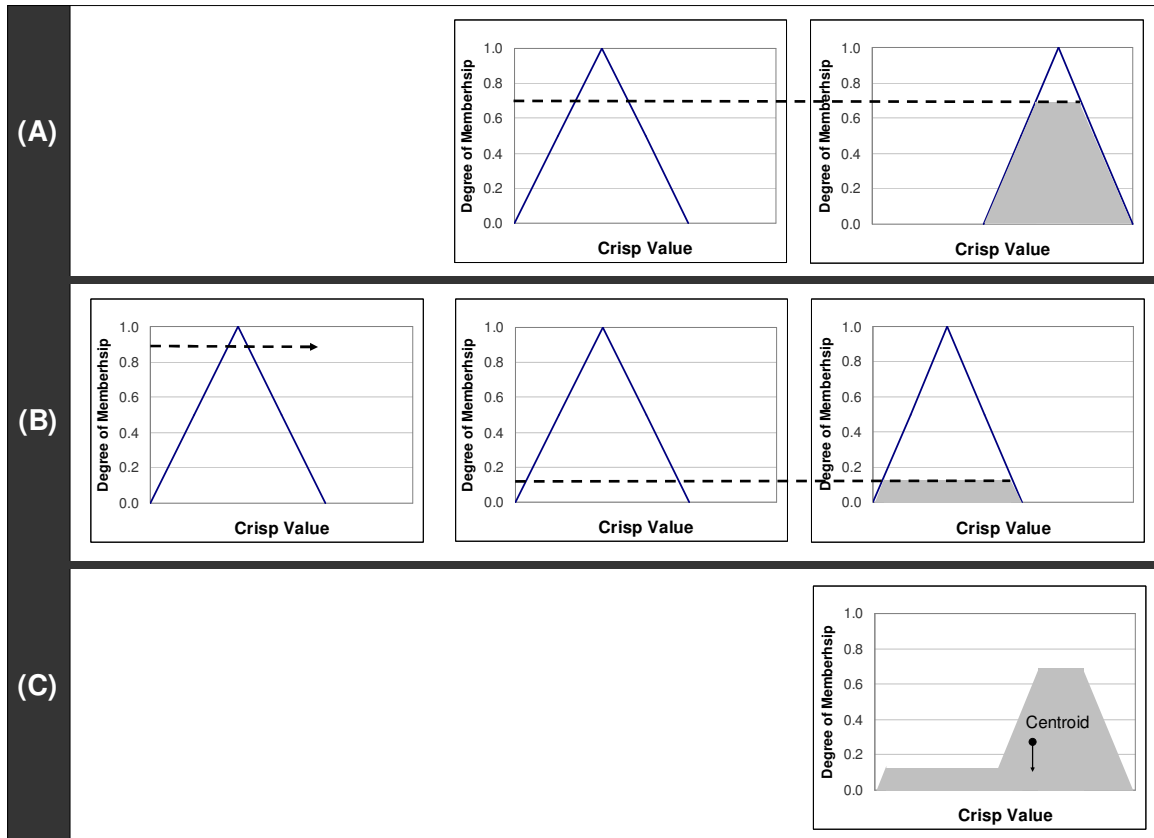
Figure 3.4 - Mamdani Max-Min Inference

An antecedent with a truth value greater than zero automatically implies that its consequence also has a truth value greater than zero. In fuzzy reasoning terms, a true

antecedent causes a rule to fire. The fired rules are then combined into a new fuzzy set which will be used to make final inferences (see Figure 3.4c).

3.3.2.6 Defuzzification

Defuzzification is the process of converting a set of fuzzy conclusions into a single crisp value. Several methods are available for defuzzification. One of such methods is the center of gravity approach, which calculates the area of a combination of fuzzy sets using integrals. A more commonly used method which is reliable, less complicated, and less time consuming is the weighted average method shown in equation (3.7) to approximate the center of gravity [91]. Figure 3.4c shows an example of the estimated center of gravity of a fuzzy set composed of two fired fuzzy rules.

$$y = \frac{\sum_{j=1}^{r} \mu_j * s_j}{\sum_{j=1}^{r} \mu_j} \qquad (3.7)$$

In equation (3.7), μ_j is the degree of membership of the fuzzy set resulting from fuzzy rule r, and s_j is the center of gravity of the fuzzy set resulting from fuzzy rule r.

3.3.3 Expert System Data Flow

This section describes the stepwise flow of data within the expert system architecture as shown in Figure 3.2. Following is a concise description of each step. Implementation details are later described through an example in Section 3.3.

3.3.3.1 Pre-conditions

The solution approach requires three pre-conditions to be satisfied. First, decision-makers must agree on a crisp rating scale to evaluate employees' capabilities. Second, linguistic terms (e.g., High, Low) must be established to denote the levels of expertise of employees in skills. Third, fuzzy sets must be created for each linguistic term to determine the degrees of membership of crisp evaluation ratings in each fuzzy set.

3.3.3.2 Step 1: User Inputs

In the first step, a subcomponent in the presentation layer (e.g., GUI) gathers user information to define three critical problem parameters. The first parameter involves the selection of skills that are of interest to decision makers. The second parameter involves a decision regarding the personnel to be evaluated (i.e., either all available resources or a selected group). The third parameter is the selection of the membership functions (e.g., triangular, trapezoidal, sigmoidal) to be used in the fuzzy logic system to fuzzify employees' expertise ratings.

3.3.3.3 Step 2: Fuzzification

In the second step, the presentation layer subcomponent forwards user data to the fuzzy logic system to begin the capability assessment process. Then, the logic system interacts with the Employee_Rep subcomponent to collect the crisp personnel capability evaluation ratings representing the expertise of employees in various skills. Subsequently, the logic system interacts with the Knowledge_Rep subcomponent to

convert the crisp evaluation ratings into fuzzy ones based on the types of membership functions selected by the user through the presentation layer.

3.3.3.4 Step 3: Inference Engine and Fuzzy Rules

Based on a set of pre-determined fuzzy rules and actual expertise ratings, the system evaluates the complete capability set of a resource to make inferences about his/her fuzzy expertise in a skill that is required for a task.

3.3.3.5 Step 4: Defuzzification

The system employs the weighted average defuzzification method to convert the capability of the resource in the required skill from a fuzzy value to a crisp one.

3.3.3.6 Step 5: Display Results

The fuzzy logic system forwards its data inference conclusions to the presentation layer. Finally, the presentation layer displays the results to the user.

3.4 Example - Software Development Setting

A capability assessment problem in a software development setting was formulated to illustrate the implementation of the solution approach. This particular setting is relevant given that personnel assignments are considered one of the most critical decisions that affect the performance and quality of software projects [6]. This is confirmed by Tsai et al. [43] with the following quote: "evidence reveals that the failure of software development projects is often a result of inadequate human resource project planning". Considering that effective capability assessments are critical for efficient

personnel assignments, efforts to improve capability evaluations are necessary to significantly upgrade the outcome of personnel assignments decisions.

Quality, as evidenced in the U.S. General Accounting Office Report in [2], continues to be a major struggle to software companies. The report states that in 2004 the U.S. Department of Defense spent nearly 8 billion dollars to rework software because of quality-related issues. Even more important than huge monetary costs is the fact that software failures, especially in safety-critical systems, may result in life-threatening situations.

Another reason that makes this example relevant is that it directly addresses areas of future research from the current software development literature. Recently, Otero et al. [5] presented an approach for resource allocation in software projects. Their methodology used precise parameters to determine capabilities of resources. The authors acknowledged the limitations of using precise parameters and encouraged researchers to develop methodologies that incorporate fuzzy parameters instead.

3.4.1 Problem Statement and Pre-conditions

The problem formulated to implement the solution approach involves evaluating the capabilities of various software engineers in the C++ programming language. For this example, two experts from leading software engineering companies agreed to act as decision-makers for developing the required fuzzy rules. Using real industry experts adds value to this example and helps to properly execute the solution approach. Both decision makers have an average of 16 years of experience working for top U.S.A.

organizations that specialize in the development of software applications for the defense industry.

Following the solution approach described in the previous section, decision makers must ensure that pre-conditions are satisfied. The first pre-condition is to establish a crisp rating scale to evaluate skill levels. The decision-makers agreed on a rating scale from 0 to 5, where higher ratings represent higher evaluations. This rating scale is commonly used for yearly evaluations of the performance of engineers.

The second and third pre-conditions involve establishing fuzzy sets to associate crisp evaluation ratings with degrees of membership. The selected linear and triangular fuzzy sets, shown in Figure 3.5, correspond to the following levels of expertise: None, Novice, Proficient, Highly Proficient, and Expert.
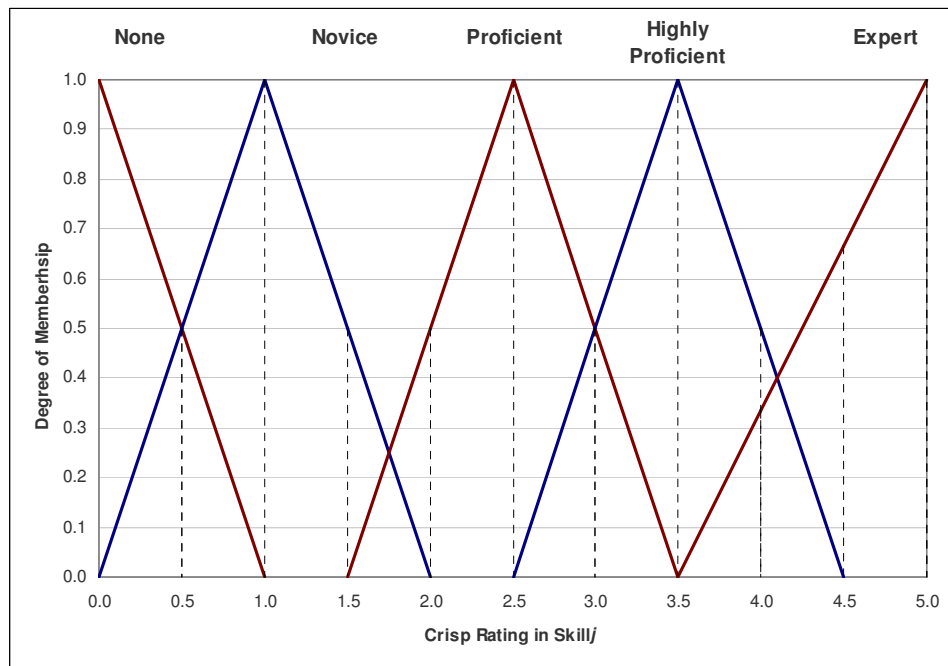
Figure 3.5 - Fuzzy Sets of Skill Levels

The membership functions for each fuzzy set are shown in Figure 3.6.

$$\mu_{None}(x) = \begin{cases} 0 & \text{for } x > 1 \\ 1 - x & \text{for } 0 \le x \le 1 \end{cases}$$

$$\mu_{Novice}(x) = \begin{cases} 0 & \text{for } x < 0.5 \text{ and } x > 2.5 \\ x - 0.5 & \text{for } 0.5 \le x \le 1.5 \\ 2.5 - x & \text{for } 1.5 < x \le 2.5 \end{cases}$$

$$\mu_{Proficient}(x) = \begin{cases} 0 & \text{for } x < 1.5 \text{ and } x > 3.5 \\ x - 1.5 & \text{for } 1.5 \le x \le 2.5 \\ 3.5 - x & \text{for } 2.5 < x \le 3.5 \end{cases}$$

$$\mu_{Highly\,Proficient}(x) = \begin{cases} 0 & \text{for } x < 2.5 \text{ and } x > 4.5 \\ x - 2.5 & \text{for } 2.5 \le x \le 3.5 \\ 4.5 - x & \text{for } 3.5 < x \le 4.5 \end{cases}$$

$$\mu_{Expert}(x) = \begin{cases} 0 & \text{for } x < 3.5 \\ \dfrac{2(x - 3.5)}{3} & \text{for } x \ge 3.5 \end{cases}$$

Figure 3.6 - Membership Functions for Fuzzy Sets of Skill Levels

3.4.2   User Inputs

The definition of the problem parameters are as follows. First, the skill that is of interest to decision makers is the level of expertise of personnel in the C++ programming language. Second, seven software engineers are selected as the personnel to be evaluated. Third, the membership functions to be used to fuzzify crisp evaluation ratings are those shown the previous section.

3.4.3 Fuzzification

The crisp evaluation ratings for the software engineers in the C++ and Java programming languages are shown in Table 3.4. Evaluation ratings in the Java skill were included because they can potentially improve the skill ratings of engineers in the C++ language. The decision makers explained that in practice, a crisp evaluation rating of an engineer in a particular skill is heavily based on the number of years of industry experience with the skill. Therefore, it is common in industry to encounter situations were an engineer would have significantly different ratings in two similar skills (e.g., Java and C++).

Table 3.4 - Crisp Evaluation Ratings in Various Programming Languages

Resources	Crisp Evaluation Ratings	
	C++	Java
Engineer_1	1.0	3.0
Engineer_2	2.5	3.5
Engineer_3	2.5	4.5
Engineer_4	0.5	5.0
Engineer_5	2.0	3.5
Engineer_6	1.5	4.0
Engineer_7	3.5	2.5

Using the membership functions from the previous section, the fuzzified evaluation ratings obtained for each engineer are shown in Table 3.5.

Table 3.5 - Fuzzy Evaluation Ratings

Fuzzy Set	Degrees of Membership													
	Engineer_1		Engineer_2		Engineer_3		Engineer_4		Engineer_5		Engineer_6		Engineer_7	
	C++	Java	C++	Java	C++	Java	C++	Java	C++	Java	C++	Java	C++	Java
No	--	--	--	--	--	--	--	--	--	--	--	--	--	--
Novice	0.5	--	--	--	--	--	0.5	--	0.5	--	1.0	--	--	--
Proficient	--	0.5	1.0	--	1.0	--	--	--	0.5	--	--	--	--	1.0
Highly Proficient	--	0.5	--	1.0	--	--	--	--	--	1.0	--	0.5	1.0	--
Expert	--	--	--	--	--	0.67	--	1.0	--	--	--	0.33	--	--

62

3.4.4 Inference Engine

Table 3.6 shows the set of fuzzy rules that was developed by the decision makers. Using rule number 5 as an example, the table reads as follows: If the initial C++ rating is Novice, and the Java rating is Highly Proficient, then the Modified C++ rating is Proficient.

