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OPTIMIZING HUMAN RESOURCE ASSIGNMENT IN ENGINEERING DESIGN COMPANIES

by
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AN ABSTRACT OF THE THESIS OF

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Human capital is a major asset for engineering companies. On-time completion of project tasks and cost effectiveness are contingent on proper allocation of human resources. In practice, most engineering managers assign resources according to availability without considering the level of employee's expertise when taking the decision. This may result in lower quality of design production or difficulty in meeting deadlines. To better attain project requirements, the assignment practice could be improved by including resource characteristics and critical project information. This thesis presents a reliable resource assignment mathematical model that considers engineers' years of experience, their level of familiarity with different software programs used by the company, and other task-related attributes. The output of the model consists of assignment variables through pairing a group of human resources to a group of tasks with the objective of minimizing project duration and cost while maximizing resource utilization. Extensions to the model can allow engineering managers to monitor and control the progress of the project or the lack thereof.

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CHAPTER I

INTRODUCTION

The environment we surround ourselves with is a combination of engineering solutions that were developed through creative collaboration of scientific methods and technological tools. These solutions need to go through several stages before reaching their final stage. They start off as abstract ideas and then flourish into ‘concrete’ systems serving a purpose (Koehn 1985). When it comes to the construction industry, in particular, studies have found that this field makes up between 9-18 % of the total GDP of most countries, with some extreme variations of course (International Comparison Program 2005). Traditionally, creating a facility involves three consecutive major processes: designing the concept, competitively bidding for the contract and eventually, constructing the facility. The traditional method has proven to be a beneficial approach over the years. However, projects have become more and more complex and are now characterized by a unique set of requirements due to the growing economy and technological breakthroughs. Hence nowadays, it is possible, and sometimes more likely, to find construction projects following different mechanisms for delivering the end-product. The new methods are variations of the traditional process that include new components and may enhance the delivery method for certain projects through completing the facility in lesser time, allowing the introduction of changes during construction without major damages, diminishing adversarial relationships, supporting different financing mechanisms, incorporating the contractor's opinion during the design stage and providing the latter with incentives to reduces costs for the owner (Gordon 1994). Even though variations of the project delivery method do exist, there will always be certain major milestones that are common for all projects, one of which is producing design drawings to communicate the formulated concept. This research will be focusing specifically on the design process under the traditional delivery method, however, the same logic can be applied for delivery methods that include a separate and clearly defined design phase.

Design is an intellectual process that revolves around creating a concept that serves as a solution to problem. It requires the input of everyone who is involved and thus the result is an interpretation of their perception of the solution. Design evolves through several stages with the three major phases being the schematic design phase, the design development stage, and the construction documentation phase. The first stage includes a representation of the proposed concept of experienced individuals. Expert designers suggest ideas as potential solutions to what the client is asking for. They then delegate the concepts to younger designers to translate them into design drawings that would be shared with the project participants. There may be several options and ideas for the concept of the facility and the outcome of this stage would be to choose a final design concept after comparing all possible alternatives. It is important to note that senior level engineers are more involved at this stage compared to the input of younger designers. The second stage of the design phase consists of delving into the details of the chosen concept and designing the functional systems of the facility. Since the scope of the project would be clearer at this point, senior level engineers step aside and young designers become more involved in producing output with the help and supervision of their managers. Meetings are done during this phase to discuss the results and this phase, along with the first, allow for high incorporation of changes without drastically affecting the budget of the project. The final stage of the design involves generating design drawings with a very high level of detail that allows the contractor to execute the project. During this phase, minimal changes are introduced into the design of the facility and young designers are responsible for translating all the elements of the functional systems of the facility into drawings ready to be used for construction guidance. Looking at the difference design evolution stages, we notice that the first relies heavily on senior managers who have 10+ years of experience and the last two stages require the power of the young designers who usually have been working as designers for around 4-5 years. Designers with experience ranging between 5-10 years would be team leaders who serve as a connection between the senior and young designers. The number of young designer far exceeds that of senior engineers, however, it is the responsibility of the senior managers to plan and control the teams they lead (Gray and Hughes 2001). This implies that during the design development and construction documentation phases, human resource management becomes essential to avoid time and cost inefficiencies. Thus, the focus of this research is to look into how the young designers are managed, and allocated, during the last two stages of design.

The firm's resources are defined by the strengths and weaknesses of the organization. They include its assets, competences, organizational strategies, information, etc., which allow companies to implement their procedures (Barney 1991; Daft 1983; Wernerfelt 1984). Human resources, in particular, refer to the individuals working in an organization (Batarliene et al. 2017). The recent technological revolution characterized by automation and digitization, which is the process of converting information into digital format, has undoubtedly lessened the need for large numbers of individuals to perform the job. Despite these advancements, large-scale design companies are still characterized by their main asset: human resources. The latter play a critical role in determining the level of quality of the company's work, which in turn translates into project success or failure. The accomplishments of firms are not only dependent on applying client satisfaction strategies, but also extend to characteristics of their employees (Hecker 1996). This competitive advantage that companies gain stems from the knowledge, experience and skills that human resources possess (Batarliene et al. 2017), and the way the workforce is utilized (Shaw 2004). Nonetheless, companies tend to focus more on the technical perspective of a project and less so on human resources. To be able to survive the adversarial and competitive market, corporations need to continuously enhance their performance (Garavan et al. 1999; Hodgetss et al. 1999; Losey et al. 1999) which can be achieved through proper human resource management (Ngwenya and Aigbavboa 2017).

The objective of this research is to develop a robust human resource allocation tool for engineering design companies that bases its assignment decision on resource-related and project-related factors when nominating individuals to work on specific tasks. Previous studies show that existing design time estimation models have not considered the complexity and size of tasks, managerial expertise, and resource experience together for computing the required effort. Additionally, limited research has been done to create a human resource assignment model specific to engineering design and consultancy companies. These companies generate and review work under various disciplines such as structures, architecture, environmental, transportation, mechanical, electrical, planning and urban development, and façade engineering divisions. As human resources are the underlying assets of these companies, their proper allocation should remarkably enhance the degree to which a project can be considered successful. The significance of this study lies in guiding design firms to better allocate their human resources while considering multiple resource and project related factors. The developed tool also aims at (1) making sure the time required to complete the demand of tasks does not exceed the allocated time for each task and (2) minimizing the total cost of engineering work-hours devoted to finalizing the project. Accordingly, this research adds to the existing literature by address the following questions:

- What human related factors influence the engineering design task duration? And how can these factors be incorporated in the estimation tool?
- How can resources be optimally allocated in engineering design firms to ensure minimum labor cost while meeting project deadlines?

The rest of the thesis is organized as follows. The next section covers background information on elements related to human resource allocation. This is followed by a description of the methodology adopted to perform this study. Next, the discussion of formulating a mathematical model for resource allocation in design companies is presented alongside a description of the developed algorithm. A case study is then presented to demonstrate how the model works. And the final section offers conclusions, discusses limitations of the work, and provides suggestions for moving forward with this study.

CHAPTER II

LITERATURE REVIEW

The majority of human resource allocation problems are evaluated based on classical resource allocation planning examples. Having a standard plan that is independent of which resource will be performing the task implies that the individuals are considered to be equal. In other words, managers implementing the plan expect all resources to take the same duration to complete an activity and under all circumstances (Eskerod 1998). Not focusing on individual attributes along with project specific characteristics renders the allocation process inaccurate. This led to several studies that were carried out to come up with reliable human resource allocation models and tools in different work fields ranging from health-care organizations, software developing companies and contracting companies. These tools were also developed using different methods like goal programming, decision making support system, multi-objective multistage combinatorial optimization models, dependency structure matrix, Taguchi's parameter design, and constraint satisfaction problems, to name a few. The existing but advanced human resource allocation cases now analyze task-related features, like duration and complexity, or individual-related factors alongside the original planning perspectives due to their valuable enhancement to the allocation model.

This section is divided into four subsections: first, it introduces resource allocation as part of human resource management. It then dwells on elements that are related to the assignment process and that will be considered in the developed decision tool like former methods for estimating design task durations in specific and the different factors that affect the job performance of an employee. Finally, it highlights the previous work of researchers done for developing human resource allocation models while pointing out the methods used for formulation.

A. Human Resource Management/Allocation

According to Prizada et al. (2013), managing employees is thought to be a troublesome activity that differs from handling capital or technology. It is a tricky process that helps determine how well the company performs since it provides the firm with its competitive advantage in the market (Prizada et al. 2013). Researchers describe human resource management (HRM) as a tool that adds value to the company's profile and allows the organization to achieve its goals. It includes various fields that require attention like the processes of selection, training, rewarding and much more (Wright and McMahan 1992). Great focus is given to HRM practices due to their positive effect on firms' performance and the ambitious added value resulting from proper HRM (Rolim et al. 2013). This practice has also proved to lower risks especially in an international environment (Lin 2011). One form of managing human resources is the process of resource allocation whereby individuals are assigned to certain tasks within the chosen development projects. Rolim et al. (2013) state that a vital management strategy is to guarantee that the proper human resources who have the suitable skill set are assigned in an efficient manner that meets the project requirements. This process is peculiarly critical since several attributes relating to the individual need to be taken into account and current allocation practices usually neglect the aforementioned and distribute resources according to the managers' intuition and availability of the resource (Yoshimura et al. 2006; André et al. 2011). An employee ends up working on tasks whose skillset requirements do not match the worker's profile, and this translates into inefficient performance throughout the execution of the project. In addition to that, the estimated duration for design tasks may be inaccurate due to the lack of quantifiable features and the uniqueness of projects that leads to imprecise estimation of the effort an individual would need to invest to complete a certain task. Evident consequences of these inaccuracies are schedule and cost overruns (Bashir and Thomson 2001). Such overruns may lead to the project's failure if it is not completed within the suitable time range or if it exceeded the intended budget according to a study by Bashir and Thomson (2001). Moreover, and in that same study, the investigators found that other researchers identified several reasons behind schedule and cost overruns in design projects where around 40% of these causes were related to human resources. Hence, it is crucial to dive into the essence of human resource management practices within companies and not have them be made by default in order to allow firms to make use of the competitive advantage due to their employees (Maloney 1997). One of the elements that directly affect a company's performance would be time required to deliver projects and hence the following section reveals various estimation methods adopted by previous researchers.

B. Design Task Duration Estimation

This section revolves around identifying previously developed methods for estimating the time required for employees to complete certain tasks. It is important to understand these methods due to their significant effect on employee performance. The time duration required by a human resource to work on an activity should take part in determining where should the employee be assigned to. Much of these past investigations dealt with estimating design time required for the manufacturing and industrial sectors. Bashir et al. (2001), Nasrallah et al. (2015), and Liu et al. (2017) proposed models for estimating design time under these sectors but each took different paths to do so and focused on diverse factors that they believe will have a significant impact on design time.

Bashir et al. (2001) concentrated on product and functional complexity of the project and developed design time estimation models based on the aforementioned, while taking into account the severity of requirements. The researchers aim was to come up with a model that could be applied to a variety of projects. The model is divided into two main parts; the first quantifies the complexity of the project and then the second part uses that level of complexity to predict how long would the design require. However, the formulation does ignore any information specific to the human resources like their years of experience for example. This leads to a huge assumption that any individual/team performing the task will be able to complete it with the same effort, which is not quite accurate.

