

AMERICAN UNIVERSITY OF BEIRUT

INVESTIGATING OPERATIONAL WORKFORCE
MANAGEMENT DECISIONS UNDER UNCERTAINTY

by

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A thesis

submitted in partial fulfillment of the requirements
for the degree of Master of Engineering Management
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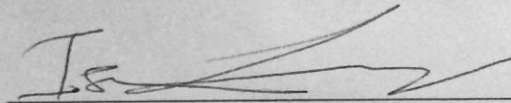
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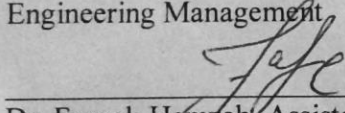
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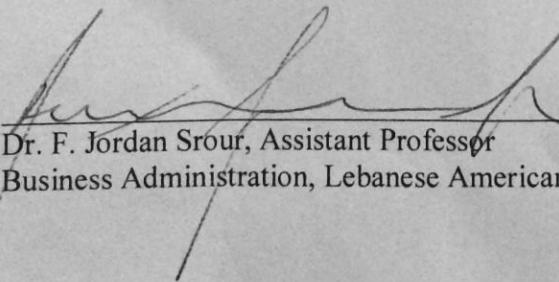
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Special thanks are for Dr. Issam Soudki and Dr. F. Nadim Soudki for their continuous support and guidance throughout my research.

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AN ABSTRACT OF THE THESIS OF

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Title: Investigating Operational Workforce Management Decisions under Uncertainty

Workforce management decisions (e.g., hiring, training, and staffing) have a direct impact on the cost, schedule, and quality of work. Researchers have developed several mathematical programming models to optimize such decisions. Most of these models are of a deterministic nature, i.e. they rely on well-known and pre-set input parameters such as supply and demand characteristics. However, in practice, there is significant uncertainty in these parameters, which jeopardizes the optimality of solutions obtained from these models. Moreover, they provide strategic decisions to be made over the entire project duration. This can prove to be inapplicable in projects which make use of a transient workforce, since these projects typically suffer from frequent changes in the supply and demand of workers.

Lebanon has an unregulated construction labor market. It mainly depends on migrant workers from Syria who typically work on several projects in a short period of time. This highly transient workforce can cause difficulties in managing construction projects, and might lead to unpredictable rates of absenteeism, unsatisfactory productivity, and increased labor costs. This study identifies the characteristics of a transient construction workforce and measures the impact of several internal and external factors on absenteeism rates. Furthermore, it makes use of the results to present an optimization-based framework to make operational workforce management decisions for a transient workforce. The research method relies on a survey targeting 60 site engineers, construction managers and project managers who have access to labor related information.

The results show that unskilled and skilled workers have different characteristics in terms of demographics, tenure of work, and wage structure. Furthermore, most of the respondents believe that external factors (e.g., holidays and political instability) have a bigger impact on absenteeism than internal factors (e.g., working conditions, interpersonal relationships). Therefore, an integer linear program is built to act as a tool that construction managers can use to reduce costs and meet the demand for workers, while also taking into account absenteeism, skill level, and supply of workers. Moreover, the model can be used across several planning horizons and demand forecast horizons. Results from application of the model to a real world case study with different real world scenarios are presented, and recommendations for workforce management strategies are made.

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CHAPTER I

INTRODUCTION

The construction industry in the Middle East has been growing steadily over the past few decades. The amount of planned construction work in the region for the next 5 years is estimated at around \$2.4 trillion (GCC 2010). In 2012, the construction industry in Qatar grew by 5.1% contributing about \$7.7 billion to the overall GDP (Deloitte 2013). This steady growth of the Middle Eastern construction industry warrants the development of tailored, workforce management tools.

This study examines the construction workforce in a Middle Eastern country, namely Lebanon. Lebanon is a developing country with a substantial number of construction projects, which are mostly residential in nature. As such, the construction industry plays a prominent role in the economics of the country. In 2012, the investment in the real estate and construction sector constituted 21% of Lebanon's GDP (Project Lebanon 2013). Even with the instability surrounding the region, the construction sector is still the second highest growing sector in terms of value added after services and trade (Presidency of the Council of Ministers 2010).