Table 3.6 - Fuzzy Rules for C++

Rule No.	Skills		Modified C++ Rating
	C++	Java	
1	None	Proficient	Novice
2	None	Highly Proficient	Proficient
3	None	Expert	Proficient
4	Novice	Proficient	Novice
5	Novice	Highly Proficient	Proficient
6	Novice	Expert	Highly Proficient
7	Proficient	Highly Proficient	Highly Proficient
8	Proficient	Expert	Highly Proficient
9	Highly Proficient	Expert	Expert

These rules were developed for cases were particular levels of knowledge in the Java language result in improved skill ratings in the C++ language. Therefore, in cases were none of the rules apply, the initial skill rating in C++ is used. For example, consider the case where a software engineer possesses a 2.5 crisp rating in C++ and no experience in Java. This means that the fuzzy rating in C++ is Proficient and in Java is None, which causes none of the rules from Table 3.6 to fire. In this case, the initial crisp rating in C++ cannot be improved based on the actual Java knowledge of the engineer. Therefore, the capability assessment of the engineer in C++ remains at the initial crisp rating of 2.5.

As an example, Figure 3.7 shows the fuzzy inference process for Engineer_6. Based on the initial crisp evaluation ratings of this engineer, only Rules #5 and #6 are fired. For

each of these two rules, equation (3.1) is used to resolve the AND logical operator of the antecedent into a single degree of membership $\mu_{antecedent}(x)$. This value also represents the degree of truth of the antecedent. Recall that in the Mamdani process, the truth value of the antecedent equals the fuzzy relation R that is embedded within the rule. Hence, for Rule #5 the fuzzy relationship R between the Novice C++ and Highly Proficient Java fuzzy sets is calculated as R = min (μ_{Novice_C++} = 1.0, $\mu_{Highly\,Pr\,oficient\_Java}$ = 0.5) = 0.5 = $\mu_{antecedent}(x)$. For Rule #6, the fuzzy relationship R between the Novice C++ and Expert Java fuzzy sets is calculated as R = min (μ_{Novice_C++} = 1.0, μ_{Expert_Java} = 0.33) = 0.33 = $\mu_{antecedent}(x)$. Subsequently, the compositional rule of inference is invoked using equation (3.6) to develop a modified fuzzy set for each rule. Therefore, the fuzzy inference for Rule #5 is $\mu_{ModifiedC++}(x)$ = $\sup_{x\in X}$ min[$\mu_{antecedent}(x)$, R(Novice_C++, Highly_Proficient_Java)] = $\sup_{x\in X}$ min[0.5, 0.5] = 0.5. Since the Modified C++ rating for Rule #5 corresponds to a Proficient fuzzy set, the inferred conclusion based on this rule is that $\mu_{Proficient\_C++}$ = 0.5. Similarly for Rule #6, the inferred conclusion is that $\mu_{Highly\,Pr\,oficient\_C++}$ = 0.33.
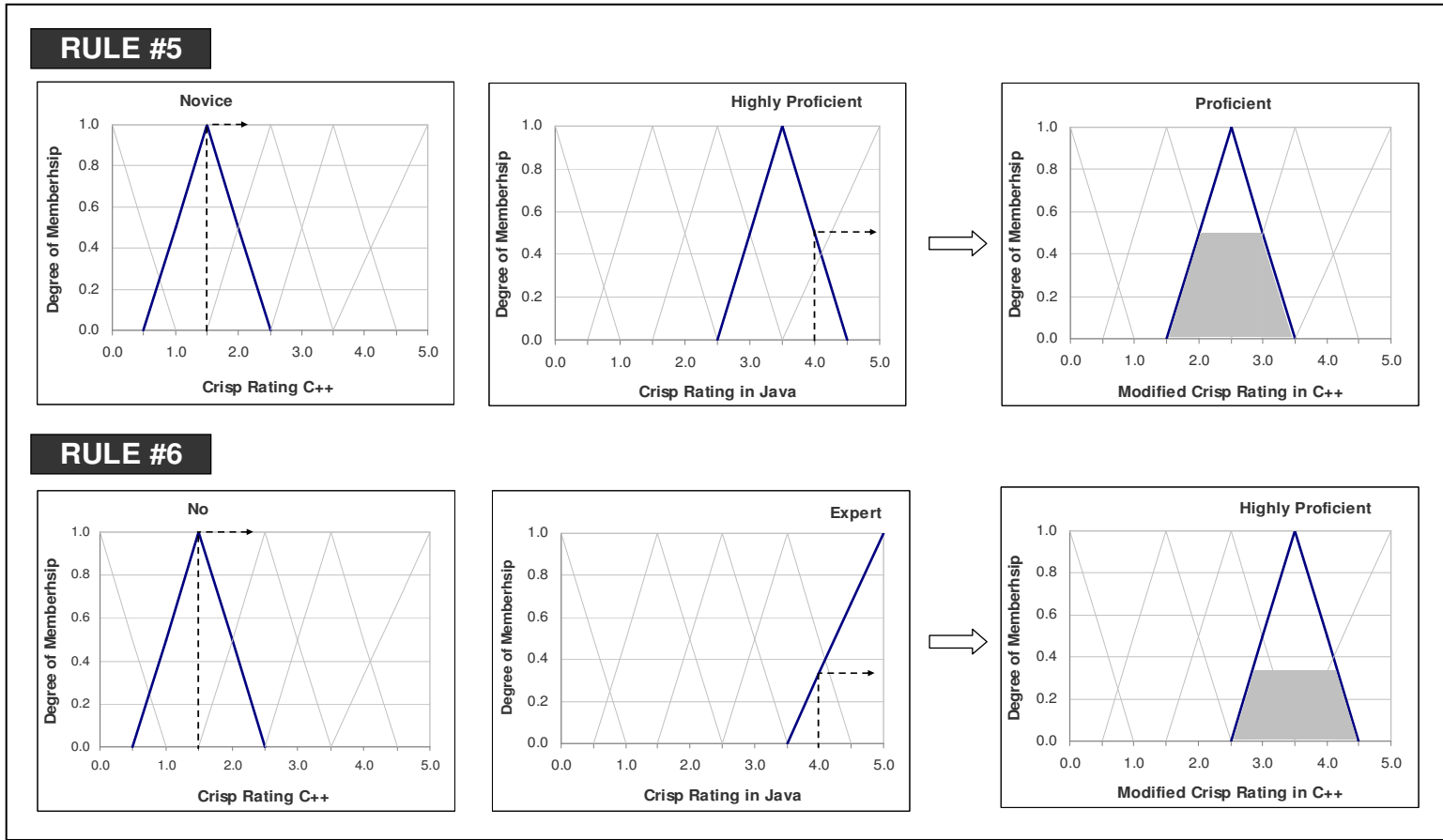
Figure 3.7 - Capacity Assessment for Engineer_6

65

Figure 3.8 shows the combination of the inferred fuzzy sets into a single set to begin the defuzzification process via the weighted average center of gravity. Using equation (3.7), the defuzzified rating is computed as $\dfrac{0.5(2.5)+0.33(3.5)}{0.5+0.33}$ = 2.9. This means that the evaluation crisp rating in C++ of Engineer_6 is improved from 1.5 to almost 3.0 due to the engineer's level of expertise in Java.
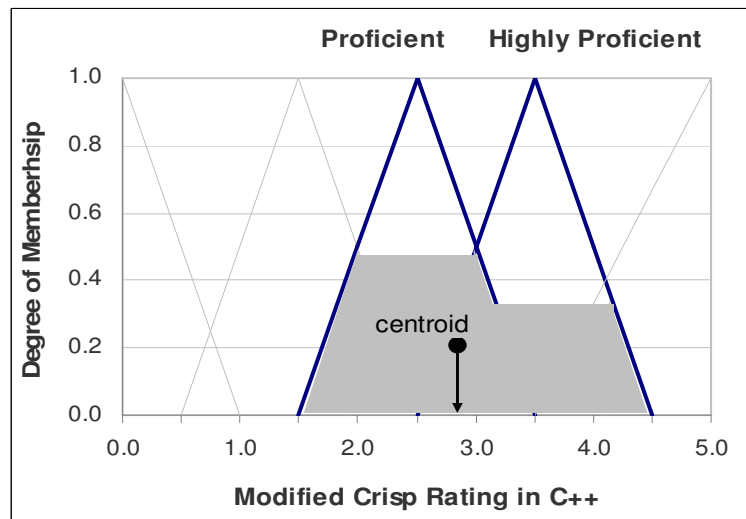
Figure 3.8 - Defuzzified Rating in C++ (Modified)

Table 3.7 shows the modified C++ ratings for each of the engineers. Notice that the initial and modified ratings for Engineer_7 are equal since none of the fuzzy rules were fired based on the engineer's initial C++ and Java ratings.

Table 3.7 - Initial and Modified C++ Ratings

Resources	Initial C++ Rating	Modified C++ Rating
Engineer_1	1.0	2.0
Engineer_2	2.5	3.5
Engineer_3	2.5	3.5
Engineer_4	0.5	2.5
Engineer_5	2.0	3.0
Engineer_6	1.5	3.0
Engineer_7	3.5	3.5

3.5   Summary and Contributions

This research presents a four-layered fuzzy expert system architecture for evaluating personnel capabilities. Although a description of each of the layers is presented, the main emphasis of this research is on the development of the fuzzy logic system layer. A personnel capability assessment problem in a software development setting was formulated to demonstrate the implementation of the solution approach.

There are two major contributions that this research study makes to the personnel capability assessment body of knowledge. The first significant contribution is the introduction of a high-level layered architecture where each layer is adaptable to context-specific subcomponents. That is, each layer can be customized with different sub-components without major changes to the architecture. This is accomplished through a global layer that is used as the only channel of interaction between any two layers. Therefore, implementation details of any layer are hidden from the others. This way, a layer is not susceptible to changes due to modifications in other layers. This provides decision makers the flexibility to add/delete/modify subcomponents in any layer based on

their particular needs without having to incur in expensive architectural system modifications.

The second significant contribution from this work is the approach taken to resolve the following three main areas of the personnel capability assessment problem: modeling personnel levels of expertise, establishing relationships between skills, and making inferences about the capabilities of personnel. These critical areas are considered to be naturally imprecise; therefore, they are established using fuzzy concepts. Personnel levels of expertise are modeled with fuzzy sets instead of using the common classical set theory. Relationships between skills are described with fuzzy rules, and capability assessments are performed via approximate reasoning based on the compositional rule of inference. This realistic representation of imprecise parameters and activities with fuzzy concepts has the potential to provide a high practical value to the expert system proposed in this research.

3.5.1 Research Extensions

A major challenge for any researcher is to develop new methodologies that become widely accepted by practitioners. To achieve this, it is important for researchers to properly market their solution approaches by bringing these novel methodologies into industry scenarios to show field experts the capabilities of such new approaches. With this in mind, the approach developed in this research needs to be applied to different industry settings to validate its applicability and acceptability. For this, it is necessary to complete the design phase of the expert system and move into the coding phase. Since this research provides the high-level software design architecture, the next step would be

to divide the architecture into components and develop detailed designs for each component using object-oriented tools such as class diagrams. The final product must include proper software engineering documentation, such as: software requirements specification, software design document, software manual, and test description document.

Another potential research extension is to conduct a survey analysis to investigate if it is reasonable to develop baselines of membership functions for general/common skills in particular environments. For example, it may be possible to interview experts from different software development organizations to come up with fuzzy sets for technical capability assessments that can be used as standards across companies. A similar survey analysis can be conducted to examine the possibility of establishing fuzzy rules' baselines to describe the relationship between various skills.

CHAPTER 4

A FUZZY GOAL PROGRAMMING MODEL FOR SKILL-BASED RESOURCE ASSIGNMENT PROBLEMS

4.1 Abstract

This research presents a fuzzy goal programming (FGP) model for personnel assignments in skill-based environments. The prioritized goals for each resource assignment are to meet desired target values for technical expertise, team parameters, and personnel preferences. These target values are represented with fuzzy sets which are developed with the help of decision makers. A personnel assignment problem in a software development industrial setting is formulated to demonstrate the proper implementation of the solution approach. Two software engineering field experts acted as decision-makers and participated in the development of the fuzzy sets for the goals.

The contribution of this research to the literature is two-fold. First, it develops a new FGP model for personnel assignments that considers imprecise parameters such as personnel capabilities and tasks' requirements. Second, it presents an innovative methodology that is capable of representing relative priorities of skills and tasks. This methodology, denoted as membership function relaxation, is incorporated into the FGP specification. To the best of our knowledge, this study presents the first multi-objective optimization model that simultaneously considers the following fuzzy parameters:

competence levels of resources in various skills, motivation levels of resources with tasks, priorities of tasks and skills, and required levels of skills.

4.2   Introduction

Effective personnel assignment approaches in skill-based environments are essential to achieve high-quality products in a timely manner and within budget constraints. Skill-based environments are characterized by the need to assess the ability of candidates to successfully complete specific tasks. Examples of such environments are: software engineering, research and development (R&D), and healthcare organizations.

The review of current literature highlights research opportunities to improve the effectiveness of personnel assignment decisions. One of these opportunities which represents a significant contribution to the literature involves the development of enhanced assignment models that consider critical parameters which are typical of skill-based resource assignment situations. Table 4.1 shows some of these parameters and provides possible definitions for these factors in various industrial settings. A major challenge is to effectively model these essential parameters, given their highly imprecise nature. Moreover, complexity in the decision-process increases when there are several levels of these parameters. Due to the lack of adequate methodologies to undertake these complexities, decision-makers would typically approach the problem as a non-skill-based assignment. That is, human resources are considered as uniform entities. This results in ignoring important characteristics such as specific capability levels and motivation factors [38].