Nasrallah et al. (2015) conveyed the importance of having proper managerial skills and enough domain knowledge in design teams for improved performance. Managerial skills are defined by values relative to the capabilities of the most proficient manager, while the domain knowledge is defined according to the amount of work fields that the manager has considerable experience in. The input managers give significantly affects the output of their team. They are responsible for setting up the action plan, task structure and objectives and this becomes critical for large teams. Hence, the researchers believe that increasing the team's size does not always have a positive influence on performance due to the increased coordination that results from adding multiple members to a unit. However, the formulation is mainly based on managerial characteristics, and it disregards any information pertaining to the project or task. It is centralized around estimating design time based on which project managers are working and not enough attention is given to the remaining human resources, i.e. the team members, and to the size and complexity of the activities.

Liu et al. (2017) emphasize that previous estimation models assume that resources are unlimited when in fact they are. To compensate for such an assumption, the researchers aimed at developing their own formulation. They divided the resources depending on the discipline they work under, then computed the total skill level for each employee which is a result of the knowledge due to his/her own experience and skills and due to the knowledge gained from learning from other employees. The resulting resource characteristics were used to estimate the duration of a task that was considered to be a fuzzy number. This fuzzy number is defined by three categories: the most likely time which is based on the characteristics of the pool of available resources and eventually, the resource that is most likely to be obtained when choosing an employee, the optimistic time which is estimated as the duration required for completing the task under the best condition and consequently, the pessimistic time that is similarly estimated as the time needed to finish an activity under the worst conditions. Nonetheless, it is important to note that in this study, the researchers have not accounted for the size and complexity of projects and the input of managers, but rather focused on estimating the duration for tasks based on resource attributes.

In addition to the design task time, employee attributes also have an impact on the company's performance and thus, former studies analyzing the employee characteristics will be explored in the following section.

C. Factors Affecting Performance

The output of individual employees whose job positions mainly require their personal input and effort highly depends on the worker's performance. This performance can be evaluated against several factors that are mainly related to job satisfaction. Van Saane et al. (2003) and Lu et al. (2012) identified each of task autonomy, which is allowing the individual to freely choose and control the method they wish to use to execute the task (Langfred et al. 2004), and task variety, which means putting a range of employee skills to work and not having repetitive work all the time, to be some of the major factors that have a remarkable effect on the satisfaction level of the person employed. Both studies also concluded that providing the employee with promotional openings like training and educational opportunities would positively affect the worker's satisfaction. In other words, as the employee becomes more knowledgeable about their job, he/she would feel more content towards the work. Other factors include, but are not limited to, supervision, communication, salary, and feedback. Moreover, there is a direct link between job satisfaction and organizational performance whereby the first can strongly determine the level of success of a firm (Bakotic 2016) indicating that focusing on improving factors affecting job satisfaction can ensure an overall enhancement in a company's performance.

On a more technical level, construction and engineering companies need to recognize and comprehend the areas of expertise that lie within the firm (Trejo et al. 2002). This is because these companies often work on large-scale projects, and looking into their own competencies is an important factor in optimizing profitability and productivity. To do so, the authors suggest that these capabilities are divided into four main groupings: knowledge, skills, abilities, and experience. The human resource allocation process can then be done based on proper mapping between the individual capabilities and the necessary company competencies. The suggested framework includes evaluating the companies resource allocations and determining strategic and functional competencies, done by an individual in a management position. The ultimate goal is to check for alignment between the competencies when allocating human resources, and identify which capabilities are needed but non-existent in the resource pool. The latter become a main target for future human resource management practices and proper mapping of the needed and the existing capabilities can help ensure better production.

After understanding what features influence the performance of the company and why they need to be taken into consideration when allocating human resources within a company, it becomes essential to learn about previously developed resource allocation model and their formulation, which will be covered in the next and final section of the literature review. This would eventually support the reasoning behind the designed model.

D. Existing Literature on Human Resource Allocation Models

Otero et al. (2009) detected delay in delivery software development projects due to the need for training employees who do not have the required skill set for certain tasks. Such an issue may rise when qualified staff members are preoccupied with other projects/tasks. Thus, Otero et al. developed systematic personnel assignment methods that evaluate the skill sets of employees against required skills for certain tasks using the Best-Fitted Resource approach. Their study, however, only focuses on the skills acquired by each employee and does not include other factors that normally affect the performance of the designer.

Similarly, Silva et al. (2013) and Tsai et al. (2003) analyzed possible human resource allocation alternatives depending on the capabilities of employees and skill requirements for tasks related to software development projects. However, the authors also added the complexity of each project as a factor to be considered to weigh the type and number of professionals needed. Their ultimate goal was to minimize, or at least decrease, the cost and amount of time necessary to complete a project since software design projects almost never meet their deadlines.

Albers et al. (2012) handled human resource allocation with the use of Dependency Structure Matrices (DSM) which are normally used for modeling the structure of complex systems for organizational and planning purposes. The used model presents a multi-domain framework of the activities required for product development and a number of human resources responsible for fulfilling these tasks. It elaborates on the effect of different resource allocation options on the flow of information between activities, and how it enhances the dynamic relationships between the objective of a project, the objects used for completing the work and the operation systems. Nevertheless, the model does not discuss the characteristics relating to resources, or whether each resource is considered as being unique. The main focus is on how dependent the activities are on one another and if they require common resources to work on them.

Kwak et al. (1997) used a variation from linear programming model, referred to as goal programming (GP) that also aims at minimizing total payroll costs while addressing the needs of patients at a healthcare organization. This technique gives goal constraints in addition to system constraints like minimum payroll goal, physician utilization goal, and physician assignment goal.

It is important to note that several human resource allocation models can be found in the literature that cover engineering/construction site work. However, the nature of the work on construction sites and the structure of teams differ greatly from that of design, in the sense that, construction activities are more specific, easily quantifiable and can be broken down into distinct processes. Design activities, on the other hand, are iterative steps that form a virtual visualization of the intended final product. Hence, when developing the mathematical model for resource allocation in design companies, little emphasis was given to the principles behind resource allocation on sites. Their respective models were taken as an inspiration for the layout of the allocation formulation.

CHAPTER III

METHODOLOGY FOR CREATING RESOURCE ALLOCATION MODEL

The aim of this study, as previously mentioned, is to develop a decision tool for design companies that optimizes the allocation of human resources across the firms' tasks while meeting deadlines and minimizing the costs associated with assigning the employees. To achieve the stated research objectives, extensive literature review was done covering various design task duration estimation tools done. The majority was found under the manufacturing industry. The review also examined numerous human resource related factors that affect the job satisfaction of an employee and hence the organization's performance. Finally, studies on previously developed human resource allocation models were inspected and dissected to better understand appropriate allocation formulations and commonly used tools that would be suitable for such an exercise. The literature review was structured in a way to encompass all components that may influence the human resource assignment process specific to engineering design and consultancy companies. As a result of this review, the researcher was able to identify the gaps that needed to be filled, and hence this helped define the scope and aim of this study to focus on solving the problem with currently applied allocation methods for human resources.

Next, a conceptual model was built based on a human resource allocation model developed by Laura Florez (2017) aimed at assigning masonry crews to work on building walls on a construction site. The formulation was adjusted to serve the purpose of this research whereby the crews represented the individual employees and the walls resembled the tasks at hand. Several equations were also altered due to the difference in nature of work between construction and design. Construction activities are tangible, and the output can be directly computed by looking at the volume of work and productivity of the crew. While, on the other hand, design activities are abstract and iterative processes that cannot be easily measured. And so, representing design tasks in the model was based on the time estimated by the resource to complete the task, which in turn was the result of combining the managerial expertise, resource skills and size and complexity of the project. The mathematical formulation consisted of linear function of several variables that represent the objective function that needs to be minimized. This objective function is the cost of employment and was subject to several constraints that are also linearly related. And in order to find the optimal solution that ensures meeting the restrictions with the least cost possible, linear programming was applied to the function. This mathematical technique is the fastest way that could yield the required results.

A refined computational model shaped due to the conceptual formulation was generated and which allows for testing numerous resource allocation case studies. This model was coded using the commercial computational language, MATLAB. MATLAB is a high-performance language for technical computing and includes built-in functions typically used for reaching optimum solutions and other applications. Therefore, this language was used due to its suitability for solving our objective of allocating resources while minimizing incurred costs and meeting all project deadlines. To do so, the model was designed to first read the input that represented the resource and task attributes. MATLAB is somewhat limited when it comes to reading input and that is why the attributes were listed in separate excel files that would be eventually imported into

MATLAB as matrices. Next, the code began estimating the time required by any resource to complete all the tasks. The logic behind this estimation will be discussed in Chapter IV, but this is part of the code that took into account all factors that affect the design process when computing the activity duration. Then, a built-in function was used to find the optimal solution, and this assignment was compare to current methods of allocation for quantifying the benefits of the model. A sensitivity analysis was done after that to understand the relationship between the factors of the model and the resulting output.

To verify that the code is functioning properly, a sample toy problem was created that showcases a small example of a typical allocation exercise. The developed MATLAB code ran simulations to get the optimal assignment solution. The resulting answers were compared to manual calculations done using Microsoft Excel. Microsoft Excel is famous for its “Solver” add-in that could easily find the optimal answer after setting an objective function and defining its constraints and so, this program was chosen as a suitable/reliable method for verifying that the modeled algorithm is in fact outputting the correct answers.

The final step towards the model formulation consists of validating the results generated by the algorithm. This process is defined by the act of ensuring that when the computerized model is applied, it holds a reasonable range of accuracy compatible with the intended function of the model (Schlesinger et al. 1979). According to Sargent (2005), there are several ways for validation that allow researchers to analyze the resulting figures and test them against required error tolerances. It all the depends on the type of data available for validation of the model, and the role of the people carrying out the validation activity. For example, the model developers themselves can decide to test the validity of the model based on assessments done as part of the creation process. Or, the final user of the developed model may take part in determining whether the generated results of the model are valid or not. Finally, one can invite a third independent but knowledgeable party that can judge the accuracy of the model outcome. Moreover, the techniques adopted include animation and conditional tests, comparison of the developed model to other previously formed ones that serve a similar purpose, confirmation of historical data, interviews with professionals who are experts on the matter and much more (Sargent 2005). The technique that will be considered in this research is called face validity and it involves taking the opinion of specialists on how reasonable the assumption, inputs, relationships and results of the model are. This method was chosen since engineering design companies do not always keep record of how long a resource needed to complete a task. And even if they did, this information would not be readily available online. Hence, for simplification, a manager, which is also a potential end user of this model, will be asked to provide feedback.

CHAPTER IV

HUMAN RESOURCE ALLOCATION MATHEMATICAL MODEL

A. Parameters, Variables and Assumptions

The aim of the human resource allocation model is to assign a pool of resources to a pool of tasks while taking into account the attributes that are related to both. This assignment aims at minimizing the total cost of work-hours spent completing the design tasks and ensuring that the task duration does not exceed its scheduled time. Table 1 defines the element sets, parameters, and decision variables used for the basic human resource allocation model formulated for design firms.

The wage (w_j) corresponding to each employee depends on the individual's years of experience and software program level of familiarity. As estimated by the U.S. Bureau of Labor Statistics (BLS) in 2010, Table 2 corresponds to the typical range of wages for civil engineers.

The expected time (e_{ji}) required by a specific resource to complete a particular task is estimated by combining resource and task related attributes. The optimistic, pessimistic and most likely to occur durations define the boundaries for the computed expected time. Then, the combination of resource attributes defines which sub-range corresponds to which resource. Finally, the time expected by the resource to perform a certain task is estimated accordingly.