Despite its relatively high share in GDP, the Lebanese construction sector is responsible for a mere 5.6% of total employment (UNDP 2006). This is because most of the construction workforce is from the neighboring country of Syria (UNDP 2013). This migrant labor pool is similar to the one found in the Southern United States, while also bearing similarities to the industrial sector labor pools found on projects throughout the Arabian Peninsula (Lattouf et al. 2014). The use of a migrant workforce is largely due

to the economies of the region as migrant workers are used to long working hours and are willing to accept lower wages (Meardi et al. 2012).

However, the use of a migrant workforce has several drawbacks. Most migrant workers are not officially employed by contractors and are often un-documented, which is the case of the vast majority of projects in Lebanon. Another problem is the lack of labor unions in developing countries which increases the likelihood of short term employment of workers. Buckley (2013) found that the lack of labor unions and formal labor organizations is one of the main reasons behind the temporary employment of construction workers in Dubai, since most of these workers are foreign and hence have no laws to protect them.

While dependence on migrant labor poses multiple managerial and policy challenges, it is actually the lack of permanent employee status that defines a transient workforce. Not granting permanent employee status allows a company to remain flexible in the face of uncertainty. However, a dependence on transient labor can actually increase uncertainties in construction projects and make it difficult to judge the presence of a systemic labor shortage.

Specific characteristics should be studied so that supervisors can manage transient workers effectively. Hence, a few research questions arise: What are the characteristics of a transient workforce that affect its availability or absenteeism? What other project factors correlate with high rates of absenteeism?

The main goal of this research is to study the characteristics of a transient workforce, and consequently develop an optimization based framework to assist construction site managers in making optimal hiring, firing, and assignment decisions.

In particular the objectives are to: (1) describe the characteristics of a transient workforce (staffing requirements, skill or craft types, skill levels, pay scale, and length of service); (2) study absenteeism and its relationship with project factors; and (3) propose and illustrate a decision making model and tool for making optimal operational workforce management decisions under uncertainty.

The remainder of this thesis is as follows. Chapter 2 and 3 present a review of the literature on the sources of uncertainty in construction workforce management and the characteristics of a transient workforce respectively. Chapters 4 and 5 explain the survey methodology and the results that were obtained. Chapter 6 illustrates the model formulation and Chapter 7 talks about the model dynamics and the results of the case study. Finally, Chapter 8 talks about the conclusions, recommendations, and future work.

CHAPTER II

SOURCES OF UNCERTAINTY IN CONSTRUCTION WORKFORCE MANAGEMENT

Wincha (1989) classified the sources of uncertainty in construction workforce management into three types: labor related factors, internal project factors, and external factors. These factors affect the cost, time, and quality of construction projects as they increase uncertainty and hence cause more unpredictability. The factors are reviewed next.

A. Labor Related Factors

Developing countries like Lebanon do not usually have modern equipment and techniques, and hence mainly rely on manual labor, whose productivity is unpredictable (Koehn and Regmi 1993). This explains why, despite low daily wages, labor costs in such countries can be as low as 30% or as high as 50% of a project's overall cost (Kazaz et al. 2008).

Construction labor productivity rates have always been one of the greatest sources of uncertainty in the cost and schedule of projects to owners and contractors alike (Chui and Bai 2010). A study by Wu, et al. (2007) stated that the labor productivity of the Chinese construction industry could be as low as 30% of its US counterpart. This difference can be explained by many factors such as worker skill level which is the case of China and other countries such as Qatar (Abdulaziz et al. 2012). Attracting sufficiently skilled workers in developing countries is still proving to be a major challenge.

Another factor affecting construction workforce management is absenteeism. Absenteeism is defined as the failure to appear to work, and can be of two types: excused and unexcused. Excused absence is when the workers ask their superiors for a fixed period vacation, while an unexcused absence is when the workers do not show up to work without prior notice (Hinze et al. 1985). Absenteeism and productivity are also closely related. An analysis by Hanna, et al. (2005) found that an absence rate of 6% to 10% decreases productivity by as much as 25%. Developing countries suffer from a high rate of absenteeism due to the transient workforce usually employed in such countries. This is because low job security and a long workshift schedule can lead to higher absenteeism rates (Hinze et al. 1985).