Table 4.1 - Characteristics of the General Skill-Based Personnel Assignment Problem

Types of parameters	Characteristic	Examples		
		Software Engineering	Health Care	R&D Projects
Resources	Imprecise competence level	The level of knowledge of a software developer in C++ is described as *average* .	The level of fluency of a registered nurse (RN) in the Italian language is described as *poor* .	The level of knowledge of a researcher in Data Envelopment Analysis is *excellent* .
	Motivation to work in particular tasks	Skill Preference: A software developer prefers a task that involves developing code in C++.	Skill Preference: An RN enjoys and has experience working with elderly patients.	Skill Preference: A researcher prefers working with projects that involve the use of non-parametric analyses.
		Workplace Preference: A software developer prefers a task that does not require overtime.	Workplace Preference: An RN prefers to assist Dr. Jones, instead of assisting Dr. Smith.	Workplace Preference: A researcher prefers working with projects related to advancing the quality of education of young students.
Task	Imprecise priorities of tasks	A safety critical task (i.e. involves human safety) is *more* important than any other task.	Assisting a patient that is recovering from a heart attack is *much more important* than attending another patient with minor cuts.	Research studies that are expected to have *major impacts* to society are *more important* than studies with *lower expected impacts* to society.
	Imprecise priorities of skills required	Programming language (PL) experience is *more important* than domain experience for task X, but domain experience is *more important* than PL experience for task Y	To assist patient X, an RN's fluency in foreign languages is *more important* than the RN's knowledge on cancer treatments.	For research study X, knowledge of Markov processes is *much more important* than knowledge in a particular statistical software package.
	Imprecise level of skill required	The development of a particular Windows application for Project X requires an *expert* level of skill in Visual Basic programming.	To attend patient X, the required level of fluency in the Italian language is expressed as *very fluent* .	Research study X requires a researcher with a *high level* of knowledge in Markov processes.
	Imprecise task complexity and duration	The time that will take to complete the development of a software application is described as *long* .	The time that will take to diagnose and treat a patient's condition is described as *short* (depending on the stage).	The time that will take to complete research project X cannot be accurately estimated. .
Environment	Fixed limited resources	A software manager must assign readily available software engineers to software tasks.	A hospital manager must assign readily available registered nurses to patients.	The manager of a R&D division must assign available researchers to a set of research studies.
	Limited or no training time	A project that is running late needs a software developer to design and develop a Windows application.	An RN attending a patient with several cuts does not have time to learn how to sanitize cuts.	A proposal for a funded research study related to stochastic processes did not bid for a researcher to be trained in Markov processes.

Another common and challenging situation in skill-based environments is that
candidates with the exact required skills to work on a task are seldom available [5]. This

is mainly due to the continuous and rapid introduction of new technologies to improve the development of products. This limitation often results in inefficient allocation of resources that increase costs and the probability of developing unreliable products [5], [62].

Challenges such as the ones mentioned above drive researchers to advocate for improved personnel assignment models. For example, Acuña et al. [6] mentioned the need to incorporate a diverse set of factors related to employees such as personal preferences, psychological tests, technical knowledge and skills, career goals, promotion records, and job leveling. Baykasoglu et al. [37] also discussed future research needs in the area of team formation and assignment of tasks based on individual skills. The authors stated that "there is a need to develop analytic models and software systems that can incorporate important factors and multiple objectives". Furthermore, there are other studies such as [43] where the authors acknowledged critical limitations in their model, including the absence of quality and performance parameters.

In the study by Faraj and Sproull [64], the authors concluded that "while expertise is a necessary input, its mere presence on the team is not sufficient to affect performance effectiveness if team members cannot coordinate their expertise". In other words, successful expertise coordination requires that each team member knows the expertise areas of each other in order to seek help when needed. The point that can be made here is that it seems far more efficient to correctly match individual skills of team members with the skills required by tasks in order to minimize the number of times that team members encounter difficulties completing their tasks.

Patanakul et al. [34] stated that "the methodologies proposed in the literature for assigning projects are based solely on project requirements and skills of project managers". This statement could be generalized for current personnel assignment approaches where many important parameters are omitted, thus limiting the applicability of most assignment methods in diverse industrial settings.

Enhanced assignment models may represent benefits such as increased employee and customer satisfaction, as well as higher profits for companies. Moreover, efficient employee assignments can significantly improve the reliability of products, resulting in a positive impact to important social aspects such as public safety (e.g., software for airplanes). Therefore, it is imperative to follow the "continuous improvement" paradigm and pursue further research to improve the outcome of personnel assignment decisions.

The principal research question that guided this study is the following: How can a novel approach for the assignment of resources to tasks in skill-based environments be developed? An extensive review of the literature has been conducted to address this important research inquiry. As a result, this research develops a personnel assignment fuzzy goal programming (FGP) model for skill-based environments. The model considers employees with various skills and preferences, as well as tasks with imprecise requirements.

This research study is organized as follows. Section 4.2 presents a summary of relevant literature. Section 4.3 discusses the justification for using FGP as a solution approach. Section 4.4 provides the solution approach and model development. Section 4.5 demonstrates the capability of the model with an example of a personnel assignment

scenario in a software development setting. Finally, Section 4.6 provides conclusions and future research directions.

4.3   Related Literature

The purpose of the literature review effort for this research was twofold. The first objective was to identify the methods used for personnel assignments in skill-based environments. The second objective was to identify the parameters that were considered for assignments and how were these parameters modeled (e.g., index values or fuzzy variables).   The following sections describe the findings corresponding to both objectives.

4.3.1   Approaches for Personnel Assignments

The literature shows various methodologies for assigning employees to tasks. These approaches include the use of tools such as mathematical programming models and artificial intelligence techniques. Other approaches such as Taguchi's parameter design and subjective measures have also been used by researchers. The following subsections discuss these approaches in more detail.

4.3.1.1   Mathematical Programming Approaches

The approaches based on mathematical programming techniques include integer and goal programming (GP). Patanakul et al. [34] developed an integer programming model to optimize the assignments of projects to project managers. The objective function considered the suitability between projects and managers, and the strategic importance of projects to an organization. Boon and Sierksma [42] presented a linear

programming model to create teams based on the aggregated value that each team member adds to the team. Subjective precise weights were used to represent the value of a team member to a specific position. Karsak [47] introduced a multi-objective linear program to minimize cost and maximize the number of required skills that are fulfilled for a single task.

Bassett [46] presented a mixed integer linear programming approach for personnel assignments. First, an initial list of available resources and their suitability with tasks is constructed based on subjective opinions. Then, assignments are made as a function of the candidates' available time and the estimated effort required to complete the tasks. Therefore, this approach relies heavily on estimated durations of tasks and will cause problems to managers if tasks take more time to complete than their expected completion time. Majozi and Zhu [39] also used mixed integer linear programming as a solution approach.

Very recently, Peters and Zelewski [4] developed a GP model for personnel assignments in a software development setting. The model considers goals that include meeting technical requirements and preferences of employees regarding general workplace conditions. Team parameters such as team cohesiveness and communication skills are not considered. The objective function is to minimize the deficiencies of resources with the goals required by tasks. The analytical hierarchy process (AHP) method is used to assign weights to goal deficiencies to determine their relative importance to the decision maker. This approach is based on the assumption that the experience levels of resources are defined by crisp values. For example, consider the situation depicted in Figure 4.1 in which a decision maker has to determine the

76

compatibility between two resources and a task. The decision maker gathers the required information, goes through a decision process, and finally comes up with a solution. In this case, the task requires four years of experience in a particular skill. Although both resources have four years of experience in this required skill, the actual experience of each resource with the skill in previous tasks will most likely be different. This will make the experience level of one resource more at par with the task than the experience level of the other resource, even if both resources have equal years of experience. Particular characteristics of this problem, like the one just mentioned, create an important opportunity for significant research in skill-based resource allocation environments by incorporating fuzzy set theory to determine degrees of membership of resources to tasks. In fact, Peters and Zelewski [4] emphasized the need to develop FGP models for the skill-based assignment problem.
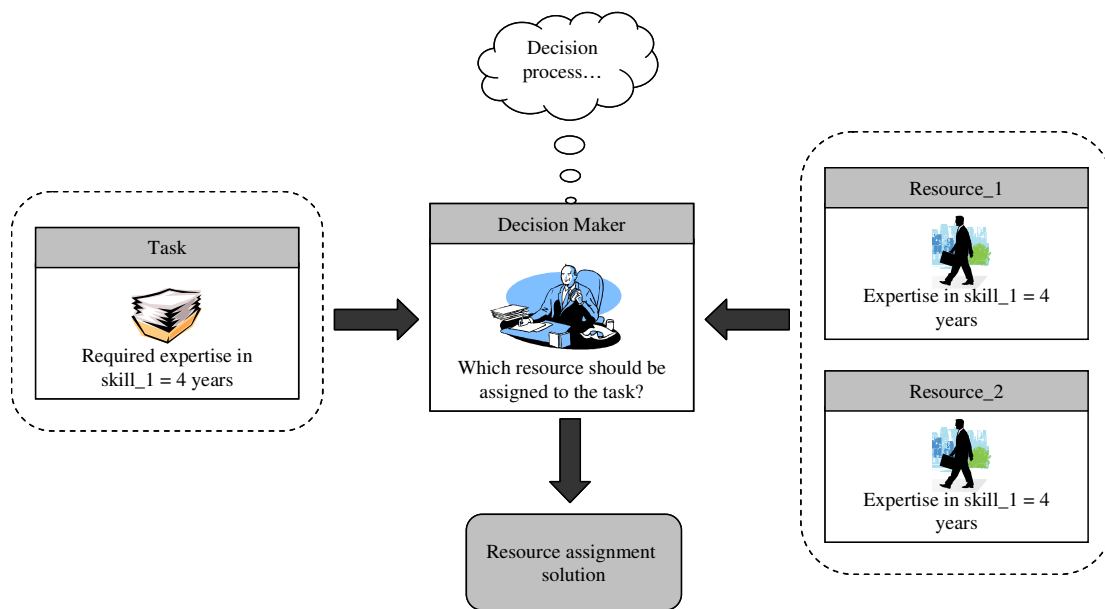
Figure 4.1 - Sample Scenario

In [92], the authors developed a nurse-scheduling GP model. The authors mentioned that nurses posses various levels of capabilities due to their training, allowing them to work as registered nurses, practical nurses, or aids. The authors proposed the creation of subgroups of nurses in order to assign nurses to shifts. No distinction is made between the capabilities of nurses within subgroups. This means that nurses within subgroups are assumed to be equally capable so that performance is not affected by the selection of nurses. The authors included preferences of nurses as an assignment criterion. These preferences were not modeled based on the preferences of available nurses. Instead, they were modeled based on survey results and therefore they represented the preferences of the majority and not of the individual nurses that correspond to a particular assignment problem.

Another GP assignment model was developed by [93]. Here, the objective was to assign multiple projects to managers. The model uses estimated times for resources to complete projects as a proxy for resource capability.

4.3.1.2 Artificial Intelligence Approaches

There are two main artificial intelligence approaches that are used for personnel assignments methodologies. The first one deals with fuzzy set theory to represent the imprecise nature of particular parameters. The second one corresponds to global optimization methods. The following subsections show studies that have implemented methodologies using these artificial intelligence concepts.

4.3.1.2.1 Fuzzy Set Theory Approaches

There are several methods in the literature that involve fuzzy parameters. An example is the study by Drigas et al. [41], where fuzzy variables are used to determine the suitability of candidates with tasks. This study only considered the skills of candidates as parameters for assignments. Motivation and other important factors were not taken into account. Petrovic-Lazarevic [45] also developed a personnel selection fuzzy model that considered only imprecise competence levels of resources.

In [49], the authors developed a methodology for the personnel assignment problem based on fuzzy set theory and fuzzy rules. The authors used fuzzy variables to describe competence levels of resources and priorities for assignment parameters. For example, one of the factors considered was communications, which had the following measure indicators to determine the level of competency of a resource in this skill: listening, oral communication, oral presentation, and written communication. The "listening" measure indicator was given the highest priority, meaning that it will be the most important factor considered when evaluating the level of competence of a resource. This consideration of imprecise priorities of the required skills is one of the strengths of this study. However, this study considered only the single-task-multiple-resources case, making it not suitable for multiple-tasks-multiple-resources situations. The authors used fuzzy rules for the selection of the best resource for a task.

Part of the results from the research conducted by Liang and Wang [94] was a methodology to adequately pair candidates with jobs. The authors used fuzzy variables to describe the subjective importance of skills required for a job and the expertise of a candidate on each skill. Incorporating the extension principle for fuzzy sets [85],

assessments made by a panel of decision makers were aggregated into a fuzzy suitability index between candidates and jobs. Liang and Wang [53] presented a very similar methodology with the main distinction being that the authors incorporated objective criteria to their methodology. The methodology considers priorities of individual skills but excludes required levels of skills. Methodologies that consider required levels of skills are more complete and therefore more valuable to decision makers in the field.

In the study by Yaakob and Kawata [52], the authors developed a methodology for the personnel assignment problem similar to the one developed by Liang and Wang [53]. The distinction in this study is that the authors incorporated an evaluation of the fuzzy relationships between team members to avoid conflicts. This parameter was defined as an average fuzzy value of the relationships of every pair of workers. Shen et al. [51] developed a multi-criteria decision model that used the pair comparison method described by Yaakob and Kawata [52] to denote a social relationship factor between team members. This methodology considers the case where employees are responsible for multiple tasks at any given time. Furthermore, the methodology considers capabilities of candidates with respect to the skills required to perform a task, and whether tasks are conflicting or complementary with the current workload of candidates. Fuzzy variables are used to evaluate a candidate's suitability with each task.