Table 1. Element Sets, Parameters and Decision Variables Adopted in Mathematical Model

	Element Sets
J	Set of human resources
I	Set of tasks to be completed
T	Time step
t	Time period
	Parameters
w_j	Wage of resource (j)
v_{jt}	Binary variable that takes the value 1 if resource (j) is available at time (t), 0 otherwise
x_j	Level of experience of resource (j): EXPERIENCED vs. JUNIOR
s_{jh}	Level of familiarity of resource (j) with software program (h): NOVICE vs. EXPERT
c_i	Deadline of task (i): maximum number of days for task (i) before it is considered late
e_{ji}	Time period required by resource (j) to complete task (i)
o_i	The optimistic time estimated by the manager to complete task (i)
m_i	The most likely to occur time estimated by the manager to complete task (i)
p_i	The pessimistic time estimated by the manager to complete task (i)
	Decision Variables
b_{ijt}	Binary variable - takes the value 1 if resource (j) is assigned to task (i) at time (t),0 otherwise

Based on the above, the primary assignment solution appoints human resources to specific tasks in a way that guarantees the minimum cost needed to complete all activities in a timely manner. Elaboration on reaching the optimal solution will be presented in the upcoming sections.

Table 2. Estimated wage of civil engineers as published by the U.S. BLS.

Employee Characteristics	Employee Wage ($/hr)
Experienced & Expert	45
Experienced & Novice	36
Junior & Expert	28
Junior & Novice	20

The following assumptions were made when developing the model:

- Every working day is comprised of ten hours;
- Employees are not interrupted while working;
- Each employee is to work on only one task at any given time; and
- The level of compatibility between individuals working on the same team does not affect the productivity of each designer.

B. Proposed Integer Program

Objective function:

$$min \sum_{t \in T} \sum_{j \in J} \sum_{i \in I} (w_j)(b_{jit})\,(e_{jit}) \tag{1}$$

subject to

$$\sum_{t=1}^{T} \sum_{j \in J} b_{jit} = 1; \qquad i \in I \tag{2}$$

$$\sum_{i \in I} b_{jit} \leq 1; \qquad j \in J, t \in T \tag{3}$$

$$\sum_{j \in J} \sum_{i \in I} b_{jit} \leq \sum_{j \in J} v_{jt}\,; \qquad j \in J, t \in T \tag{4}$$

$$\sum_{i \in I} b_{jit} \leq v_{jt}; \qquad i \in I, j \in J, t \in T \tag{5}$$

$$(e_{ji})(b_{jit}) \leq c_i; \qquad i \in I, j \in J, t \in T \tag{6}$$

$$b_{jit} \in \{0,1\}; \qquad i \in I, j \in J, t \in T \tag{7}$$

$$v_{jt} \in \{0,1\}; \qquad j \in J, t \in T \tag{8}$$

$$w_j, c_i > 0 \qquad i \in I, j \in J, t \in T \tag{9}$$

Equation (1) shows that the model aims to minimize the total cost spent for performing the tasks at hand. This cost is the product of the wage of each resource and the time expected by the resource to complete a certain task, multiplied by the binary assignment variable showing whether or not the resource is working on a certain task. The constraints in Equation (2) make sure that every task will be executed. The set of constraints in Equation (3) make sure that every resource works on at most one task at any time. The group of constraints in Equation (4) takes into account that the supply has to at least meet the demand by making sure the number of assigned resources is less than or equal to the number of available resources. The set constraints in Equation (5) make sure that the resource assigned to the task is an available resource. The group of constraints in Equation (6) ensures that the expected time needed by a resource to complete a certain task is less than the assigned due time for the task, that is if the resource is chosen to perform this task. Variable-type constraints Equations (7)-(8) define the variables b and v as binary variables. Finally, variable-type constraint Equation (9) sets w and c as non-negative variables.

C. Model Input: Resource and Task Attributes

The formulated algorithm consists of several steps that lead up to the optimal human resource assignment solution. The main inputs required are two separate Microsoft Excel documents: the first document contains information related to the human resources such as their time availability, level of experience, level of familiarity with a certain software and their wage. The second document contains characteristics pertaining to the tasks that the company needs to finish. These characteristics include the optimistic, pessimistic and most likely to occur durations to complete each task. These three values are estimated by the manager leading the team of engineers, purely based on his/her knowledge, and are specific to each task alone. Hence, there is no specific formula that may be followed in order to calculate these three task related durations. However, the difference between the pessimistic value and the mode value will be assumed to be 3 times the difference between the mode duration and the optimistic durations. This assumption is due to the fact that there is no available data that shows the correlation between the duration of the task and the size and complexity of a project. It gives consistency to the assumed duration values. Ultimately, these three values are used to create a range for the duration that each task should typically take to be completed. The optimistic and pessimistic values form the lower and upper bounds respectively of this range. The most likely to occur value separates this range into smaller subranges that form duration intervals from which the duration required by a resource to complete a task will be computed (based on the resource's attributes). This approach is thought to be a more realistic representation of task durations because resources with different characteristics will require different durations. The second document also contains the deadline after which the task will be considered as late. The formulated algorithm extracts all the necessary data from the two Excel files and thus the number of resources and tasks may be adjusted at any point in time making it more convenient for the user.

D. Task Completion Time Estimation

The expected time required by a specific resource to complete a particular task is estimated as follows: Each task duration follows a triangular distribution characterized by three values that are set by the manager. These values represent the optimistic, pessimistic, and most likely to occur durations for completing each task. It is important to note that the difference between the pessimistic and most likely to occur durations will be 3 times the difference between optimistic and most likely to happen durations. Again, this is an assumption made since there are no readily available data that records any trends on such duration, hence making such an assumption will provide consistency to the values used. The resulting graph is divided into four zones that mimic the different combinations of employee characteristics. These zones are defined by the midpoints of the segments joining each of the optimistic, pessimistic, and most likely to occur durations. Consequently, the first group is a sub-range that has the pessimistic value as its lower bound and the average of the pessimistic and most likely to occur time as its upper bound. The second group has that same average as its lower bound and the value of the most likely to occur duration as its upper bound and so on. In order to come up with a value for the time expected by a resource to complete a certain task *(e_{ij})*, a random value is assigned to each employee if they were to work on a certain task. This random value is bound by the sub-range that corresponds to the combination of resource characteristics specific to that employee.

E. Optimization of Allocation

'Intlinprog' is a built-in function characterized by solving integer linear programming problems in MATLAB and was used to generate our optimal solution. The function takes as an input the objective function's coefficients, inequality and equality coefficient constraints, upper and lower bounds for decision variables, and allows the user to specify that all decision variables are integers. In order to use this solver, the coefficient values need to be expressed in a specific form of matrices and this is what the second part of the algorithm does. The constraints matrices express the need of finishing all the tasks at hand while making sure that every employee is only working on one task at a time and that the task will be completed before or at its due date.

Accordingly, an optimized human resource allocation solution would result from running this algorithm and allows for the computation of the final optimal cost associated with such an assignment.

F. Model Verification

To verify that the algorithm is properly allocating and optimizing the problem, a simple case study was created that involved 10 human resources and 5 incomplete tasks, each with their own series of features. Human resources were characterized by their availability, level of experience, level of familiarity with a certain software program, and respective wage. The tasks are defined by the optimistic, pessimistic and most likely to occur times, which are in turn defined by the manager, and their deadline. The expected time needed by each resource to perform a task was computed based on the method explained in Section D of this chapter and copied into an excel document. The set of decision variables were initially set to be equal to 0. Two additional sets of matrices were also formulated: the first considers the duration each resource spends working on a certain task, and this was computed by multiply the assignment decision variable by the resource expected time, and the second computes the cost associated with employing a certain resource to work on a specific task, this is calculated by multiplying the assignment decision variable by the resource expected time and also by the respective resource wage. The objective function is then the sum of all entries in the last matrix. The optimization tool provided by excel for solving linear programming is SOLVER. This add-on was used to minimize the objective function while making sure that the elements in the duration matrix met the deadline of each task, that all of the assignment variables across the same resource were always less than or equal to 1 – which ensures that employees are working on at most one task at a time -, and finally that all of the assignment variables across the same task were always equal to 1 – which in turn makes sure that all of the tasks will be performed. The final constraint was to make sure that the assignment decision variables are only binary variables.

To make sure that the algorithm was giving proper, and most importantly optimal, solutions, the same values computed for the time expected by any resource to perform any task were used in both the MATLAB solver tool and MS EXCEL solver. The tools were then asked to search for the optimal binary allocation solution and the results were matching. The tools also calculated the value of the objective function which is the total cost of employing certain resources to finish the tasks at hand. The outcomes also had equal values. Please refer to the tables A1 through A6 in the appendix for examples on the verification of the algorithm.

CHAPTER V

CASE STUDY

A. Case Description

To test the formulated model on a larger scale, one that represents real life scenarios of engineering design teams and the resource allocation process, a sample case study was created. It considers one sub-team in a single department that has a senior engineer as a manager who is responsible for assigning tasks among his team. Seeing that for a large-scale design company, the number of engineers and resources inside a single department can be anywhere between 30 and 100 individuals. Due to this substantial amount, the department is divided into teams that comprise fewer number of resources and a manager who oversees the work being done. Considering a transportation department as an example, the different teams that may be found under this discipline are the traffic team, highway team, airport team, urban team, railway team etc. and each of these teams may have up to 15 engineers working under the sub-discipline. In this case study, the selected department is the Transportation team were 10 different resources are working under the Urban Design sub-team. What is meant by Urban Transportation Design is the development of the roadway network of towns and cities by analyzing the right circulation of vehicles to allow access to the different functions built in that community like residences, schools, hospitals, recreational areas and much more. The geometric design of the roadway network must accommodate for the largest design vehicle that may utilize this network and should be in accordance with the developed drainage plan prepared by the Environmental department. The design may also need to provide on-street or off-street parking to the final users. The developed model can be used for any design discipline however, the transportation department is chosen for this case study since the researcher has had a couple of years of work experience as a transportation design engineer. This experience allowed the researcher to breakdown the project activities into tasks that junior engineers are responsible for on a daily basis. Thus, the researcher is able to benchmark the number of resources found in a typical team and the number of tasks a manager is responsible of delivering. Which leads to the assumption that a single senior engineering manager may have up to 4 projects simultaneously being developed implies that the manager is most likely responsible for the submission of 3 to 10 tasks every day. This case study therefore examines 7 different tasks that need to be worked on.

The following is a detailed description of each of these tasks. The description includes an explanation of what the task asks for. Table 3 summarizes the deadline before which this task should be finished and how long does the manager estimates the task should take. The manager's estimate is divided into 3 parts that are the pessimistic, most likely to occur, and optimistic times. As mentioned earlier, the difference between these three durations is assumed to be consistent for all the tasks due to lack of records that correlate the duration of the tasks to the size and complexity of requirements of each project.

Table 3. Summary of Task Parameters (in hours)

Task Number	Optimistic Time	Most Likely Time	Pessimistic Time	Deadline
1	16	20	32	34
2	27	30	39	40
3	43	50	71	56
4	20	24	36	40
5	18	20	26	24
6	12	16	28	32
7	22	25	34	24

Task #1: Develop the base plan of a transportation network for community development in a city in a Gulf Country Council member. The designer needs to take into consideration any existing infrastructure and location of plots set by the client. The design is also based on guidelines set by the country codes and regulations which in turn define minimum dimensions for lanes, parking lanes, sidewalks, shoulders, turning radii and so on.