B. Internal Project Factors

Rework is an example of an internal (i.e. project related) source of uncertainty which relates to labor management (Gosling et al. 2013). Rework is mainly due to change orders. Love and Li (2000) studied the causes and costs of rework in the Australian construction industry. They found that changes initiated by the client and end-user were the primary causes of rework, which in turn increases the cost of a project by 3%. Change orders can also have a negative effect on labor productivity. A study done in Malaysia showed that change orders were the third most important factor that affects productivity following skill level and amount of building material available (Kadir et al. 2005). Another study by Jarkas and Radosavljevic (2013) showed that rework was the second most important factor affecting the motivation of workers in Kuwait after payment delay.

There are many strategies that help in reducing the number of variation orders and consequently rework. Arain (2005) found that using a Knowledge-Based Decision Support System (KBDSS) assisted decision makers in controlling the number of change orders. However, developing countries such as Lebanon suffer from a lack of expertise in these technologies which makes the application of such strategies difficult. The size of the project can also increase the level of uncertainty in a project. A study by Samset (1998) found that larger, more ambitious projects have higher uncertainty and are less likely to be considered successful than mediocre projects.

C. External Factors

External factors that might affect construction workforce management include the environment, availability of resources, political instability, and weather (Samset 1998). Some of these factors can have a significant effect on labor availability. For instance, in the war of 2006 between Lebanon and Israel, thousands of workers left Lebanon for fear of their own safety (Chalcraft 2009). Similarly recent political instabilities in the region have affected the availability of workers, both skilled and unskilled, because many workers are fleeing Syria towards Lebanon in search of a job. Developing countries are more prone to these kinds of uncertainties because they tend to have a second tier infrastructure and less institutional capability for implementing projects.

D. Strategies to Mitigate Uncertainty

The problems of uncertainty in the construction industry, and particularly with respect to workforce management, have led to an increased interest in developing strategies that can handle these problems. Strategies to manage the problems of absenteeism and productivity in particular are abundant in the literature. Ahn, et al. (2013) studied how social norms emerge and how they play a role in controlling worker's absence habits. Using an experimental analysis with simulation, they found that managers who consider how to raise the workers' feeling of attachment to their work have lower absenteeism rates on their sites. Several strategies also aimed at increasing the self-regulation among workers. For example, Banerjee, et al. (2006) looked into several strategies that were used to reduce absenteeism in government and non-governmental organizations. They evaluated each of these strategies using several evaluation methodologies. They concluded that increasing wages provides an incentive for workers to work harder and hence be less absent.

The distance that workers have to traverse to get to the workplace can also affect absenteeism. Hinze, et al. (1985) studied construction worker absenteeism on several construction projects. One of their conclusions was that contractors who offer housing units to their workers have lower rates of absenteeism, since those units are usually located near the project.

Strategies to increase productivity are also very important. Randolph et al. (2006) explored several methods to increase a construction crew's productivity. Using deductive reasoning, they came up with a strategy to make use of symbiotic crew relationships. This is when several crews work together in order to finish the work, i.e.

two or more crews working at the same time rather than waiting for one to finish. This strategy helps in increasing the productivity of workers and decreasing the time needed to finish an assignment.

The above mentioned strategies were tested and verified in the context of developed countries like the US, UK, or Canada. However there is little data on the transient construction workforce in developing countries such as Lebanon, which means that there is no guarantee that the workforce strategies discussed above are applicable in the region. Because most of the workforce is transient, strategies that aim to reduce absenteeism by increasing the workers' feeling of attachment may not be very efficient. Another problem is that those strategies do not differentiate between skilled and unskilled workers. Unskilled workers are defined as workers with no more than a basic education, whereas skilled workers are defined as workers who have acquired special skills through certification or experience (Wood 1995). Skilled and unskilled workers can have a wide variety of differences in their workforce characteristics. For example, Shi (1999) found that unskilled workers in the US had a sizable wage inequality when compared to skilled workers. Additionally, unskilled workers had more volatile working hours. Therefore, some of the workforce management strategies might work on one group of workers but not the other.