Kozanoglu and Ozok [50] provided an approach to solve the single-task skill-based personnel assignment problem. Their approach relates customer requirements to engineering solutions using the Quality Function Deployment technique. The authors defined customer requirements as the characteristics, or subtasks, of a task that need to be completed, and engineering solutions as the required skills to successfully complete

subtasks. Fuzzy parameters described the importance of subtasks, the priorities of the skills required, and the capability of candidates. Although no particular assignment method was specified, the authors recommended the selection of the most appropriate candidates using ranking fuzzy methods. Although the study presented a significant contribution to the literature, its value could be significantly enlarged by extending their approach to consider parameters such as preferences of candidates, required levels of skills, multiple tasks, and task priorities.

In [44], the authors used fuzzy set theory to compute an index representing the relation between required skills and actual skills of candidates. A particular aspect of their methodology is that it inflates the suitability level of a resource with a task if the resource exceeds the required levels of skills. A different and arguably more appropriate approach would have been to maximize the number of times that required skill-levels are met. In addition, priorities for required skills should be considered.

4.3.1.2.2 Global Optimization Approaches

Recent studies show the use of artificial intelligence search and optimization methods, such as simulated annealing and genetic algorithms, for personnel assignments. The goal of these methods is to find a reasonable approximation to the global optimum solution of a function in a large search space. In [37], the authors presented a multi-objective assignment approach based on simulated annealing. The objectives were to maximize the minimum suitability of each candidate to a team and the minimum team sizes. In [38], the authors adopted genetic algorithms for their multi-objective assignment approach. The objectives were to meet career path satisfaction levels of

resources, levels of skills required by projects, and resources' motivation levels. Duggan et al. [95] also developed an optimization model for task allocation based on genetic algorithms. The competencies of employees were modeled using a categorical variable with five levels. Each of these competency levels was associated with an expected productivity per day, as well as an expected number of defects per unit of productivity.

4.3.1.3 Other Approaches

Methodologies for personnel assignment in skill-based scenarios also include techniques such as cluster analyses, assessment of behavioral competences, subjective assessments, and AHP. Furthermore, the goal of some team assignment methods is simply to create heterogeneous groups, since research has shown that these groups are usually more creative, innovative, and cooperative [13]. Examples of such methodologies are provided by [13], [14], and [15].

The method proposed by Hauschildt et al. [20] uses cluster analysis to classify candidates into five categories based on pre-defined assignment criteria. Then, a discriminant analysis determines the types of tasks that are more suitable with each of the five categories. The assignment policy is to assign the candidate that is most suitable with a task based on the results from the discriminant analysis. Other studies such as [6] and [16] developed procedures for allocating personnel to tasks based on the assessment of behavioral competencies.

The AHP and Taguchi's parameter design techniques are also used in the literature for resource assignments. Al-Harbi [25] presented an assignment method that uses AHP for the prequalification contractor problem. The method relies on assignment

criteria such as experience, quality performance, and workload. In [43], the authors proposed a methodology for assigning employees to tasks based on a critical resource diagram and the Taguchi's parameter design approach. The performance measures of the assignments were cost and cycle time. The critical resource diagram focused on resource scheduling rather than activity scheduling to represent human-resource workflow and tasks' precedence. The Taguchi's parameter design was used to obtain a scheme that would optimize the selection of resources for tasks under dynamic and stochastic conditions such as task complexity.

The authors in [48] developed a multiple objectives methodology for personnel assignment in an R&D environment. The objective functions were to maximize the satisfaction of skills required by each project, maximize the skills available throughout the project's duration based on a learning curve factor for each candidate in each skill, and maximize the average preference of each pair of resources to work together. The skill levels of candidates and the preferences of pairs of candidates to work together were expressed using fuzzy variables. The methodology first approximates a Pareto-optimal frontier of solutions using the lexicographic goal programming, weighted sum, and ε-constraint methods. This way, the number of solutions to be analyzed is reduced significantly. The methodology then uses the ELECTRE III multi-criteria decision-making procedure to select the best solution among the ones in the Pareto-optimal frontier.

4.3.2 Modeled Parameters

The second objective of the literature review was to identify parameters that were taken into account for personnel assignments and how were these parameters modeled. Table 4.2 contains selected literature on personnel assignment methodologies and describes the parameters considered.

Table 4.2 - Selected Recent Literature on Skill-based Resource Assignment

	Resources		Tasks		
Research Study	**Competence level of resources**	**Motivation with tasks**	**Priorities of tasks**	**Priorities of required skills**	**Level of skill required**
[40], [42]	Precise (Index)	Not considered	Not considered	Not considered	Not considered
[45], [41]	Imprecise (Fuzzy)	Not considered	Not considered	Not considered	Not considered
[94], [53], [50]	Imprecise (Fuzzy)	Not considered	Not considered	Imprecise (Fuzzy)	Not considered
[16], [6], [96]	Index	Not considered	Not considered	Not considered	Weight (High, Medium)
[44], [39], [47]	Imprecise (Fuzzy)	Not considered	Not considered	Not considered	Imprecise (Fuzzy)
[43]	Probabilistic	Not considered	Not considered	Not considered	Not considered
[46]	Precise	Not considered	Not considered	Not considered	Not considered
[20]	Precise	Not considered	Precise (Index)	Not considered	Not considered
[49], [52]	Imprecise (Fuzzy)	Imprecise (Fuzzy)	Not considered	Imprecise (Fuzzy)	Not considered
[4], [38]	Precise (Index)	Precise (index)	Not considered	Not considered	Precise (index)
[93]	Precise	Not considered	Precise (Index)	Not considered	Not considered
[37]	Imprecise (Fuzzy)	Precise (index)	Not considered	Not considered	Imprecise (Fuzzy)
[51]	Imprecise (Fuzzy)	Imprecise (Fuzzy)	Not considered	Imprecise (Fuzzy)	Not considered
[48]	Imprecise (Fuzzy)	Imprecise (Fuzzy)	Precise (Index)	Precise (Index)	Not considered
[96]	Precise	Not considered	Precise (Index)	Precise (Index)	Precise (index)

Table 4.2 shows that most personnel assignment methodologies exclude critical parameters related to resources and tasks. Undoubtedly, levels of competences of resources in required skills are key parameters for successful assignments. However, the literature shows that other factors such as motivation levels and priorities of tasks are also critical factors that must be considered in the decision process [4], [38]. This is evidenced by various studies in the literature. For example, Matsuodani [97] stated that the outcome of complex tasks that depend on the competences and other individual characteristics of people is strongly related to the motivation of personnel to engage in specific tasks. In addition, Hendriks et al. [98] indicated that the dedication of a candidate to a particular task increases efficiency.

Furthermore, it is very important to decide how to properly model these parameters. The values of these parameters are more imprecise than random or crisp, which represent a good opportunity for the application of fuzzy set theory techniques [45].

4.3.3   Summary of Findings

In summary, the current literature shows that there are opportunities to improve the effectiveness of personnel assignment decisions. The following list highlights the major gaps found in the literature:

- Critical parameters such as levels of motivation of employees with tasks, priorities of required skills, and priorities of tasks are seldom included in personnel assignment approaches.

- Most approaches model parameters that are imprecise in nature (e.g., capability levels of employees) as crisp values.

- A FGP model for personnel assignments in skill-based scenarios is non-existent in the current literature.

4.4   Justification for FGP as a Solution Method

Before discussing the use of FGP as part of the solution approach, it is important to justify it as an appropriate modeling tool for personnel assignments in skill-based environments. To this end, it is necessary to briefly discuss and justify GP and fuzzy set theory separately, followed by the combination of these approaches into FGP.

4.4.1   Goal Programming

Personnel assignment decisions in skill-based scenarios typically involve multiple objectives. These objectives are associated with expectations from decision-makers and employees. That is, for a set of tasks, decision makers expect personnel assignments to meet the tasks' required levels of technical skills. At the same time, employees expect assignments to agree with their personal preferences such as working with particular skills or in small teams. Consequently, personnel assignment policies formulated with single objectives can produce results that fall very short from meeting expectations that are essential to decision makers and employees. Logically, the best-case scenario would be to make assignments that fulfill the complete set of requirements from managers and workers. However, many times it is impossible to make such assignments, resulting in unfeasible solutions to accomplish these multiple objectives. An alternative approach to problems with various objectives is to find a solution that satisfies a set of constraints

86

and, at the same time, is close to meeting each of the objectives. Such an approach is called GP.

GP is a multi-objective optimization mathematical model based on linear programming techniques. GP minimizes unwanted deviations from target values (i.e., goals) subject to a set of constraints [99]. A standard GP formulation requires precise target values and priorities for each goal. The classic GP simple additive model is the following [100]:

$$\text{Minimize } Z = \sum_{i=1}^{m} (d_i^+ - d_i^-) \tag{4.1}$$

$$AG_i(x) + d_i^- - d_i^+ = g_i \tag{4.2}$$

$$AX \leq u, BX \geq l \tag{4.3}$$

Equation (4.1) shows that the objective function is to minimize the overall sum of deviations from targets. Equation (4.2) adds a d_i^+ or subtracts a d_i^- amount to the value achieved in goal "i" ($AG_i(x)$) in order to reach the target value of g_i. Incorporating deviations in equation (4.2) guarantees that the model finds a feasible solution. Equation (4.3) ensures that any upper and lower value constraints are met. There are a vast amount of studies that have used GP for solving decision problems with multiple criteria [101].

GP models are either preemptive or non-preemptive. In preemptive GP, each goal is assigned a priority level, where higher priority levels are infinitely more important than any lower priority level. This means that a "series of mathematical programming problems are solved sequentially, first considering highest priority goals only, and then continuing with lower priority ones, under the constraints imposed by the alternative optimal solutions of the problems that included the higher priority goals" [101]. In non-

preemptive (a.k.a. "weighted") GP, a weight is assigned to each goal to quantify their relative importance. The objective is to minimize the weighted sum of the deviations.

4.4.2 Fuzzy Set Theory

In classical set theory, the decision to determine if an individual meets the skill levels demanded by a task is a crisp one (i.e., yes or no). Considering the case depicted in Figure 4.1, a resource with two years of experience in the required skill would not meet the required skill level of four years. In other words, this resource does not belong to the set of resources that meet the skill level demanded by the task. A different approach to the classical set theory is the fuzzy set theory, which utilizes degrees of membership of elements to sets [85]. In the example just mentioned, the individual with two years of experience possesses a degree of membership to the set of resources that meet the skill level demanded by the task. Furthermore, an individual with four years of experience in the specialized skill may still not completely meet the demanded skill level of the task, depending on the prior experience and the environment in which the individual utilized the skill. Using the degrees of membership concept provides a more realistic way to describe the fit of resources with tasks.

4.4.2.1 Membership Functions

Fuzzy set theory allows parameters to be defined using simple linguistic terms (e.g., high, low). These factors are then translated into quantitative values using membership functions. More specifically, the job of membership functions is to map elements from any universal set into real numbers within the range 0-1. The resulting

values represent the degrees of membership of elements to particular sets. Values closer to 1 represent higher degrees of membership.

Fuzzy set theory provides various forms of membership functions. The capability to determine appropriate membership functions in the context of each particular application is crucial for making fuzzy set theory practically useful [85]. Triangular, trapezoidal, and linear shapes of membership functions are most commonly used to represent fuzzy numbers. Triangular membership functions are usually preferred due to their combination of solid theoretical basis and simplicity [86]. However, there are situations that require more complex functions to more accurately represent the degrees of membership of elements to fuzzy sets.

There are several methods for constructing membership functions. Klir and Yuan [85] discussed direct/indirect methods that involve single/multiple experts. These methods involve gathering and processing responses from experts in particular fields or from extensive literature reviews.

4.4.3 FGP for the Skill-Based Assignment Problem

As previously mentioned, personnel assignment problems involve imprecise parameters and multiple objectives. In order to develop feasible solutions to such imprecise multi-objective problems, fuzzy set theory has been used since the early 1980s in combination with GP to form what is known as FGP [101].

The main difference between FGP and GP is that the latter requires crisp values for each objective to be achieved, whereas in FGP these values are specified in an

imprecise manner [100]. Basically, instead of minimizing deviations from targets as GP

does in equation (4.1), FGP maximizes the degrees of membership to each of the goals.

The simple weighted additive FGP model is shown in equation (4.4) [100].

Parameters μ_i and w_i represent the degrees of membership (from a linear membership

function) and relative weight of the ith goal, respectively. Zimmermann [102] defines the

degrees of membership for the ith fuzzy goal $AG_i(x) \succ g_i$ and $AG_i(x) \prec g_i$ with

equations (4.5) and (4.6), respectively [100]. The operator $\succ$ means approximately

greater than, whereas $\prec$ means approximately less than.

$$\text{Maximize } Z = \sum_{i=1}^{m} w_i \mu_i \qquad (4.4)$$

$$\mu_i = \begin{cases} 1 & \text{if } AG_i(x) \geq g_i \\ \dfrac{AG_i(x) - L_i}{g_i - L_i} & \text{if } L_i < AG_i(x) \leq g_i \\ 0 & \text{if } AG_i(x) \leq L_i \end{cases} \qquad (4.5)$$

$$\mu_i = \begin{cases} 1 & \text{if } AG_i(x) \leq g_i \\ \dfrac{U_i - AG_i(x)}{U_i - g_i} & \text{if } g_i \leq AG_i(x) < U_i \\ 0 & \text{if } AG_i(x) \geq U_i \end{cases} \qquad (4.6)$$

Equations (4.5) and (4.6) state that it is acceptable to come short of meeting goal

g_i up to a specified lower (L_i) or upper (U_i) boundary. A FGP model for skill-based

personnel assignments can be obtained as an extension to the simple additive model

presented in equations (4.4) - (4.6). This extension includes modifications to the objective and membership functions which will be described in Section 4.5.