Task #2: Develop the horizontal alignments and vertical profiles for the road network of also another community development in Qatar. What needs to be taken into consideration to complete this task is the base plan of the development and the guidelines pertaining to the horizontal and vertical geometry of the alignments/profiles. This includes length of alignment and dimensions of horizontal and vertical curves, super-elevation of turning radii, minimum and maximum vertical slopes and so on.

Task #3: Compute the earthwork quantities needed in order to reach the proposed ground level of a community development in the UAE with predesigned base plan, alignments and profiles. The process involves assembling a corridor that eventually creates 3D surfaces which incorporate the vertical and horizontal alignments along with the respective cross section of each road. The process involves combining all the elements into one corridor element and defining the limit of each sub-assembly in the cross section and then generating the desired surfaces. Two main surfaces are used for computing earthwork quantities which are the existing ground surface, typically obtained from external sources, and the proposed ground surface before placing pavement and infrastructure material.

Task #4: Compute the earthwork quantities needed to reach the proposed ground level of a community development in another city in the Gulf Country Council member with predesigned base plan, alignments and profiles. The process involves assembling a corridor that eventually creates 3D surfaces which incorporate the vertical and horizontal alignments along with the respective cross section of each road. The process involves combining all the elements into one corridor element and defining the limit of each sub-assembly in the cross section and then generating the desired surfaces. Two main surfaces are used for computing earthwork quantities which are the existing ground surface, typically obtained from external sources, and the proposed ground surface before placing pavement and infrastructure material.

Task #5: Place all roads signing and marking for a community development in Angola. The process involves recognizing the country code for signing and marking and placing all necessary elements while keeping in mind the traffic circulation, pedestrian crossing, parking zones and so on. After placing all traffic signs and road markings, a spreadsheet has to be created to keep record of the quantity of signs and road markings to determine the price of executing this activity.

Task #6: Generating drawings of the detailed design of a community development in UAE. The phase includes design for base plan, alignment, profiles, existing ground surface, and finished ground surface. Live Civil 3D elements need to be exported into CAD units and placed properly in the sheets corresponding to the phased package submission. Assume entities are already designed and this exercise is mainly a drafting one.

Task #7: Develop drawings for each road cross section. This activity involves determining the cross slope of each road and the different elements of its assembly, i.e., lane, parking lanes, shoulder, sidewalk, and medians and so on. Roads with varying cross sections would have multiple cross sections that indicate the station range.

Table 4 summarizes the different characteristics of the human resources who make up the urban design team in the considered transportation department. These attributes are hypothetical values that were inspired by the researcher's humble work experience in the same environment.

Table 4. Summary of Resource Parameters

Resource Number	Availability	Design Experience	Software Program Experience	Wage ($/hr)
1	Yes	Experienced	Expert	45
2	Yes	Junior	Novice	20
3	Yes	Junior	Novice	20
4	Yes	Junior	Expert	28
5	No	Experienced	Expert	45
6	Yes	Experienced	Expert	45
7	Yes	Junior	Expert	28
8	Yes	Experienced	Novice	36
9	No	Experienced	Novice	36
10	Yes	Junior	Novice	20

B. Reaching Optimal Solution

The parameters mentioned above were introduced as input to the model's algorithm and the results are summarized below. Table 5 reveals the time expected by all the resources to complete any of the tasks as calculated by the developed algorithm that combines all the parameters at hand. These durations are estimated as per section IV-D as follows: after breaking down the range of duration estimated by the manager into smaller subranges depending on the optimistic, pessimistic, and most like to occur durations, the model choses one of the subranges for each human resource depending on their characteristics and then assigns a random value from this subrange as the completion duration for this specific resource to finish a certain task. To help put things into perspective, the following elaborates on how the first entry in Table 5 was computed: according to the manager of the team, T1 will need a minimum of 16 hours to be done, most likely 20 hours and at most 32 hours. This range is broken down into 4 parts (depicting the 4 combinations of human resource attributes) as follows: 16-18 hours for resources who are experienced and software program experts, 18-20 hours for those who are experienced by novice program users, 20-26 hours for resources who are junior designers and experience program users, and finally 26-32 hours for those who are junior designers and novice program users. Since HR1 is an experienced designer who is an expert in using the required software program, the model will randomly assign a duration that has a value between 16-18 hours (18 hours in this case), and so on.

Table 5. Time Expected for Resources to Complete Tasks (in hours)

Expected Time	T1	T2	T3	T4	T5	T6	T7
HR1	18	27	46	20	19	13	22
HR2	28	37	65	32	25	26	32
HR3	32	36	68	35	24	25	30
HR4	20	32	58	30	20	19	27
HR5	N/A	N/A	N/A	N/A	N/A	N/A	N/A
HR6	17	27	45	21	19	13	22
HR7	21	34	52	29	22	22	25
HR8	19	29	50	22	20	16	25
HR9	N/A	N/A	N/A	N/A	N/A	N/A	N/A
HR10	28	35	62	35	25	25	30

Table 6 presents the optimal assignment solution that depicts which resource is to work on what task in order to meet the deadlines of all of the tasks at the least possible cost. The model arrived at the solution by first ignoring all of the resources who are not available to work, then by disregarding any engineer that will exceed the deadline of the tasks before completing them. And then finally, by choosing the best resource-task combination that will generate the lowest overall incurred costs. Therefore, even though some resources may be able to work on other tasks and complete them on time, they would be negatively contributing to the overall cost incurred by the company to assign the engineers. The final total optimal cost is $5,484 to assign 7 resources to complete 7 tasks.

Table 6. Optimal Assignment Solution

Optimal Assignment Solution	T1	T2	T3	T4	T5	T6	T7
HR1	0	0	0	0	0	0	0
HR2	0	0	0	1	0	0	0
HR3	0	1	0	0	0	0	0
HR4	0	0	0	0	1	0	0
HR5	0	0	0	0	0	0	0
HR6	0	0	0	0	0	0	1
HR7	0	0	1	0	0	0	0
HR8	0	0	0	0	0	1	0
HR9	0	0	0	0	0	0	0
HR10	1	0	0	0	0	0	0
MINIMUM ASSOCIATED COST = $ 5,484							

C. Comparison of Optimal Solution versus Random Assignments

As mentioned earlier, current allocation practices involve randomly assigning whoever is available to work on a certain task without really taking into consideration the skills set acquired by the human resource and if they match with task requirements. Potential outcomes of such assignments include cost and time overruns which could be mitigated for by applying the optimizing algorithm. To better visualize the savings that would result from optimizing the allocation process, 100,000 random assignment solutions were generated and the associated cost of each was computed. Each cost was compared to the optimal price found in the previous sub-section. The percentage difference between the cost of each random solution and the optimal solution was computed. The results show that, on average, using the model to generate an optimal assignment solution may save the company on average around 34% (first entry of table 7) of the incurred costs, had the allocation process been random.

Similarly, the algorithm was run 9 more times to observe the fluctuation in the amount of savings due to optimally allocating resources. Each simulation generates new values for the time expected by resources to finish the tasks then comes up with an optimal solution for each and generates random assignments that are compared to the optimal value. Table 7 compiles the average percentage difference between the cost of optimally allocating human resources and randomly assigning the resources for each of the 10 simulation runs. Each run takes, on average, 1 minute to finish.

Table 7. Comparison of Optimal Assignment Cost and Random Assignment Cost

Trial	Optimal Assignment Cost	Random Assignment Cost	Percentage Difference
1	\$5,639	\$7,544	33.8%
2	\$5,321	\$7,512	41.2%
3	\$5,325	\$7,499	40.8%
4	\$5,509	\$7,549	37.0%
5	\$5,470	\$7,542	37.9%
6	\$5,417	\$7,495	38.4%
7	\$5,497	\$7,538	37.1%
8	\$5,492	\$7,519	36.9%
9	\$5,392	\$7,515	39.3%
10	\$5,332	\$7,551	41.6%

The table shows that in all the simulations, every time a manager tries to use the model to find an optimal answer for allocation the members of their team across the different tasks they wish to deliver, s/he would be saving, on average, around 38% of the incurred costs had they chosen to randomly allocate designers and not take into consideration the attributes pertaining to the tasks and the resources themselves.

D. Sensitivity Analysis

The developed model is dependent on several attributes that affect the optimal assignment solution and thus it is important to understand the trend under which the model is affected. This section of the research analyzes how changing the values of some independent variables will impact the ultimate outcome of the model which depends on these variables. The elements across which the model is tested are the number of resources who are taken into consideration and the number of resources who have a specific level of experience or level of familiarity for using a software program. The aim is to observe the change in value of the optimal cost and the change in value of the difference between the optimal cost and the average cost of multiple random assignments. The analysis also serves the purpose of identifying the scale of the assignment problem at which it becomes profitable to use the model.

1. ***Sensitivity analysis for increasing the number of resources:***

The aim of this subsection of the analysis is to examine the change in difference between the value of the optimal cost of allocation and the value of the average of the cost of 100,000 random assignments when it comes to changing the number of human resources from which the selection will happen. Hence, as the pool of human resources increases in size, the values of the optimal cost are noted to observe the trend. The method adopted involves considering 7 predefined tasks that need to be completed and a random pool of 7-15 resources, with randomly associated attributes, and finding the optimal solution for each of the combinations of tasks and resources. A detailed description of the methodology followed is presented below.

The formulated hypotheses for this section of the analysis are as follows:

a. The first hypothesis states that as the number of available resources increases for the same number of tasks, the model will always generate an average solution that is better than the random assignments.

b. The second hypothesis indicates that also as the number of resources being considered for the assignment problem increases, while keeping the same number of tasks to be complete, the difference between the optimal cost and the average cost of all random assignments becomes larger.

It is important to study these hypotheses because as the number of employed resources increases, the costs incurred by the company will increase too. Hence, this will help understand at what point does it become inefficient to use the developed model for assigning employees and when is the optimal cost generating savings the most for the company.

To test these hypotheses, the model begins by considering 7 tasks defined by the minimum, maximum and average time required to complete them. As previously explained, the three task-related attributes are set by an experienced manager who can estimate these durations. The vast knowledge of the manager will allow him/her to identify on average how long each task should take along with the best-and-worst-case scenarios for completing these tasks. These values will eventually help evaluate how long specific resources will require to complete the tasks depending on their level of expertise. Then, since one of the main restrictions is that each resource will work on one task at a certain point in time, having fewer resources than tasks will generate no solution by the model. Therefore, the case studies begin with considering 7 resources in the initial pool of engineers who are to complete the 7 tasks. The results are recorded after finding the optimal solution and comparing the answer to 100,000 other random assignments. In the next run, the pool of resources expands to 8 engineers and the optimal result is again recorded along with the values of random assignments. The same steps are repeated by increasing one resource at every run until the number of resources was 15 resources. The number of tasks was chosen to be 7 which represents the average number of tasks that a manager and his team would be responsible of delivering.

Moreover, the number of resources ranged from 7 to 15 to represent the typical size of a technical team working on a project within a discipline. Note that the resources that were added each time were randomly chosen.

The results are as follows:

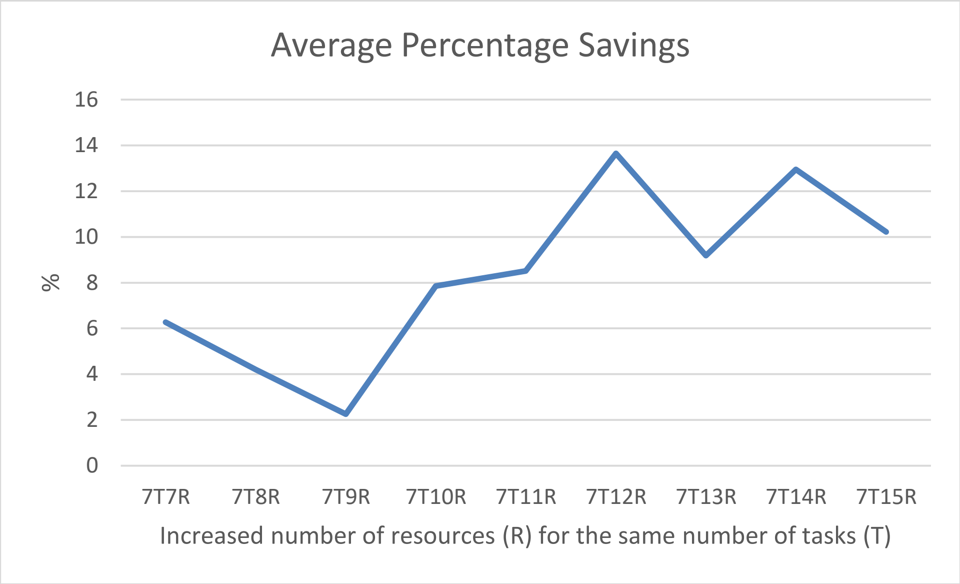

Figure 1. Percent Difference Between Optimal Cost and Average of Random Costs when increasing the number of resources

Figure 1 is generated by plotting the values of the difference between the optimal cost and the average of all the random costs computed at every run where the number of resources increases, and the number of tasks remains the same.

Figure 2 is generated by plotting the value of the optimal cost and the value of the average of all 100,000 random costs as the number of resources increases at every run.

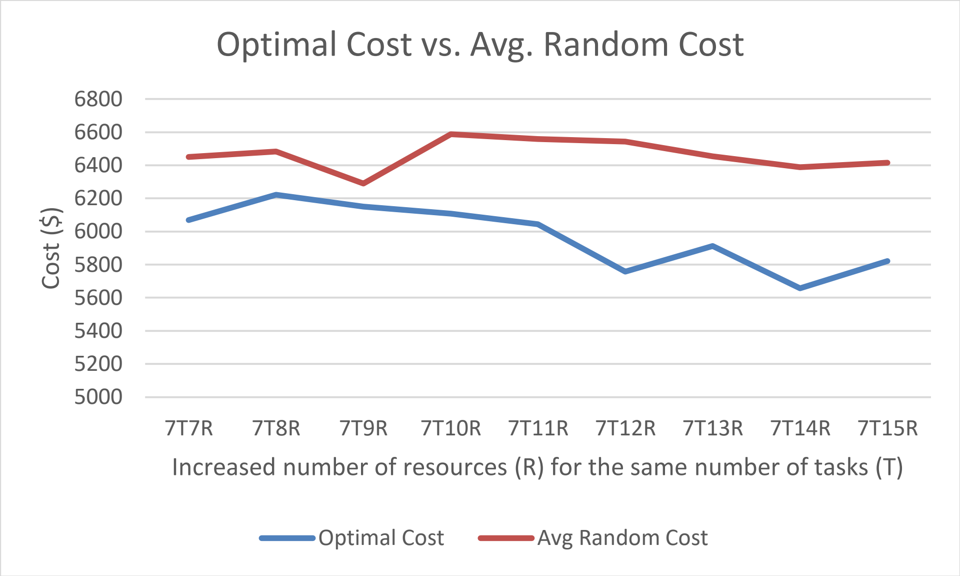

Figure 2. Optimal Cost vs. Average Random Cost for increasing the number of resources

The following can be observed by analyzing the two graphs:

a. Regardless of the number of engineers who will be considered for completing the tasks, using the model to find an optimal solution can save on average a value between 2-14% when compared to other random assignments. Thus, the average quantities are always positive percentages. This is also evident in the second graph where the line corresponding to the optimal cost seems to always be lower than that of the average cost of randomly assigning resources to tasks. Looking also at the maximum and minimum values of cost savings generated by the model, these amounts are in the ranges of 30% and -15% respectively. This proves that the model may save significant monetary sums. Also, the model still seems to be a better option than randomly assigning resources even when there are negative savings, i.e, the optimal cost is higher than a random cost, due to the fact that the optimal solution guarantees completing all the project tasks on time while a random assignment does not. Hence, even if the company may need to pay extra for assigning specific resources, it would guarantee submitting the deliverables on time. This reflection confirms the first hypothesis.

b. The value of the average percentage difference between the costs generally increases as the number of resources increases. The difference first slightly decreased then considerably increased. It came to attention that the value of the optimal cost generally decreased as the number of resources increased while the value of the average cost of randomly assigning resources remained within the same range. This indicates that as the number of resources becomes larger than the number of tasks, the optimal solution becomes further in value to the average of the cost of the random assignments. This could be due to the fact that when the number of resources and number of tasks almost equal, the formulated model will have limited options to choose from since it has to assign all the designers in order to complete all of the tasks. Moreover, the random assignment also includes the same resources who have the same distribution of wages. This would result in relatively close values of the optimal and random costs because the optimal cost is the only option that would guarantee meeting all project deadlines while keeping the total cost at a possible minimum. However, as the number of resources becomes larger, the amount of possibilities the model can choose from becomes greater. And since the model only needs to choose 1 resource for every task, the model has greater possibilities that would give a lower cost and meet all the deadlines. This justifies why there is a decrease in the value of the optimal cost. On the other hand, since every average random cost is computed by sampling 7 resources out of the pool of engineers – regardless of the total number of resources – 100,000 different times, this procedure should generate similar average costs regardless of the number of resources in the pool. This justifies the stable trend in average random cost. As a result, the difference between the random and the optimal costs will increase making it more efficient to use the model for large numbers of resources. This observation validates the second hypothesis.

2. Sensitivity Analysis for increasing the number of tasks:

The objective of this part is to observe and understand the alteration in the value of the optimal cost and the associated savings resulting from using the developed model for resource assignment for the case where the number of tasks is increased. Thus, in this illustration, the number of resources will be set to a total of 15 engineers and the number of the tasks that the company needs to work on will start at 7 tasks and then gradually increase until the designers have to complete a total of 15 tasks. It is important to remember that the number of tasks cannot exceed the number of resources due to the fact that the model is set to assign one resource for every task meaning no resource can work on more than one activity. This is why the analysis will first look into finishing a few tasks with a large number of resources and then this pool of tasks will be maximized as much as possible.

The formulated hypotheses for this part of the sensitivity analysis are as follows:

a. Similar to the previous subsection of the analysis, it is hypothesized that for any number of tasks and for the same number of resources, the average result of comparison between the optimal cost and all the random costs will be a positive average indicating that using the developed allocation model will produce an optimal assignment that is generally better than randomly assigning designers to work on tasks.
b. The next hypothesis states that as the number of tasks increases and becomes closer to the number of resources in the pool of available engineers, the difference between the optimal cost and the average of all the random costs will decrease.

Testing for these hypotheses is crucial since it allows us to point out when the developed resource allocation model is generating cost savings and benefitting the company specifically as the number of tasks increases. This change in number of activities is bound to happen at least once daily, so it is necessary to examine its effect on the incurred cost of engineer assignment.

To do so, the model begins with a set of 7 tasks that have their predefined attributes – optimistic time, pessimistic time, most likely to occur time and deadline – and a set of 15 resources that have their own series of attributes that are randomly assigned to them. The algorithm searches for the optimal assignment and computes its associated cost. Then, it generates 100,000 random resource allocation solutions and their respective costs and compares these values to the optimal values obtained. After recording these findings, 1 random task is added to the group of tasks to be completed resulting in a total of 8 tasks that need engineers to work on them, and the same steps are repeated again until the final number of tasks is 15.

The results of the simulations are as follows:

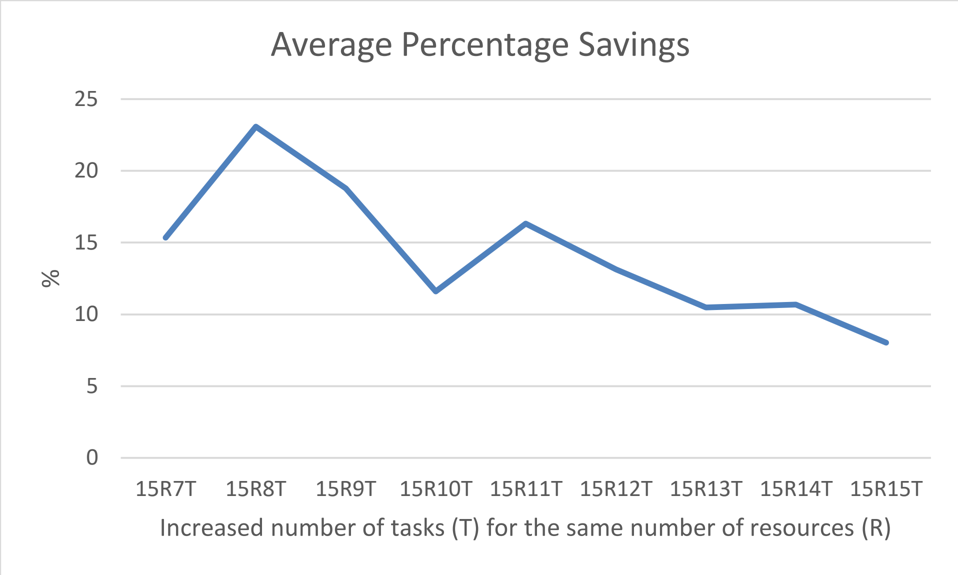

Figure 3. Percent Difference Between Optimal Cost and Average of Random Costs when increasing the number of tasks

Figure 3 is created by mapping out the value of the difference between the optimal cost and the average of the cost associated with randomly assigning the resources as the number of tasks gradually increases while keeping the same number of resources.

Figure 4 is created by plotting the different values of optimal cost obtained during each run as the number of tasks increases against the value of the average cost of random assignments.