Specifying precise target values and priorities for each goal can be a difficult task for decision makers [103]. Consequently, FGP has been the modeling tool of choice for researchers to solve a variety of problems in different applications. However, FGP has not been applied to the specific area of skill-based resource assignments. This is evidenced by statements from very recent research studies, stating that "future research should be directed towards developing fuzzy goal programming models for the competence and preference-based workplace assignment" [4]. Furthermore, Baykasoglu et al. [37] mentioned that there is an unfortunate lack of adequate approaches and procedures for assigning workers to teams.

4.5   Solution Approach and Methodology

This section presents the proposed stepwise solution approach to the personnel assignment problem. Figure 4.2 provides a diagram showing each of the steps and their associated activities. Satisfying necessary pre-conditions, defining imprecise parameters, and identifying traits of resources constitute the first three steps of the methodology. The fourth step is to properly develop fuzzy sets for the goals. In the fifth step, membership functions are adequately manipulated to represent fuzzy priorities. The final step is to set up and run the assignment model to obtain a feasible solution that considers several goals corresponding to technical capabilities, team parameters, and personnel preferences. The following subsections explain the procedure to properly execute the last three steps and ensure a successful implementation of the solution approach.

Steps

Activities

Pre-conditions	-Establish a rating scale to evaluate candidates. -Establish a rating scale for resources to grade their level of motivation to work particular tasks.
Define imprecise parameters	Using linguistic terms: -Assign target values for the goals of each task. -Assign priority levels to each goal. -Assign priority levels to each task.
Identify traits of resources	-Develop a skill-matrix for each candidate. -Develop a table with the motivation levels of the resources with each task.
Develop membership functions for the goals	-Construct fuzzy sets for the target values of the goals.
Conduct MFR process	-Manipulate the existing fuzzy sets for the goals to incorporate the imprecise priorities of the goals. -Construct fuzzy sets that incorporate priorities of tasks.
Run FGP-MFR model	-Calculate priority-based degrees of membership of resources with tasks. -Run the FGP model to obtain a solution.

Figure 4.2 - Solution Approach: Steps and Activities

4.5.1 Membership Functions

Developing membership functions for the target values of goals constitute a very important step in the solution approach. Careful evaluation of the membership function shown in equation (4.5) reveals that this function must be modified for the skill-based personnel assignment problem. This equation states that beyond a lower limit L_i, every element in the solution set has a zero degree of membership. This means, for example, that for a task that requires a high level of expertise in a particular skill, resources with

medium levels of knowledge in the skill may be treated the same (i.e., have a degree of membership of zero) as those with lower levels of knowledge. To avoid this situation, this L_i parameter needs to be eliminated (i.e., set to zero). This way, each lower level of expertise results in some value added.

Outcomes of decisions based on fuzzy approaches depend heavily on the appropriateness of the membership functions used. Consequently, careful selection of membership functions is vital for effective decision making processes [104]. One way to improve the development of membership functions is to work directly with decision makers to model these functions based on their expertise. However, most FGP formulations assume linear membership functions which are established without the involvement of decision makers [105].

Membership functions corresponding to fuzzy sets of imprecise capabilities depend on whether the main objective of an assignment policy is to minimize deficiencies from target values, or minimize deviations (i.e., deficiencies plus surplus). A reason for selecting to minimize deviations is that studies have shown that assigning over-qualified personnel to tasks decreases productivity due to a lack of motivation given that tasks might not be challenging enough [106]. Figure 4.3 shows an example of a linear interval membership function to minimize deviations. Here, deviations to either side of the target value reduce the degrees of membership of an element in that particular fuzzy set. On the other hand, decision-makers may rather prefer to meet minimum requirements as much as possible, even if that means assigning an expert in a particular skill to a task that requires a low expertise level. In this case, an assignment policy to minimize deficiencies is appropriate. Figure 4.4 shows an example of a linear interval

membership function to minimize deficiencies. Here, deviations to the left side of the target value reduce the degrees of membership, whereas any deviations to the right side results in a degree of membership of one.
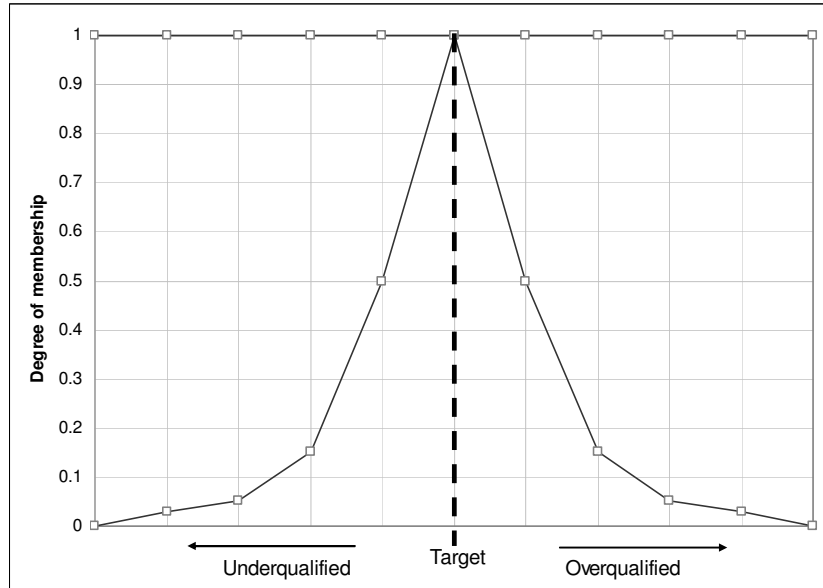

Figure 4.3 - Sample Membership Function to Minimize Deviations from a Target Value
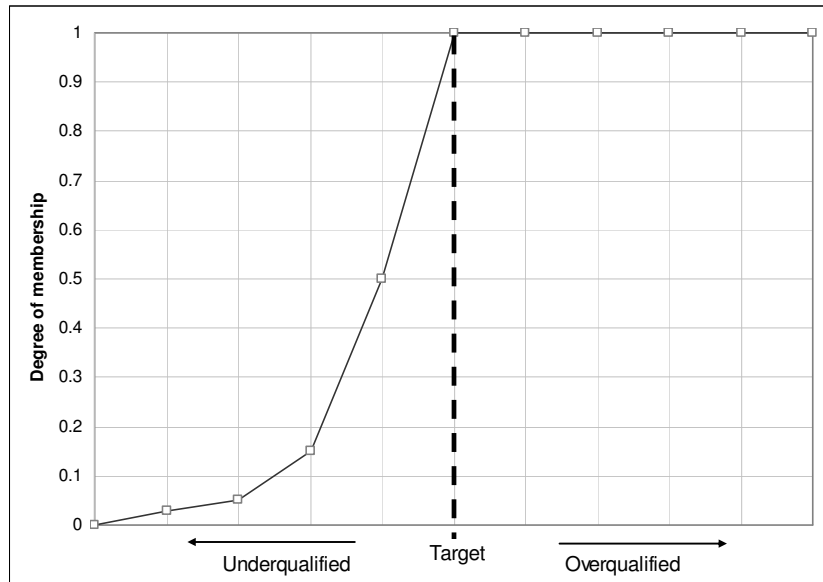

Figure 4.4 - Sample Membership Function to Minimize Deficiencies from a Target Value

4.5.2 Priorities

Personnel assignment methodologies should consider priorities of goals and tasks to develop more thorough assessments of the alternatives. The literature shows two common approaches to consider fuzzy priorities. The first approach uses a method known as fuzzy weighted average (FWA), and the second uses desirable achievement degrees. The following sections explain these approaches in more detail, as well as the method that will be used in this research to model priorities.

4.5.2.1 Priorities with Fuzzy Weighted Average

The FWA method is perhaps the simplest and most common approach to incorporate fuzzy priorities. It is used in decision problems that require assessments of alternatives with respect to some assignment criteria and the corresponding importance of such criteria. With FWA, these assessments involve three basic operations, namely scoring, weighting, and aggregating the criteria [107]. The general specification for the weighted average is shown in equation (4.7). Here, $w_i \in [0,1]$ and $\sum_{i=1}^{n} w_i = 1$. Therefore, w_i must be normalized to $w_i^{'}$ as shown in equation (4.8).

$$y = f\left(x_1, \ldots, x_n, w_1, \ldots, w_n\right) = \left(\frac{w_1 x_1 + \ldots + w_n x_n}{w_1 + \ldots + w_n}\right) = \left(w_1^{'} x_1 + \ldots + w_n^{'} x_n\right) \tag{4.7}$$

$$w_i^{'} = \frac{w_i}{w_i + \ldots + w_n} \tag{4.8}$$

The study in [37] provides an example that uses FWA. The authors categorized priorities into four linguistic terms: poor, fair, good, and very good. Figure 4.5 shows the triangular membership functions used for each of the four terms.
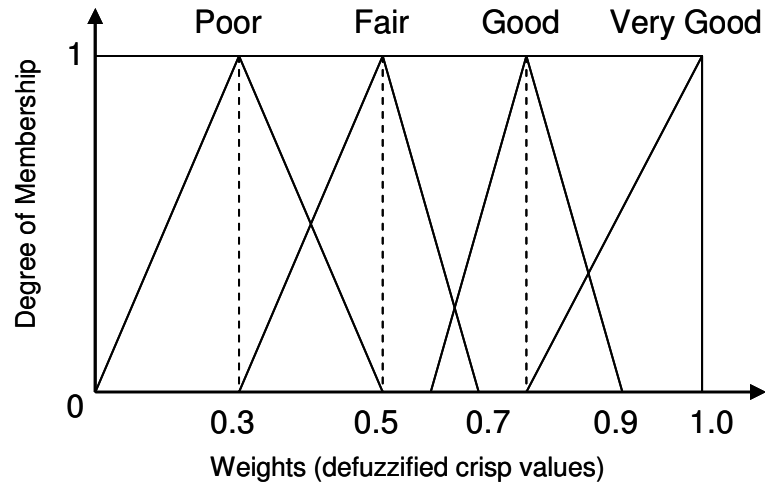
Figure 4.5 - Triangular Membership Functions for Priority

For each of the fuzzy sets, the ratings corresponding to a degree of membership of 1.0 are used as defuzzified ratings. That is, a poor priority has a defuzzified rating equal to 0.3, fair equals 0.5, good equals 0.8, and very good equals 1.0. To develop relative priorities, each of the defuzzified ratings must be normalized using equation (4.8), where $w_i \in [0.3, 0.5, 0.8, 1.0]$. This way ensures that the sum of the priorities equal to one, which is a requirement for fuzzy weighted average operations. For example, consider three goals with priorities medium, high, and very high. That is, the first goal has a defuzzified priority of $w_i = 0.5$, the second goal has $w_i = 0.8$, and the third goal has $w_i = 1.0$. The degrees of membership for the priorities of the three goals are the following:

- For goal #1: 0.5 / 2.3 = 0.217

- For goal #2: 0.8 / 2.3 = 0.348

- For goal #3: 1.0 / 2.3 = 0.435

96

Chen and Tsai [108] stated that using FWA operations to determine priorities of goals can produce undesirable results. To prove their point, the authors modified the weights in the example provided by [100]. The results showed a decreased achievement degree of a fuzzy goal after significantly increasing the goal's weight, which is an undesirable outcome. Therefore, Baykasoglu et al. [37] implies that the use of FWA priorities is justified in situations that impede more structure decision approaches. Such situations are distinguished by a strong lack of objective and reliable information [109], such as scenarios that prohibit inputs from field experts.

4.5.2.2 Priorities with Desirable Achievement Degrees

Studies such as [108] and [110] use desirable achievement degrees to represent priorities of goals. In other words, high priority goals would denote higher desirable achievement degrees. The authors use linguistic terms to denote fuzzy priorities. Afterwards, these linguistic terms are mapped to their corresponding defuzzified values, which are used as crisp constraints in a linear programming model. For example, the constraint for a "good" priority goal (using Figure 4.5) would be represented as $\mu_i \geq 0.8$. The evident drawback from this approach is that it may produce unfeasible results [108].

4.5.2.3 Membership Function Relaxation

This research presents a new method, denoted as membership function relaxation (MFR), to incorporate fuzzy priorities for goals and tasks in personnel assignment problems. The purpose of the MFR method is to modify membership functions as a result of the flexibility of decision makers to meet fuzzy goals. Such flexibility is driven by decision makers' perceived imprecise priorities of the goals.