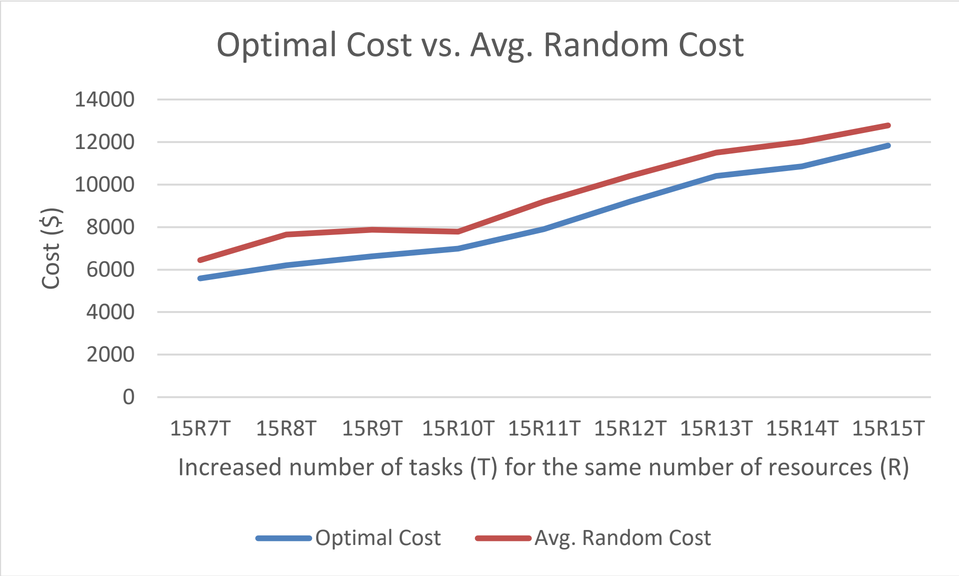

Figure 4. Optimal Cost vs. Average Random Cost for increasing the number of tasks

Observing the graphs above, we can deduce the following:

a. The optimal cost is always less than the average of the cost of randomly assigning resources to work on tasks. The value of the average percentage difference between the costs is always positive, with a value ranging between 8-23% indicating that the model generally provides better results than the random assignments. Considering the minimum and maximum values of the percentage savings, we find that the model could potentially save up to 50% on incurred costs, but the firm could also be paying 10% extra costs for using the model to find an optimal solution for assignment when compared to randomly assigning engineers. However, the last scenario does not ensure meeting the project deadlines which another major strength of the developed allocation model. This observation supports the first hypothesis.

b. The difference between the optimal cost and the average value of all the random costs gradually decreases as the number of tasks increases for the same number of resources. This supports the hypothesis that state that as the number of resources and tasks are close, the value of the average percentage savings is low. As an explanation to this observation, and while keeping in mind that the number of designers chosen by the model is equivalent to the number of tasks that need to be completed, it is evident that as the model chooses a small number of resources from a large pool of engineers optimally, the cost associated with this choice will generally be smaller than the cost of choosing randomly that same small number of designers. It is also noticed that as the number of tasks increases, the values of the optimal cost and the average random cost increase since adding more tasks means adding more work which requires additional employees.

3. *Sensitivity Analysis for resource attributes:*

This section examines the effect of the number of resources who have a certain set of attributes on the optimal cost and the amount of possible savings. As mentioned earlier, the level of resource experience may take two forms: *junior* and *experienced*, and the level of software familiarity for a using a certain program also may take two forms: *novice* and *expert*. The aim of this analysis is to identify whether there is a trend in the difference in cost between an optimal assignment and random assignment when changing the quantity of designers with a specific skill set. At every run, there are 10 resources out of which 7 will be chosen to perform 7 tasks. As an example, one of the case studies, that would be testing the effect of the change in level of resource familiarity with using a software program, may begin by having all 10 resources as *junior* designers and *novice* program users and then their attributes are changed so that eventually the pool of 10 resources become *junior* designers and *experts* in programs. The following sub-sections explore in further details what has been stated so far.

◆ Level of Experience:

In this analysis, the level of software program familiarity of each resource is taken as a constant for all 10 resources; and they all start off as junior designers. Then, the number of resources who are experienced increases gradually and the quantity of junior designers consequently decreases.

The formulated hypothesis for this section states that if the pool of resources seems to have homogenous human attributes (similar characteristics for most of the designers), then the optimal cost value will be closer in value to the average of all random costs. And in the case where the resources have diverse qualities but in similar quantities, i.e., all the resources have a constant level of software program familiarity but almost half of them are junior designers and the rest are experienced designers, the optimal cost will be lower than the average of all random cost. It is important to examine this hypothesis since it allows the manager to visualize how the resource attributes and their diversity is affecting the overall incurred cost. This could aid the manager in better choosing which resources to join his/her team.

To test this hypothesis, 2 cases are analyzed where each case represents one consistent level of software program familiarity for all 10 resources. In the first case, all the resources are *novice* software program users but as for the level of experience, we start off with all resources having a *junior* level of design experience. Then the model runs and finds an optimal solution that is recorded. In the next run, one resource moves from being a *junior* designer to an *experienced* designer. The model runs again and records the outcomes and the process is repeated until all 10 resources are *experienced* designers and *novice* program users. The results are as follows:

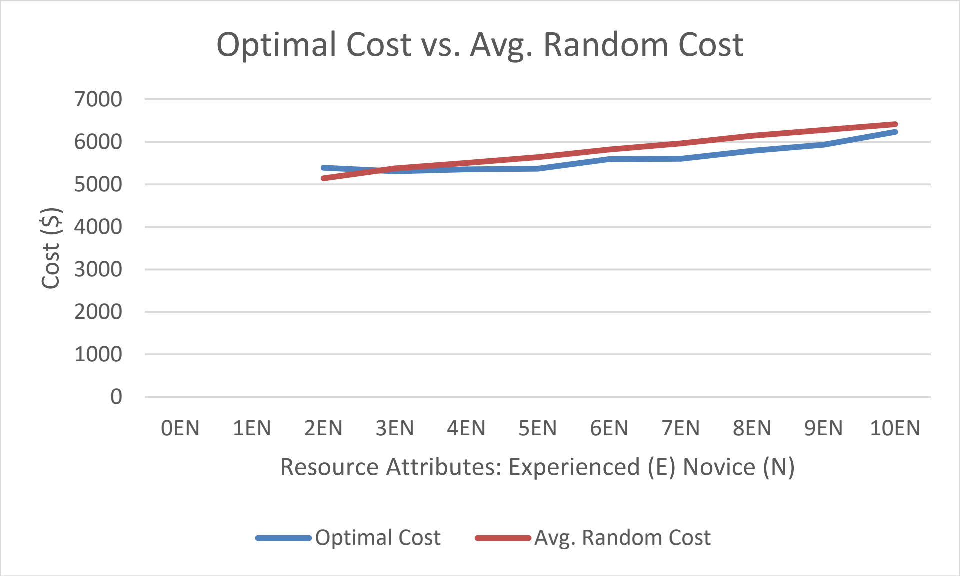

Figure 5. Optimal Cost vs. Average Random Cost for altering the level of experience of novice designers

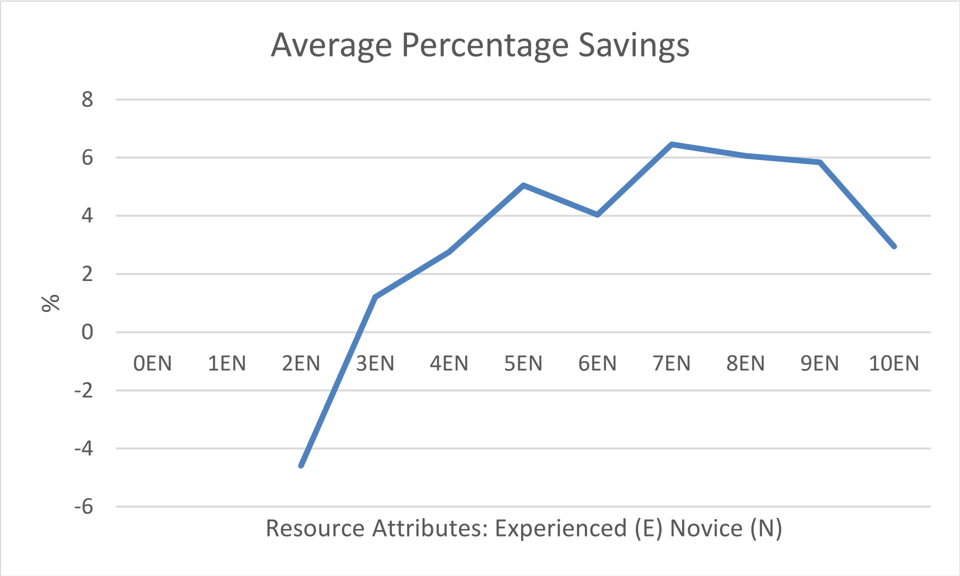

Figure 6. Average Percent Savings for altering the level of experience of novice designers

The results below represent the second case where the same steps are repeated but this time assuming that the resources all have the same *expert* level of software program familiarity. The results are as follows:

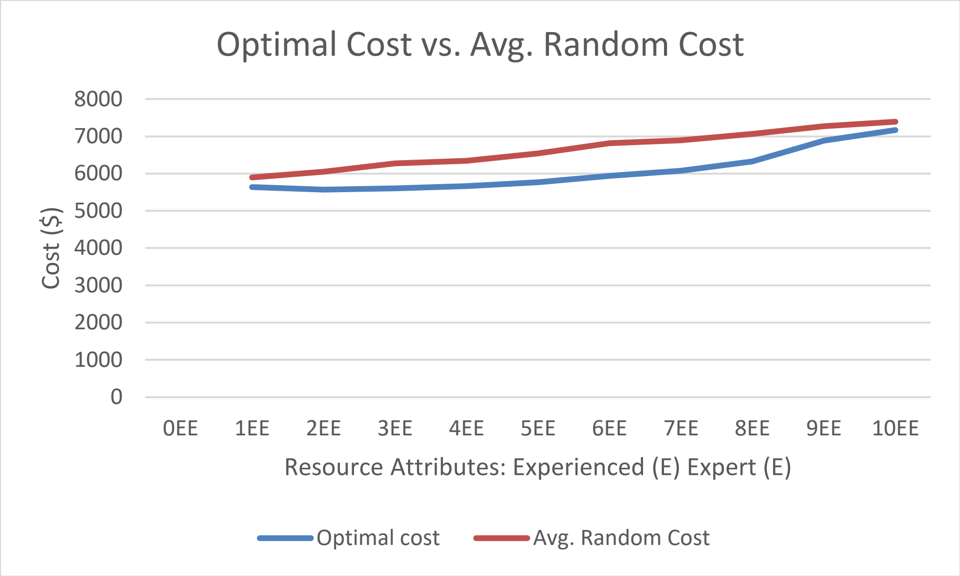

Figure 7. Optimal Cost vs. Average Random Cost for altering the level of experience of expert designers

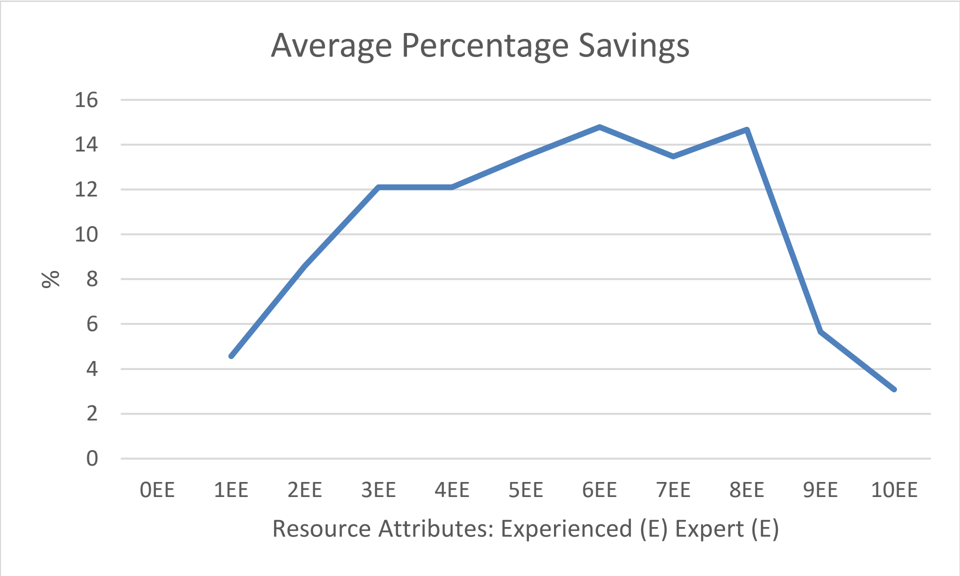

Figure 8. Average Percent Savings for altering the level of experience of expert designers

The above plots were obtained by mapping the values of the optimal cost and the average random cost at each run on one graph and that of the average savings between the two mentioned costs on another. Hence, these two graphs are directly related and represent the results in two different manners.

The following was observed:

a. The same trends are detected for the two case scenarios where the first expects all resources to be novice software program users while the second assumes that all resources are expert users. This implies that the variation of the difference between the optimal and random cost is independent of the any other constant attributes. This observation does not negate the fact that having novice or expert program users will not affect the value of the optimal and random costs. On the contrary, we notice that the costs in the case where the resources were expert program users are in fact higher than those in the case where the resources were novice program users. This is of course due to the fact that the model assumes that expert program users are more expensive to employ than novice program users. A junior novice program user has a wage of $20/hr as opposed to a junior expert designer that was assigned a wage of $28/hr.

b. The optimal cost was very close in value to the average random cost when almost all of the resources had the same characteristics. This could be explained by noticing that when all the resources have the same skill set, they will all be able to finish the tasks within the same timeframe, and they will be given the same wage value. Hence, choosing any of the resources will eventually lead to the same total final price, for the optimal case and the random assignments. This goes in accordance with the first part of the formulated hypothesis.

c. The optimal cost was significantly lower than the average of the random costs whenever the resources were almost equally divided in two subgroups with different resources (for example, almost half are *junior* and *novice* and the other part is *experienced* and *novice*). This is clarified by understanding that when the resources have different attributes, the time they need to complete a task is directly affected by their characteristics and will significantly differ depending on these attributes. Their individual wages become consequently different. And as the aim of the model is to minimize the associated assignment cost, it will look for a tradeoff between the time the resource takes to finish a task and the wage this resource is paid to do the job. But this difference in resource wages gives room for the average of all the random costs to be higher. Hence, the lowest possible cost to effectively meet the deadline of the tasks will be significantly lower than randomly assigning resources with differing attributes. This observation confirms the second part of the hypothesis.

◆ <u>Level of software program familiarity:</u>

Similarly, the analysis was done to check for the model's sensitivity to the level of software program familiarity. The same logic is considered as the previous subsection, but now looking at the level of software program familiarity as the dynamic attribute.

The same hypothesis was formulated as the one for testing the level of resource experience. It predicts that as the distribution of resource attributes is more homogeneous, the difference between the optimal cost and the average cost of randomly assigning the designers to the tasks will be low. Furthermore, as the characteristics become more diversified, the optimal cost will be considerably lower than the average of the cost due to random assignment.

To test the hypothesis, it is first assumed that all 10 resources have a *junior* level of design experience, so the level of experience is a constant attribute. Next, we start the runs by having 10 *novice* resources. After finding the optimal solution and recording the results, we change the attribute of one resource from a *novice* user to an *expert* user. This is repeated until all 10 resources become *experts* in software program familiarity. The results are as follows:

For this case, no solution was found since all resources were junior level, and since one of the tasks requires that at least one resource must be experienced to meet the predefined deadline of the task. This means that no matter how much the level of software familiarity differed, all of the resources were not competent enough to solve the tasks early enough to meet the time limit. To solve this, the task that is binding should acquire an extension of time, or an experienced resource must be added to the group of designers being assigned.

Again, the same is done but by having all the resources as *experienced* designers and then again starting off with *novice* programs users until all resources become *expert* program users. The results are as follows:

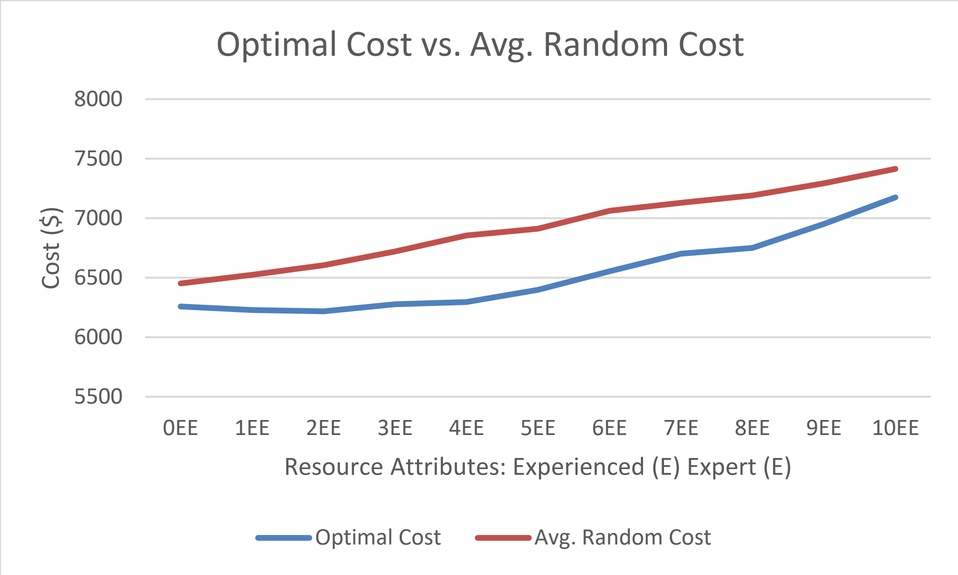

Figure 9. Optimal Cost vs. Average Random Cost for altering the level of software program familiarity of experienced designers

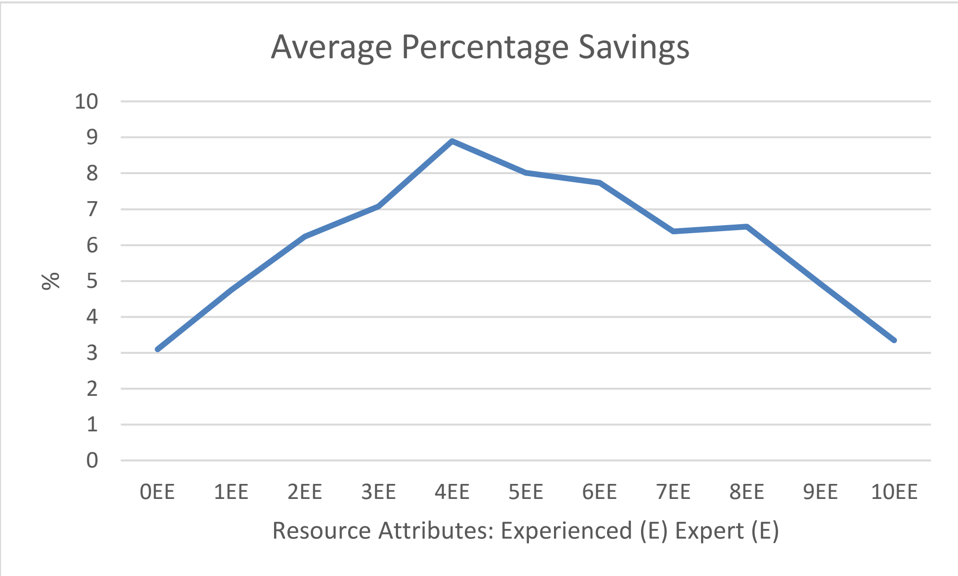

Figure 10. Average Percent Savings for altering the level of software program familiarity of experienced designers.

Similarly, the graphs show the trend in the change of average percentage saving which is a translation of the difference between the optimal cost and the average of all random costs at each run.

The same observations are noted as the previous subsection: wherever the resources have almost the same characteristics, the value of the percentage difference between the optimal cost and all the other random costs is minimal. On the other hand, when the pool of resources considered has an almost equal variation in the resource attributes, this percentage difference maximizes making the optimal cost less than the cost associated with random allocation. The same reasoning is applied to explain the results. The optimal cost will be close in value to the average of all random assignments if all the resources have similar characteristics because this implies that they will all be able to finish the tasks within the same timeframe and they all have the same wage. But if there is a variation in the characteristics, it indicates that some of the resources have higher wages than others and those resources will be able to finish a task faster than their peers. The optimal solution would then be a compromise between the most suitable time and wages that would result in the least possible cost for meeting project deadlines.

E. Validation

This section summarizes the outcome of interviewing a specialist, and potential end user of the developed model, for validating the results obtained after finding the optimization solution. The method adopted for validation was not a typical one compared to traditional methods that involve comparing the output generated by the formulated model to actual values. Instead, the output of the model was presented to an expert who is familiar with the concept of human resource allocation and the costs incurred with this activity. The specialist analyzed the steps followed for coming up with the optimal answer, judged the accuracy of the outcome and gave suggestions on how to improve the model.

The expert who was interviewed, and who wishes to remain anonymous, is a senior transportation design engineer who has 10+ years of experience working in the field. He currently specializes in the design of the infrastructure of urban community developments in the Gulf region. He has practiced engineering design with multiple companies who adopt different methods for managing human resources. The senior engineer thinks that most companies do not keep record of detailed information of the time allocated to working on specific tasks, but rather cluster all the hours spent by the designers working on a certain project into a total duration that is used for billing purposes. Some companies, however, do track in a more detailed way the amount of time spent designing and reviewing a project. Such companies require from their resources to fill out timesheets that specify not only which projects were they assigned to work on, but also the sub-discipline they were responsible of completing. While this level of accuracy might not be as detailed as the developed optimization model for human resource allocation needs, it is still a huge step towards enhancing the allocation process in engineering design companies. Moreover, the senior manager agrees that the young designers are usually assigned to work on tasks depending mainly on time availability. This is done especially when the deadlines for completing the activities becomes near. This urge to finish the work within the time limit becomes a source for inefficient allocation of resources.

When it comes to the optimization model developed in this research, the senior manager provided his feedback on the following elements: the attributes that were considered to characterize the resources, the method required for estimating the initial durations of the tasks independent from the resource's influence, the assumptions made to reach the optimal solution, the actual results obtained and the random assignments used to understand the savings, and the significance of such a model.

First, the manager acknowledges that the main qualities of a designer that distinguish a resource from the other are in fact the level of experience in a similar field and how familiar is a resource in operating the software program that the activity he/she is in charge of completing needs. Since there are no other tools that a design typically requires, then it is safe to assume these two traits as the basis for categorizing human resources. Yet, the senior believes that the model would be able to result in more accurate values if there are concrete correlations between the level of experience and program familiarity and the duration that this resource demands for completing a task. He is though apprehensive of why, at this stage of the model development, the resource attributes are discrete variables that take only two forms but advices comprehensively analyzing recorded data (when available) to propose an alternate relationship. The improved network would resolve the inexactness in duration estimation by linking a continuous form of resource variables to the time needed. It has been previously explained how this assumption was made since direct correlations between the level of experience and program familiarity and the resource completion time do not exist for such cases. Still, to mitigate for the imprecision due to this supposition, this research proposes working on a future model that could more accurately correlate resource attributes to task duration. Moreover, the manager suggested to delve into the possibility of incorporating additional traits that would render the model more representative and inclusive of the interaction that happens between human resources in engineering design companies. These interactions encompass interdepartmental relationships and dependencies and synergy between teammates.

When it comes to the method selected for designating an optimistic, most likely and pessimistic duration for every task based on the experience of a manager, the interviewee claims that this method demands considerable effort from any manager's side to execute. However, it is a very beneficial approach to defining the tasks that encompasses the manager's experience along with the size and complexity of the project. In order to obtain authentic values though, the manager estimating the durations needs to remain impartial to the team he/she is responsible for. The approximated values should be independent of the characteristics of the team so that these estimates would still be applicable even after resources are added/removed from that same team. The manager believes that this technique for defining tasks can be replaced with an automated model that would generate the three durations based on the size and complexity of the project. This model can be created after a manager defines a significant number of tasks. Then, the variation in durations can be plotted against the size and complexity of the project and these correlations would be eventually used to predict future task durations without the physical input of the manager.