97

Flexibility is represented as a manipulation to an existing membership function. More specifically, flexibility corresponds to an allowable expansion of a membership function, as well as a reduction of the maximum attainable degrees of membership for lower priority goals and goals that have lower target values. For example, assume that the goals of a decision maker are to select a resource that is an expert in skill-x and a novice in skill-y. Notice that a novice might be preferred over an expert in some tasks in order to avoid having overqualified employees. Moreover, assume that the decision maker agrees to use the membership functions from Figure 4.6 to describe the fuzzy sets for an expert and a novice. Figure 4.7 shows a possible expansion policy to minimize deviations from the target goals based on different priority levels. It can be seen that lower priority levels increase the flexibility of a decision maker to meet a goal, causing the membership function to widen around its middle value. In addition, the highest achievable degrees of membership for lower priority goals are smaller, which results in higher degrees of membership for higher priority goals. Similarly, the highest achievable degrees of membership for the novice fuzzy set are smaller than for the expert fuzzy set. This follows the rationale that resources with higher levels of expertise are usually in shorter supply than those with lower expertise levels. This way, for example, assigning an expert to a task that requires expert capability is valued more than assigning a novice to a task that requires novice capability. Degrees of membership resulting from the MFR process are called priority-based degrees of membership. Figure 4.8 shows an expansion policy to minimize deficiencies from the target goal. Here, any rating higher than the target rating has a degree of membership of one.
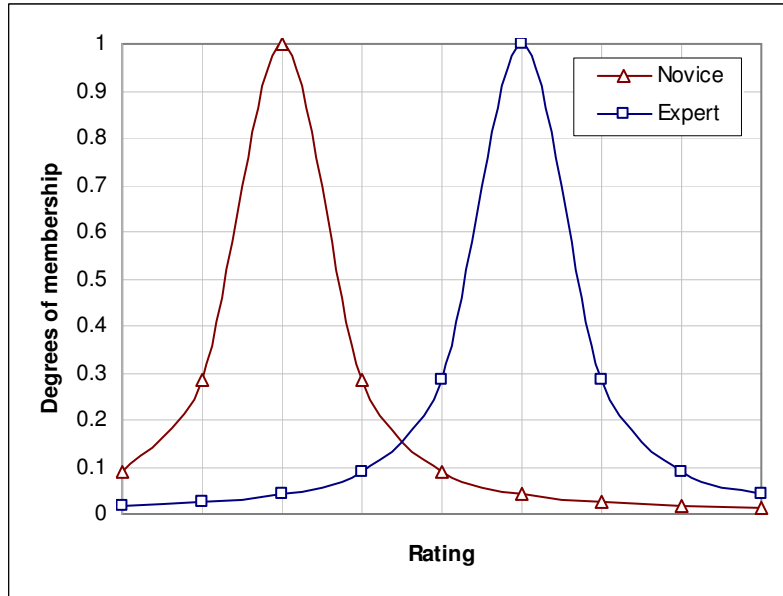
Figure 4.6 - Fuzzy Sets for Novice and Expert
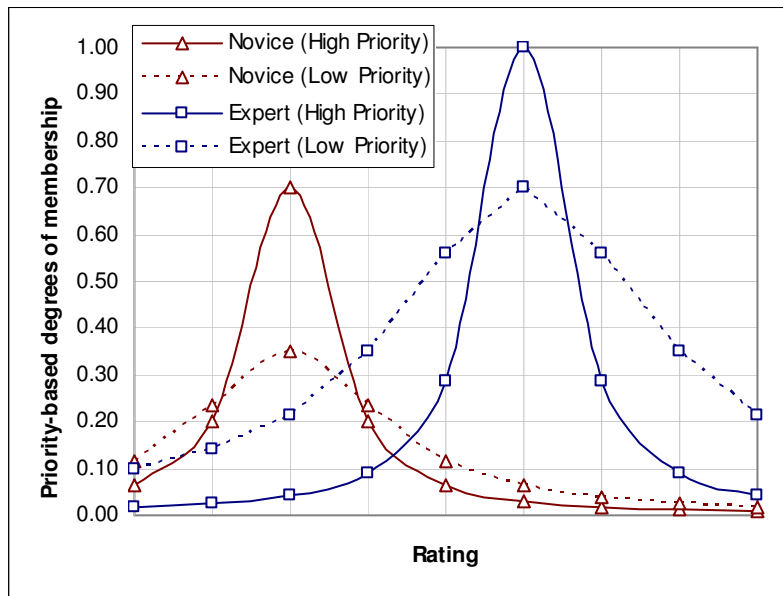
Figure 4.7 - Sample MFR to Minimize Deviations from Target Goals
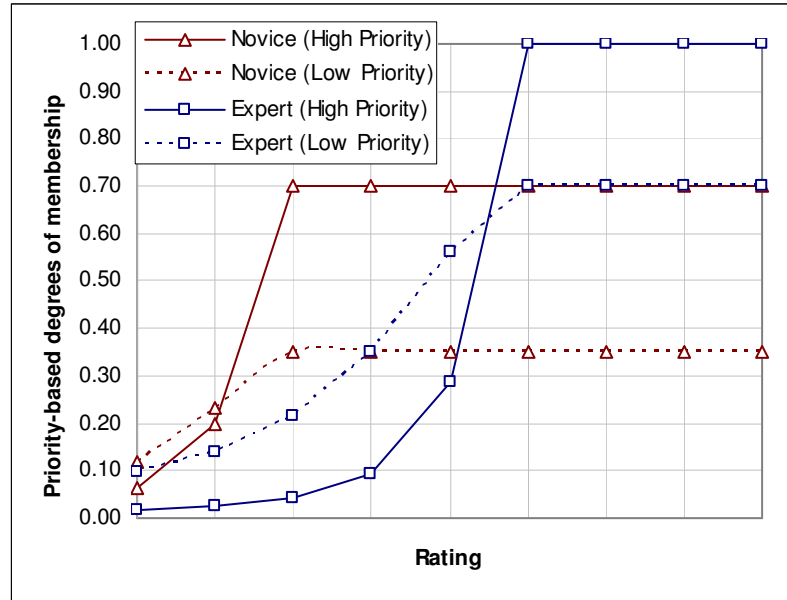
Figure 4.8 - Sample MFR to Minimize Deficiencies from Target Goals

The success of any methodology that considers imprecise parameters using fuzzy set theory depends on the use of membership functions that make sense to experts and decision makers in the particular personnel assignment scenario. Consequently, it is critical to involve decision makers throughout the MFR process. This will help to more accurately resemble the perceived priority levels of decision makers and avoid undesirable results as much as possible.

4.5.3 FGP-MFR Model

This section presents the skill-based resource assignment optimization model called the FGP-MFR model. More specifically, the model has a FGP specification where the priorities of goals are established with the MFR process. The notation for the FGP-MFR model is shown in Table 4.3.

Table 4.3 - Notation for the FGP-MFR Model

Variable Name	Description
G_t	Number of fuzzy goals for task t
$Target_{(gt)}$	Fuzzy target value for goal g of task t, where $g = 1$ to G_t and $Target_{(gt)}$ $\in$ [Low, Medium, High, Very High]
$Proximity_{(rt)}$	Measure of the proximity of resource r to the aggregated target values of task t
$PDOM\_Task_{(rt)}$	Priority-based degree of membership of resource r in task t
X_{rt}	1 if resource r is assigned to task t; 0 otherwise
$PDOM\_Goal_{(rgt)}$	Priority-based degree of membership of resource r in fuzzy goal g of task t
$MAX[\mu_{gt}^*]$	Maximum priority-based degree of membership that can be achieved in goal g of task t

The general model specification is shown in equation (4.9). Here, a goal g of task t is that a resource r closely meets the target value $Target_{(gt)}$, as shown in equation (4.10).

$$\text{Maximize } Z = \sum_{t=1}^{T} \sum_{r=1}^{R} \left(PDOM\_Task_{(rt)} * X_{(rt)} \right) \tag{4.9}$$

$$\text{Goal}_{(gt)}: \ PDOM\_Goal_{(rgt)} \cong \text{Target}_{(gt)} \tag{4.10}$$

$$PDOM\_Task_{(rt)} \cong \mu(Proximity_{(rt)}) \tag{4.11}$$

$$Proximity_{(rt)} \cong \frac{\sum_{g=1}^{G_t} PDOM\_Goal_{(rgt)}}{\sum_{g=1}^{G_t} MAX[\mu_{gt}^*]}, \quad \forall_r \ \forall_t \tag{4.12}$$

$$\sum_{t=1}^{T} X_{(rt)} \leq 1, \quad \forall_r \tag{4.13}$$

$$\sum_{r=1}^{R} X_{(rt)} = 1, \quad \forall_t \tag{4.14}$$

The objective function (4.9) states that the best assignment is the one that maximizes the sum of the priority-based degrees of membership of resources with tasks. Equation (4.12) defines the proximity of a resource to fulfill the set of goals of a task. This measure is defined as the ratio of the aggregated priority-based degrees of membership attained by the resource to the aggregated maximum priority-based degree of membership that can be achieved in the goals. Equation (4.11) considers priorities of tasks by mapping $Proximity_{(rt)}$ to a priority-based degree of membership from the membership function $\mu(Proximity_{(rt)})$. Next section provides an example that further explains the model.

The constraint in (4.13) states that a resource may be assigned to at most one task. Constraint (4.14) states that each task must be assigned to a resource. This constraint is valid only if the number of available resources is greater than or equal to the number of tasks; otherwise it must be removed.

4.6   Example - Software Development Setting

A personnel assignment problem in a software development setting was formulated to illustrate the implementation of the solution approach. This particular setting is relevant given that personnel assignments are considered one of the most critical decisions that affect the performance and quality of software projects [6]. This is confirmed by Tsai et al. [43] with the following quote: "evidence reveals that the failure of software development projects is often a result of inadequate human resource project planning".

Quality, as evidenced in the U.S. General Accounting Office Report in [2], continues to be a major struggle to software companies. This report states that in 2004 the U.S. Department of Defense spent nearly 8 billion dollars to rework software because of quality-related issues. Even more important than huge monetary costs is the fact that software failures, especially in safety-critical systems, may result in life-threatening situations.

Another reason that makes this example relevant is that it directly addresses areas of future research from the current software development literature. Recently, Otero et al. [5] presented an approach for resource allocation in software projects. Their methodology used precise parameters to determine capabilities of resources. The authors acknowledged the limitations of using precise parameters and encouraged researchers to develop methodologies that incorporate fuzzy parameters instead. In addition, the authors emphasized the need to extend their methodology to incorporate priorities of tasks. Incorporating tasks' priorities into resource allocation processes "will provide more effective staffing decisions to high-priority projects, which will result in better returns of investment for companies" [5].

4.6.1 Problem Statement and Pre-conditions

The personnel assignment problem formulated to implement the solution approach consisted of ten available software engineers and ten tasks. For this example, two experts from leading software engineering companies agreed to act as decision-makers. Involving real industry experts adds value to this example and facilitates the proper execution of the solution approach. Both decision makers have an average of 16

years of experience working for top U.S.A. organizations that specialize in the development of software applications for the defense industry.

Following the solution approach depicted in Figure 4.2, the first step is to make sure that pre-conditions are satisfied. The first pre-condition is to establish a rating scale to evaluate candidates. The decision-makers agreed on a rating scale from 0 to 5, where higher ratings represent higher evaluations. This rating scale is commonly used for yearly evaluations of the performance of engineers. The second pre-condition is to determine a rating scale for resources to grade their level of motivation to work particular tasks. Similarly, a 0 to 5 rating scale was selected where higher ratings represent higher motivation levels.

4.6.2   Establishing Imprecise Parameters

After establishing pre-conditions, the next step is to establish fuzzy target values for the goals of each task. The goals are associated with three main types of assignment criteria: technical expertise, personnel preferences, and team parameters. Desired target values are generated with the following linguistic terms: None, Novice, Proficient, Highly Proficient, and Expert. Similarly, the priority of each goal needs to be established with the following linguistic terms: Low, Medium, and High. For this particular example, different priority levels were assigned only to Proficient and Highly Proficient target goals. The rationale for having various priority levels for selective goals will be explained during the implementation of the MFR process.

Table 4.4 shows the capability levels desired for each of the tasks' required skills, as well as the priority of each skill to their corresponding task. Table 4.5 presents the priorities assigned to the tasks.

Table 4.4 - Desired Expertise Levels for Skills (Priorities of Skills in Parentheses)

Task Name	PL			Domain			Application		Team Factors
	C	C++	C#	Satellite communications	Command & Control	Avionics	Embedded Programming	GUI Programming	Communication
Task_1	0	HP (H)	N	HP (H)	0	HP (H)	0	HP (H)	P (L)
Task_2	0	HP (H)	P (L)	HP (M)	0	HP (L)	0	HP (H)	HP (M)
Task_3	0	E	HP (H)	P (L)	0	HP (M)	0	HP (H)	P (L)
Task_4	E	0	0	0	HP (H)	0	E	0	HP (M)
Task_5	0	0	HP (M)	P (L)	0	0	0	HP (H)	P (L)
Task_6	0	HP (H)	0	HP (M)	0	HP (M)	0	P (M)	N
Task_7	0	0	HP (M)	P (H)	0	HP (M)	0	HP (H)	HP (M)
Task_8	0	0	E	0	0	P (L)	0	E	P (L)
Task_9	0	0	HP (H)	0	N	P (L)	0	E	HP (M)
Task_10	HP (M)	0	HP (H)	HP (L)	0	N	0	0	P (M)

0 = No expertise

N = Novice level of expertise

P (x) = Proficient level of expertise; skill priority level is x, where x ({L=Low, M=Medium, H=High}

HP (x) = Highly proficient level of expertise; skill priority level is x, where x ({L = Low, M = Medium, H = High}

E = Expert level of expertise

Table 4.5 - Tasks' Priorities

Task Name	Priority
Task_1	Medium
Task_2	Medium
Task_3	High
Task_4	High
Task_5	Medium
Task_6	Low
Task_7	Low
Task_8	Medium
Task_9	Medium
Task_10	High

4.6.3 Identifying Traits of Resources

The next step is to develop a skill-matrix for each candidate, as well as a tabular representation of the motivation levels of the resources for each task. Data for the skill-matrix are usually readily available to decision makers from databases that store employees' self-evaluations as well as assessments made by lead personnel [5]. Table 4.6 shows the skill matrix for the available candidates in this sample case. Table 4.7 presents the motivation levels of the resources with the tasks.