The different assumptions made while developing this optimization model were explained to the senior manager. While he agrees that such assumptions are valid for the scope and purpose of this research, the senior engineer believes that as the model evolves, each assumption may be tackled for the sake of producing more accurate results that would encourage companies to use this model. For example, assuming that the young engineers are working non-stop does not illustrate what happens in reality. Employees work for a certain number of hours per day and are not efficient the entire time. Hence, this needs to be considered when estimating the duration a worker needs to complete a certain task. Another assumption is that resources will work on one task at a time. In reality, an employee may be assigned to work on more than one task, or one task may require a lot of time to be delivered so more than one resource is assigned to work on this task. Again, it would enhance the results of the optimization model if these assumptions were actually incorporated. However, given the limited timeframe of this study, the assumptions were excluded.

The interviewee had access to the optimal solution that the model found more the main case study described in this chapter. The manager reviewed the pool of resources and their respective attributes and the group of tasks that need to be completed and the assigned values that were given to the activities. There was no opposition to the values used for defining the case study; the manager thinks that the numerical figures resemble real life data. He also examined the value of the optimal cost and concluded that it is a reasonable amount to pay for employing 7 resources so complete 7 somewhat complex tasks. He also studied the generation of the random assignment matrices and skimmed through their associated costs. The manager thinks that some of the randomly generated resource assignments are exaggerated. However, simulating 100,000 different combinations mitigates for this exaggeration. He did point also that assuming that the time needed by the resource to finish a task will double in case this resource was randomly assigned to a task and the resource happens to be busy is farfetched. In other words, the effect that the availability of a resource has on the estimated duration needed by the resource is not as direct. And since employees constantly have a task to complete, this idea could be translated more accurately in the model.

Finally, and after observing the amount of savings generated due to utilizing the resource allocation model, the manager deduced that such a model could significantly enhance the allocation process. It could regulate the production of design in a way that ensures meeting deadlines and control the budget allocated for the project to avoid unnecessary costs. This attitude towards assigning resources in design companies is very much needed in the industry. And, after careful refinement of the model, companies should be willing to incorporate the model as a main part of their human resource management agenda.

CHAPTER VI

CONCLUSIONS AND EXTENSIONS

Proper human resource allocation in engineering design and consultancy firms is key in determining the success of these companies. It may have detrimental effects on projects if poorly implemented due to the high dependency of the company's performance on their employees. Current allocation practices are said to be based on time availability of human resource rather than matching the employee's skill set with task requirements. This easily translates into inefficiencies due to the criticality in estimating the duration of design tasks. How long a designer requires to finish working on a certain activity should be at the core of determining where resources will be allocated, and formerly developed tools have not addressed these factors together. Instead, they focused on formulating methods that either look at the resource's attributes or project characteristics alone. Moreover, the ultimate goal of the assignment tools either revolved around completing the projects on time or cutting down as much as possible on employment costs. And because these objectives are equally important, the researcher's effort were channeled towards creating a human resource allocation tool that incorporates the factors that may affect the design process and distributes the employees in an optimum manner that satisfies the stated purposes. To do so, this study analyzed the various elements that interfere with estimating the duration needed for completing design tasks and integrated them into an allocation model that assigns employees to work on specific tasks. Again, this was done while taking into consideration project deadlines and with the aim of minimizing the total costs incurred by the firm for delivering projects. The developed model considers the level of experience of a resource and his level of familiarity with using certain software programs, along with the time defined by a manager based on his educated guess of how long design tasks should require for completion when estimating the duration needed by specific resources to complete specific tasks. The allocation is then formulated based on the availability of the resources to work and their wages, and the deadline of each of the tasks at hand in a way that ensure on time delivery of projects and minimal associated costs.

The resource assignment tool created was used to solve a typical resource assignment case involving 10 employees and 7 tasks. Since the instrument is designed to assign one task at a time to every resource, then the model had to choose the most suitable 7 resources out of the pool of 10 employees. After thorough analysis of the results, the optimal solution was found to be the best answer to choosing which of these designers will be working on the tasks at hand. The model then generated 100,000 different random assignments that represent the current situation for allocating human resources in companies. It also computed the cost associated with each of these assignments and then every cost was compared to the optimal solution. This was done by calculating the percentage difference between the cost due to random assignment and the optimal value. It is important to remember that the random allocations do no ensure meeting project deadlines. And thus, the results indicate that using the model for assigning employees not only guarantees completing tasks on time, but also makes sure to reduce the price of assigning resources by an average of 38%.

The study was limited by the difficulty in quantifying the level of experience of resources and their level of familiarity with using certain software programs. These attributes are represented in a binary format, but future studies may include incorporating a more accurate tool that can specifically quantify these skill sets.

Some assumptions were made while formulating the optimization model which states that employees work 10 hours a day and on only one task at a time, are not interrupted during their work day, and are not affected by the level of compatibility between individual designers working on the same team. Future updates to the model may address incorporating these assumptions by taking into consideration that the working hours are not always 10 complete hours per day and by including variables that depict the level of compatibility between designers working on the same team and how that would affect the performance of resources.

When compared to commonly used allocation practices, this model run results proved to have saved significant monetary figures and increased the company's level of performance, due to meeting project timelines. The significance of using such a model is also directly related to the size of the company implementing this allocation tool.

Engineering design companies do not usually publish employees' characteristics and information about the tasks at hand so this is one limitation that hindered the use of the developed model on an existing case study and potentially comparing the optimal results to the cost of an occurring incident. However, this was accounted for by interviewing a design expert and manager who is also a potential user of the model and who gave his feedback on the assumptions and results of the model.

The model may be expanded to look into more than one discipline and therefore account for the interaction between different departments. It may also incorporate the dependency of design tasks on multiple software programs. Other potential extensions to the model may include allowing managers to monitor and control the progress of the project by asking employees to update the status of the initially assigned tasks. The model would then rerun the optimization program to make sure constraints are still satisfied or else, designers would be reallocated to maintain the model's goals.

APPENDIX

MODEL VERIFICATION

This section includes examples for verifying that the code is properly working and fulfilling its objectives. The following tables show the expected time required by all employees to work on all tasks as generated by the MATLAB code. These values are used in both the MATLAB and MS EXCEL sheet to find the optimal solution which has the same result from both software programs.

Example 1

Table A 1. **Time Expected by Resource to Finish Task**

TIME EXPECTED BY RESOURCE TO FINISH TASK		**T1**	**T2**	**T3**	**T4**	**T5**
		40	**40**	**50**	**32**	**50**
HR1	**45**	26.76512	20.07958	37.41538	30.11543	45.24283
HR2	**20**	39.11729	37.71121	53.17099	49.62667	55.17223
HR3	**20**	999	999	999	999	999
HR4	**30**	32.19372	27.86169	47.65517	40.964	50.93436
HR5	**45**	999	999	999	999	999
HR6	**45**	999	999	999	999	999
HR7	**30**	32.44882	28.3419	46.46313	40.32024	53.77343
HR8	**30**	28.19006	24.19926	39.48265	32.90653	47.79749
HR9	**30**	999	999	999	999	999
HR10	**20**	37.49182	39.69808	53.40386	46.88951	56.11906

Table A 2. **Optimal Assignment Solution**

OPTIMAL ASSIGNMENT SOLUTION		**T1**	**T2**	**T3**	**T4**	**T5**
		40	**40**	**50**	**32**	**50**
HR1	**45**	0	0	0	1	0
HR2	**20**	0	1	0	0	0
HR3	**20**	0	0	0	0	0
HR4	**30**	0	0	0	0	0
HR5	**45**	0	0	0	0	0

HR6	**45**	0	0	0	0	0
HR7	**30**	0	0	1	0	0
HR8	**30**	0	0	0	0	1
HR9	**30**	0	0	0	0	0
HR10	**20**	1	0	0	0	0

Resulting total cost:

- Computed by MS Excel = $ 5,687.07
- Computed by MATLAB = $ 5.6871e+03

Example 2

Table A 3. **Time Expected by Resource to Finish Task**

TIME EXPECTED BY RESOURCE TO FINISH TASK		**T1**	**T2**	**T3**	**T4**	**T5**
		40	**40**	**50**	**32**	**50**
HR1	**45**	26.87817	20.63774	37.75894	31.74769	47.22726
HR2	**20**	39.79646	36.60412	51.38624	43.61971	56.28754
HR3	**20**	999	999	999	999	999
HR4	**30**	34.20359	26.90712	48.14285	36.82644	54.64632
HR5	**45**	999	999	999	999	999
HR6	**45**	999	999	999	999	999
HR7	**30**	31.74992	26.47446	42.51084	39.62034	52.36644
HR8	**30**	28.37915	24.57707	39.3779	33.87431	49.79298
HR9	**30**	999	999	999	999	999
HR10	**20**	36.4292	38.179	57.53729	45.35334	57.83911

Table A 4. **Optimal Assignment Solution**

OPTIMAL ASSIGNMENT SOLUTION		**T1**	**T2**	**T3**	**T4**	**T5**
		40	**40**	**50**	**32**	**50**
HR1	**45**	0	0	0	1	0
HR2	**20**	0	1	0	0	0
HR3	**20**	0	0	0	0	0

HR4	**30**	0	0	0	0	0
HR5	**45**	0	0	0	0	0
HR6	**45**	0	0	0	0	0
HR7	**30**	0	0	1	0	0
HR8	**30**	0	0	0	0	1
HR9	**30**	0	0	0	0	0
HR10	**20**	1	0	0	0	0

Resulting total cost:

- Computed by MS Excel = $ 5,658.43
- Computed by MATLAB = $ 5.6584e+03

Example 3

Table A 5. **Time Expected by Resource to Finish Task**

TIME EXPECTED BY RESOURCE TO FINISH TASK		**T1**	**T2**	**T3**	**T4**	**T5**
		40	**40**	**50**	**32**	**50**
HR1	**45**	25.18964	20.13488	37.7962	31.94792	47.33503
HR2	**20**	35.64953	36.76618	54.69391	42.58927	56.68561
HR3	**20**	999	999	999	999	999
HR4	**30**	30.81091	30.95713	43.11215	38.964	50.82824
HR5	**45**	999	999	999	999	999
HR6	**45**	999	999	999	999	999
HR7	**30**	33.00991	26.97228	46.54079	40.16911	53.74076
HR8	**30**	28.62635	22.70955	38.84347	34.78334	47.88095
HR9	**30**	999	999	999	999	999
HR10	**20**	39.12908	36.53757	59.96135	43.08632	57.21339

Table A 6. **Optimal Assignment Solution**

OPTIMAL ASSIGNMENT SOLUTION		**T1**	**T2**	**T3**	**T4**	**T5**
		40	**40**	**50**	**32**	**50**
HR1	**45**	0	0	0	1	0
HR2	**20**	1	0	0	0	0
HR3	**20**	0	0	0	0	0
HR4	**30**	0	0	1	0	0
HR5	**45**	0	0	0	0	0
HR6	**45**	0	0	0	0	0

HR7	**30**	0	0	0	0	0
HR8	**30**	0	0	0	0	1
HR9	**30**	0	0	0	0	0
HR10	**20**	0	1	0	0	0

Resulting total cost:

- Computed by MS Excel = $ 5,611.19
- Computed by MATLAB = $ 5.6112e+03

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