Table 4.6 - Skill Matrix of Available Candidates Based on a 0-5 Rating Scale

Resource	PL			Domain			Application		Team Factors
	C	C++	C#	Satellite communications	Command & Control	Avionics	Embedded Programming	GUI Programming	Communication
R_1	2.5	5	3.5	4	3.5	3.5	3.5	5	3
R_2	1	4	3	4	1	4	0	4	3.5
R_3	1	4	5	3.5	1.5	3	0	5	2.5
R_4	5	4	0.5	5	2	5	5	3.5	3.5
R_5	0	1.5	1	1	0	2	0	2	2.5
R_6	2	3	3.5	3	0	4	0	3.5	2.5
R_7	1	5	2.5	5	0	3.5	0	5	5
R_8	0.5	3	3	3.5	1	2	1	3.5	1
R_9	0	4	4.5	3	1	2.5	0	4	2.5
R_10	4	2.5	3.5	3.5	1	3	2	3.5	4

Table 4.7 - Motivation Levels of Resources with Tasks Based on a 0-5 Rating Scale

Resource	Task_1	Task_2	Task_3	Task_4	Task_5	Task_6	Task_7	Task_8	Task_9	Task_10
R_1	5.0	4.0	2.5	5.0	4.0	1.0	1.0	4.0	0.0	2.5
R_2	5.0	1.0	4.0	0.0	5.0	1.0	0.0	1.0	0.0	0.0
R_3	1.0	2.5	2.5	0.0	4.0	2.5	4.0	5.0	0.0	0.0
R_4	0.0	1.0	1.0	5.0	0.0	2.5	0.0	1.0	1.0	2.5
R_5	4.0	2.5	2.5	0.0	4.0	0.0	0.0	0.0	1.0	0.0
R_6	4.0	2.5	2.5	0.0	4.0	4.0	5.0	0.0	5.0	4.0
R_7	4.0	1.0	4.0	0.0	2.5	4.0	0.0	0.0	0.0	4.0
R_8	2.5	2.5	2.5	0.0	2.5	2.5	2.5	2.5	2.5	2.5
R_9	4.0	4.0	4.0	0.0	4.0	2.5	2.5	4.0	5.0	2.5
R_10	4.0	4.0	4.0	1.0	4.0	5.0	2.5	4.0	4.0	5.0

4.6.4   Develop Membership Functions for Goals

The objective of this step is to construct fuzzy sets for the target values of the goals. To this end, the direct method with multiple experts approach presented by Klir and Yuan [85] was used. To facilitate this process, the decision makers were initially presented with various shapes of possible membership functions. These included linear, triangular, trapezoidal, normally distributed, and sinusoidal shapes [111]. Both experts preferred the sinusoidal shapes because these functions provided smooth non-linear transitions between fuzzy sets that span across the entire x-axis (i.e., rating scale).

Figure 4.9 shows the sinusoidal membership functions for an assignment policy to minimize deviations from target values. That is, these membership functions are used when there is a penalty associated with assigning overqualified resources to tasks. Furthermore, this figure shows that deviations to the right of the target values (i.e., over-qualified rating), for all but the Novice set, result in higher degrees of membership than similar deviations to the left (i.e., under-qualified rating). The reason for having these non-symmetrical shapes is that the decision makers preferred overachievement to underachievement.
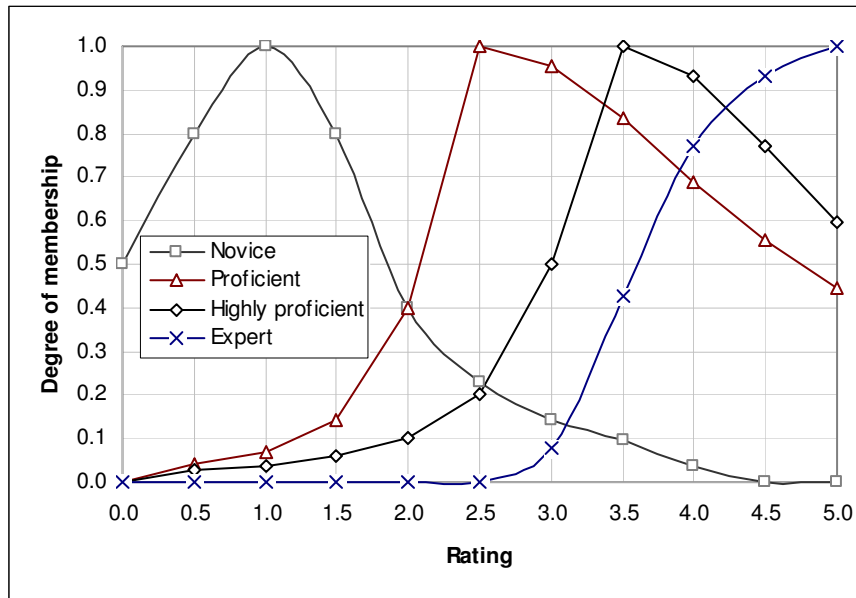
Figure 4.9 - Fuzzy Sets to Minimize Deviations from Target Values

Figure 4.10 shows the sinusoidal membership functions for an assignment policy whose objective is to minimize deficiencies from target values. These membership functions are used when there is no penalty associated with assigning overqualified resources to tasks. However, the sample scenario presented in this section assumes penalties for over-qualification; therefore, only the membership functions from Figure 4.9 will be used for the MFR process.
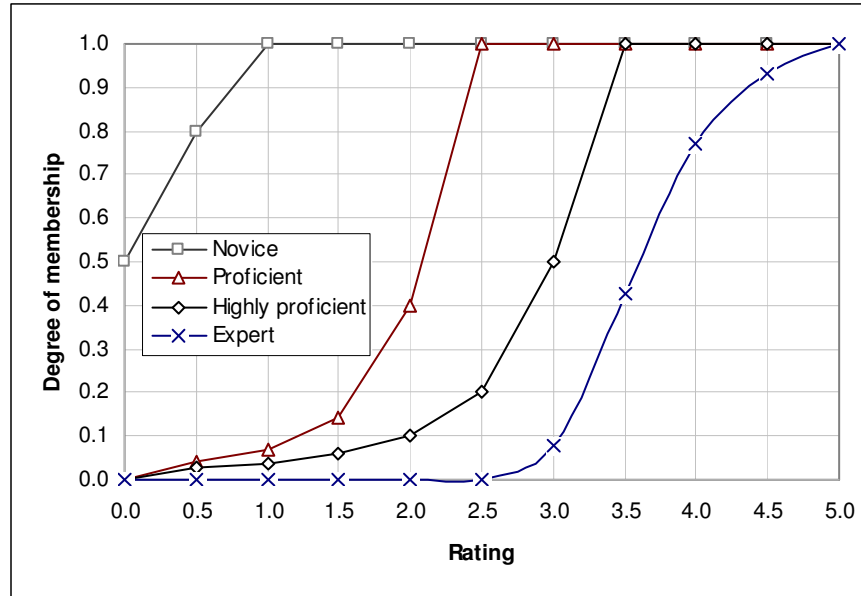
Figure 4.10 - Fuzzy Sets to Minimize Deficiencies from Target Values

To consider fuzzy goals representing the motivation of employees with each task, a single fuzzy set was identified with the following linguistic term: Highly Motivated. This means that one of the goals in every resource assignment is to match an employee with a task that he/she is Highly Motivated to tackle. The membership function for this fuzzy set is depicted in Figure 4.11.
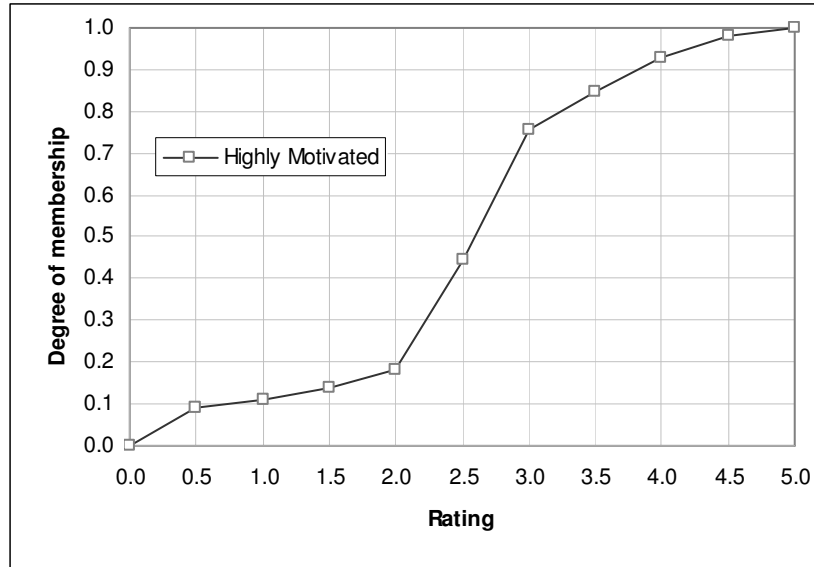
Figure 4.11 - Fuzzy Set for Highly Motivated

4.6.5   MFR Process

The next step is to consider the three possible priority levels for the goals (i.e., Low, Medium, and High) by developing expansion policies for each fuzzy set. With this in mind, the decision makers produced the set of general rules shown in Table 4.8.

Table 4.8 - Set of General Rules

Rules	Description
Rule 1	For high-priority goals over-qualification is highly preferred to under-qualification.
Rule 2	For medium-priority goals over-qualification is somewhat preferred to under-qualification.
Rule 3	For low-priority goals under-qualification is somewhat preferred to over-qualification.
Rule 4	For goals with Novice or Expert target values there is no distinction between priority levels.

The rationale for Rule 4 is that the decision makers associate novice and expert target values with a single priority level each. A goal that prefers a novice expertise is often logically viewed as low priority since they are relatively of low complexity. On the contrary, a goal that prefers an expert is usually perceived as high priority given that the number of resources with expert capabilities is often limited in industry.

The decision makers explained that there are cases where a highly proficient level of knowledge in a skill is desired for a low priority goal. For example, consider a task in which a high level of embedded programming expertise is desired to develop a software component. That is, the goal is to assign a resource that is highly knowledgeable in embedded programming. Now, assume that there is much legacy code from previous completed tasks that can be reused for this new component, in addition to detailed documentation that clearly explains this legacy code. This may cause decision makers to be more flexible and treat the desired level of skill as a low priority goal, hence expanding the set of possible solutions.

After several iterations to incorporate the preferences of the decision makers, the Expert fuzzy set remained unchanged. The resulting membership functions for the Novice, Proficient, and Highly Proficient fuzzy sets are shown in Figure 4.12, Figure 4.13 and Figure 4.14, respectively. Each fuzzy set shows reductions to their maximum attainable degrees of membership. For instance, the maximum attainable degree of membership for the Highly Proficient fuzzy set is smaller (i.e., 0.85) than for the Expert set (i.e., 1.0). This provides a higher incentive to match an expert with a task that requires an expert capability, rather than to match a highly proficient resource with a task that requires highly proficient expertise. This same rationale is applied to the remaining

111

sets. Moreover, these reductions avoid overcompensating higher achievements in lower priority goals.
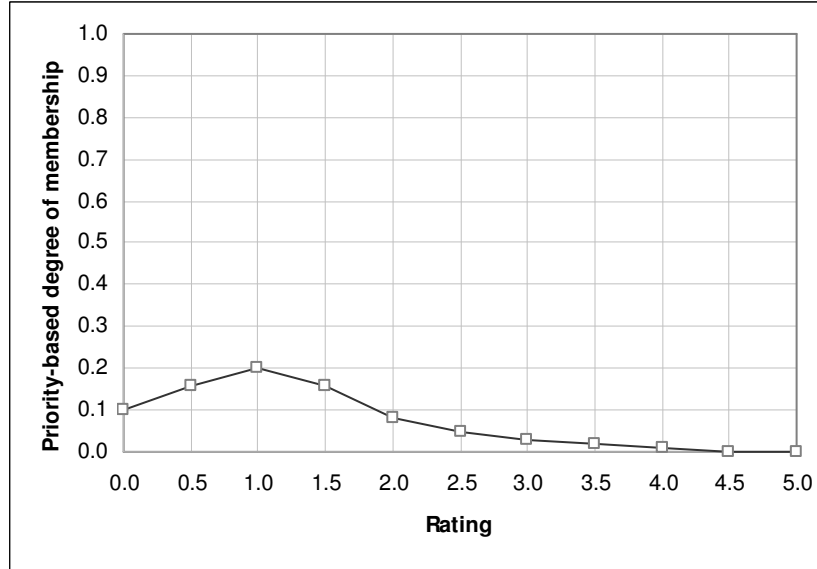
Figure 4.12 - Fuzzy Set of Novice Expertise After MFR
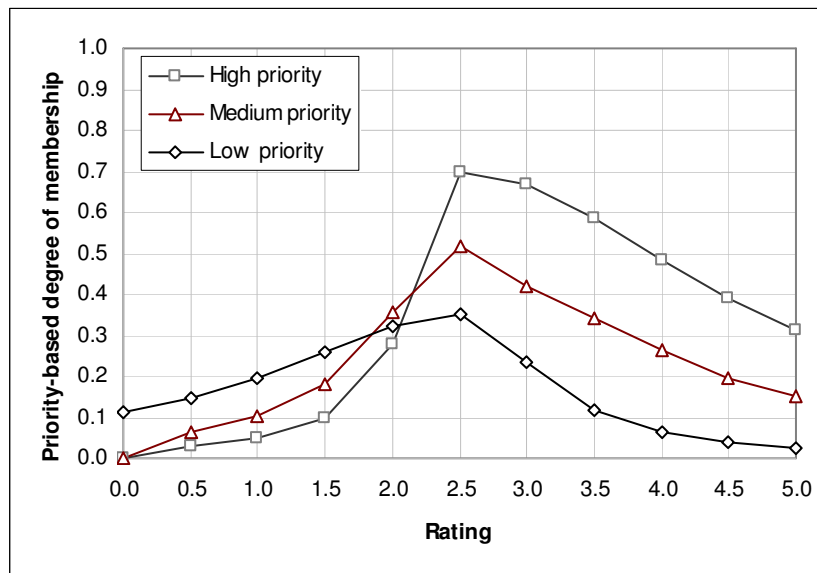
Figure 4.13 - Fuzzy Set of Proficient Expertise After MFR
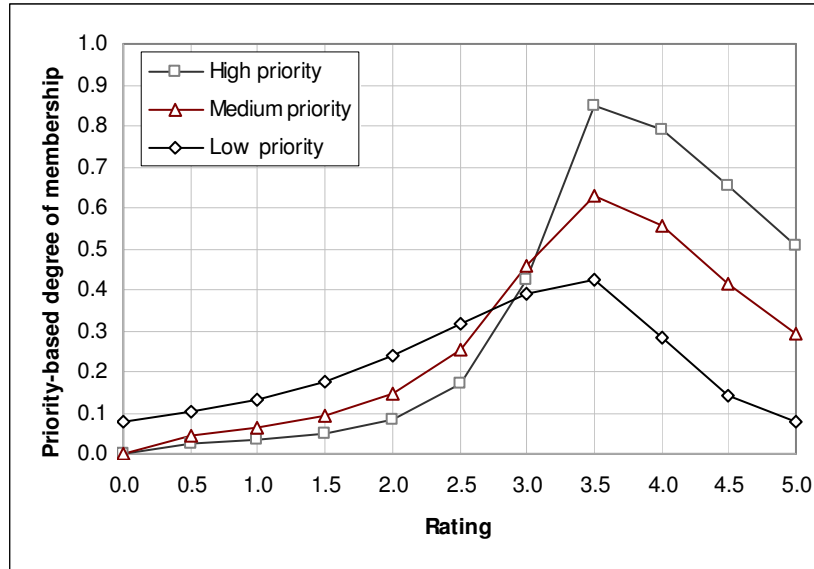
Figure 4.14 - Fuzzy Set of Highly Proficient Expertise After MFR

Finally, to consider priorities of tasks, it is necessary to construct a new fuzzy set to represent the following linguistic term: Excellent Assignment. First, a fuzzy set is developed based on the decision makers' preference of the $Proximity_{(rt)}$ values that constitute an excellent resource assignment to a high priority task. Then, this fuzzy set is relaxed and the maximum attainable degrees of membership for lower priority tasks are reduced through the MFR process. The decision makers decided that piecewise linear membership functions were adequate to model these fuzzy sets (see Figure 4.15).
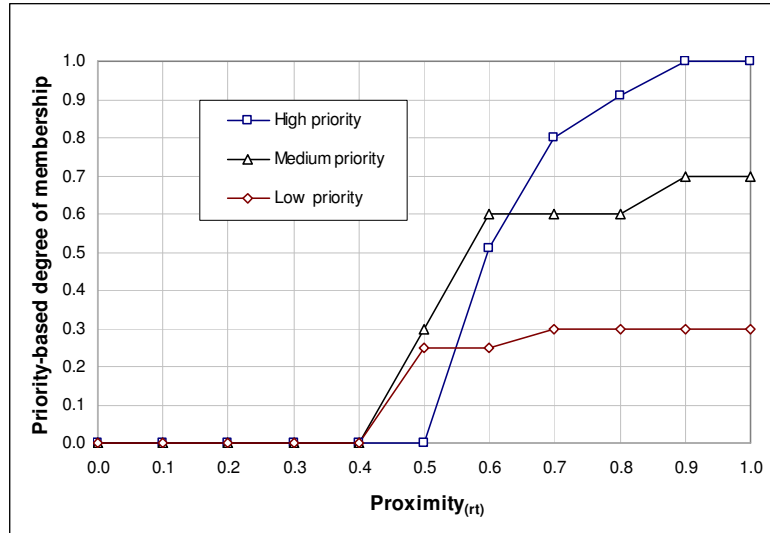
Figure 4.15 - Piecewise Linear Membership Functions for Tasks' Priorities

4.6.6 FGP Model Results

A software application was developed to compute the parameters necessary for the FGP solution. That is, the software implemented the solution approach up to the last step, which is to run the FGP model. This simplified the process of determining priority-based degrees of membership of resources with tasks (i.e., $PDOM\_Task_{(rt)}$), given the various combinations of factors involved in such calculations.

The software was implemented with the object-oriented C++ programming language. The output of the program is a DOS window with the $PDOM\_Task_{(rt)}$ values associated with all the resources and tasks. These $PDOM\_Task_{(rt)}$ values were then used as inputs to the FGP model, which produced the assignments presented in Table 4.9.

Table 4.9 shows the proximity values for the resources with the goals of the tasks, as well as the resulting priority-based degrees of membership of each assignment. These values provide a measure of the level of satisfaction of the decision makers with each allocation after carefully considering priorities of goals and tasks. For each of the three

114

high-priority tasks, the resulting priority-based degrees of membership were over 0.9. This means that based on the membership functions used for the FGP-MFR model, these three resource assignments are very close to fully belonging to the Excellent Assignment fuzzy set. The same conclusions can be made about the medium-priority tasks, since the obtained degrees of membership were close to the maximum allowable value of 0.7 that resulted from the MFR process. Notice that the assignment of resource R_5 to Task_7 resulted in a zero priority-based degree of membership. This is due to the overall limited expertise of R_5 with the set of skills required by any of the tasks. Therefore, in this case it resulted more efficient to assign R_5 to a low-priority task.

Table 4.9 - Solution to the Personnel Assignment Problem

Resource	Task	Proximity$_{(rt)}$	Task Priority	PDOM_Task$_{(rt)}$
R_2	Task_1	0.87031	Medium	0.66701
R_8	Task_2	0.60866	Medium	0.60000
R_9	Task_3	0.79067	High	0.90018
R_4	Task_4	0.82923	High	0.93080
R_6	Task_5	0.94001	Medium	0.70000
R_7	Task_6	0.65400	Low	0.27444
R_5	Task_7	0.15043	Low	0.00000
R_3	Task_8	0.96847	Medium	0.70000
R_1	Task_9	0.62524	Medium	0.60000
R_10	Task_10	0.86186	High	0.96270

4.7   Summary and Contributions

This study presented a new FGP personnel assignment approach in scenarios characterized by imprecise tasks' requirements and resources' capabilities. The goals for each resource assignment are to meet desired target values for technical expertise, team

parameters, and personnel preferences. These target values are represented with fuzzy sets which are developed with the help of decision makers. Then, priorities of goals are considered by adequately manipulating membership functions of target values. Priorities of tasks are considered in a similar way. A fuzzy set is constructed to model the decision makers perceived definition of an excellent resource assignment based on the suitability of a resource with the set of goals of a task. This fuzzy set is then modified for lower priority tasks to promote better assignments to higher priority tasks.

There are two major contributions that this research study makes to the personnel assignment body of knowledge. The first significant contribution is the introduction of FGP to the specific area of skill-based resource assignments. The second significant contribution is related to the types of parameters considered in current skill-based personnel assignment methodologies, as well as the approaches for modeling them. An extensive review of relevant literature highlighted several significant limitations in this area. The solution approach developed in this research addresses these limitations in three main ways. First, it includes several critical parameters associated with resources and tasks that must be considered in the decision process and are omitted in current methodologies. Some of these parameters include priorities of skills and tasks, as well as the motivation levels of employees to work particular jobs. Taking into account these parameters in the decision process leads to more thorough evaluations of alternative solutions. Second, the solution approach considers the definition of these parameters to be naturally imprecise. Thus, these parameters are modeled using fuzzy sets instead of using the common classical set theory. This realistic representation of imprecise parameters with fuzzy concepts has the potential to provide a high practical value to the

methodology. Third, the solution approach directly involves decision makers in the process of defining imprecise parameters through the construction of the fuzzy sets. This may also provide higher practical value to the solution approach, given that current fuzzy approaches to personnel assignments provide simple membership functions (e.g., triangular or trapezoidal) that were created without consulting decision makers.

4.7.1 Research Extensions

A major challenge for any researcher is to develop new methodologies that become widely accepted by practitioners. To achieve this, it is important for researchers to properly market their solution approaches by bringing these novel methodologies into industry scenarios to show field experts the capabilities of such new approaches. With this in mind, the approach developed in this research needs to be applied to different industry settings to validate its applicability and determine its acceptability. Furthermore, a user-friendly software implementation of the solution approach is necessary. This effort was initiated with the software developed in this research to determine the degrees of membership of resources with tasks. However, proper software engineering processes must be followed to develop a complete decision support system to meet the expectations/requirements of decision makers.

Another research extension is to conduct experimental control group analyses to determine the impact of applying the personnel assignment methodology developed in this research versus using the conventional subjective approach. This would provide evidence to support (or not) the existence of significant gains from using the new methodology.

Finally, this research could be expanded by conducting a survey analysis to investigate if it is reasonable to develop a baseline of membership functions for general/common skills in particular environments. For example, it may be possible to interview experts from different software development organizations to come up with fuzzy sets for technical capability assessments that can be used as standards across companies. This same approach can be followed and adopted in other fields.

CHAPTER 5

CONCLUSIONS AND FUTURE RESEARCH

This chapter presents the conclusions of this dissertation and summarizes extensions for further research.

5.1 Conclusions

Personnel assignment methodologies have been the focus of active research for various decades. Nevertheless, companies continue to struggle to deliver quality products on schedule and within budget constraints.

This research presents a systematic analysis approach to develop a robust solution to the personnel assignment problem in skill-based environments. First, the problem was decomposed into three main activities: identifying assignment criteria, evaluating personnel capabilities, and assigning personnel to tasks. Second, an extensive literature review was conducted to determine specific opportunities for improvement in each of the three areas. Based on the literature findings, this work presents a framework for resource allocation composed of enhanced methodologies to efficiently identify assignment criteria, conduct thorough assessments of personnel capabilities, and effectively assign resources to tasks.

The general methodology developed in this research to identify assignment criteria is based on a two-stage DEA-Tobit regression approach that determines the

impact of personnel factors to quality and productivity measures. This methodology contributes to the personnel assignment body of knowledge by presenting an analytical approach that considers multiple outputs simultaneously and eliminates subjectivity when determining relative priorities for assignment criteria in skill-based environments. This tool is of significant use and relevance to decision makers since most personnel assignment decisions in industry involve the evaluation of several performance measures and pose a challenge for decision makers to subjectively determine important parameters. The methodology was validated by analyzing data from a software development corporation, which resulted in the identification of drivers of efficiency of personnel assignments per task complexity. The resulting assignment criteria can be used by decision makers in software development settings, which is another key contribution of this research.

For evaluating personnel capabilities, this work presents an expert system architecture capable of making fuzzy inferences. This approach uses fuzzy theory to represent personnel levels of expertise, establish relationships between skills, and make inferences about the qualifications of personnel. This realistic representation of imprecise parameters and activities using fuzzy concepts has the potential to provide a high practical value to the expert system. The main contribution of the proposed approach is the introduction of a high-level layered architecture where each layer is adaptable to context-specific subcomponents. More specifically, each layer can be customized with different subcomponents without impacting the code implementation of the other layers. This is accomplished by introducing a global layer that is used as the only channel of interaction between any two layers. Therefore, implementation details of

any layer are hidden from the others, making changes concealed and imperceptible to other layers. This provides decision makers the flexibility to add/delete/modify subcomponents in any layer based on their particular needs without having to incur into expensive architectural system modifications.

Finally, this research introduces a new FGP model for personnel assignments in scenarios characterized by imprecise tasks' requirements and resources' capabilities. The goals for each resource assignment are to meet desired target values for technical expertise, team parameters, and personnel preferences. These target values are represented with fuzzy sets which are developed with the assistance of decision makers. Priorities of goals and tasks are considered by adequately manipulating membership functions of target values.

The FGP approach addresses three significant limitations from the existing literature. First, it includes several critical parameters associated with resources and tasks that must be considered in the decision process and are omitted in current methodologies. Some of these parameters include priorities of skills and tasks, as well as the motivation levels of employees to work particular jobs. Taking into account these parameters in the decision process leads to more thorough evaluations of alternative solutions. Second, the solution approach considers the definition of these parameters to be naturally imprecise. Thus, these parameters are modeled using fuzzy sets instead of using the common classical set theory. This realistic representation of imprecise parameters with fuzzy concepts has the potential to provide a high practical value to the methodology. Third, the solution approach directly involves decision makers in the process of defining imprecise parameters through the construction of the fuzzy sets. This may also provide

higher practical value to the solution approach, given that current fuzzy approaches to personnel assignments provide simple membership functions (e.g., triangular or trapezoidal) that were developed independently from decision makers.

5.1.1 Research Extensions

There are various areas for future research associated with each of the methodologies developed in this dissertation. This presents opportunities for researchers to continue investigating and enhancing the science of personnel assignments.

The DEA-Tobit approach developed to identify assignment criteria was evaluated using data from a software development organization. Given that the data were limited to four personnel factors, an apparent expansion is the necessity to confirm and extend the results with additional personnel and task factors to increase the understanding of drivers of efficiency in software applications.

A necessary research extension for the expert system presented for capability assessments is to complete its design phase and proceed to the coding phase. Since this research provides the high-level software design architecture, the next step would be to divide the architecture into components and develop detailed designs for each component using object-oriented tools such as class diagrams. The final product must include proper software engineering documentation such as software requirements specification, software design document, software manual, and test description document.

Another potential research extension to the proposed expert system is to conduct a survey analysis to investigate if it is reasonable to develop baselines of membership functions for general/common skills in particular environments. For example, it may be

possible to interview experts from different software development organizations to establish fuzzy sets for technical capability assessments that can be used as standards across companies. A similar survey analysis can be conducted to examine the possibility of establishing fuzzy rules' baselines to describe the relationship between various skills.

The FGP approach for personnel assignments presents a preliminary effort to develop a user-friendly software implementation of the solution approach. This initial step includes C++ code to determine the degrees of membership of resources with tasks. However, proper software engineering processes must be followed to develop a complete decision support system that meets the expectations/requirements of decision makers.

A major challenge prompted by the development of new methodologies is the validation of these novel approaches. Although the implementation of the FGP approach was demonstrated through an example, further research is necessary to validate the methodology. One suggestion is to conduct experimental control group analyses to determine the impact of applying the FGP personnel assignment methodology developed in this research versus using the conventional subjective approach. This would provide evidence to support (or not) the existence of significant gains from using the FGP approach.

Another major challenge of new methodologies is their acceptance by practitioners. To achieve this, it is important for researchers to properly market their solution approaches by bringing these novel methodologies into industry scenarios to show field experts the capabilities of such new approaches. With this in mind, each of the methodologies developed in this research must be applied to different industry settings to validate their applicability and acceptability.

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