CHAPTER III

THE TRANSIENT WORKFORCE

In Chapter 2, it was stated that one of the main sources of uncertainty in construction projects is labor-related. This is particularly true for the industries characterized by the use of a transient workforce. Chen (2011) defines a transient workforce as “comprised of employees who are not permanent”, i.e. workers who tend to work in a particular organization for a short period of time. Because of this unique quality, transient workers are preferred in industries where the job nature and location change frequently with time. This could explain why the construction industry is heavily reliant on transient workers (EOC 2006); the very nature of the industry makes a transient workforce a necessity. Different sets of skills are needed during each phase of work within the project, leading to a significantly different workforce at different times during construction (Rawlinson and Farrell 2008). Job location is another factor that also contributes to the transient nature of the construction workforce. Haupt and Whiteman (2004) concluded that construction workers were more likely to seek employment elsewhere if the construction site was not close to where the workers had previously worked.

There is an abundance of literature that discusses the characteristics of a transient workforce and its implications on a project. Most studies agree that while a transient workforce is beneficial, transient workers can cause several problems related to workforce management. Also, there seems to be a strong link between migrant workers and transience. These subjects are reviewed next.

A. Transience, a Property of a Migrant Workforce?

The relationship between migrant workers and transience can be explained by the fact that most migrant workers are undocumented, which makes them unofficial “employees” of the company. Therefore, they are likely to leave their jobs without prior notice (Karjanen 2011). Also, there are many benefits of employing migrant, transient workers. For example, they are used to working for long hours and are willing to accept lower wages (Meardi et al. 2012). Other benefits include improved fluidity of businesses, and increased mobility for the duration of short assignments, which can be a solution for talent shortages in various areas (Chen 2011). In addition, migrant, transient workers can increase flexibility and adjustment in the labor market, which is crucial to the construction industry (U.S. Department of Health and Human Services 2000).

There are many studies that confirm the relationship between transience and migrant workers. Wong (1997) studied foreign workers in Singapore and found that they were the leading cause behind the transience of the workforce in industries like construction. This is because most migrant workers had no official contracts with the employers. Hence, they were able to work for several different companies without any legal restriction. Another study shows that Hispanic and Latino workers constituted 81% of the residential construction industry workforce in Texas (Workers Defense Project 2013). This helped in explaining the reasons behind the transient nature of the Texan residential construction workforce. Dainty and Bagilhole (2007) found that south-east England had a high number of migrant construction workers, and that contributed to the high turnover rates in the local construction industry.

B. The Effects of a Transient Workforce on Construction Workforce Management

Sargent et al (2003) studied the effects of a high labor turnover rate, which is one of the problems associated with a transient workforce, on the electrical construction industry. They surveyed both managers and employees to find the leading causes of high turnover rates. Both parties agreed that reduced overtime and long distances to commute to work were the leading causes behind a high turnover. Moreover, by collecting data from surveyed sites and using ordinary least squares regression, they found that a turnover rate of 11-20% annually could decrease productivity by as much as 22%. Decreased productivity can have devastating effects on construction projects. This is confirmed by a study done by Assaf and Al-Hejji (2006) who conducted a field survey on large construction projects in Saudi Arabia by meeting with owners, contractors, and consultants. All three parties agreed that a low productivity rate of workers was one of the leading causes behind the delays in their respective projects.

Absenteeism, which is a characteristic of a transient workforce, is also associated with high turnover rates in construction projects. AbouRizk et al. (2010) found that absenteeism and turnover were factors that could lead to one another. They also defined absenteeism as the failure to appear to work, and they divided it into controllable and uncontrollable absences. Controlled absences involved the environment of the construction site, while uncontrolled absences involved issues such as travel, illness, and overtime on another job. Their results indicated that high turnover rates were the leading cause behind high absenteeism since job satisfaction appeared to play a major role in workers' behaviors.

Safety on site is another issue that is related to a transient workforce. This is because the transient nature of the workforce could create a site environment that is inflexible and resistant to change (Entek 2000). Consequently, incorporating safety practices in the company's culture does not guarantee better safety practices among workers since most workers do not view themselves as part of the company (Chen 2011). Neitzel et al. (2001) determined that the confusion created by a transient workforce employed in construction sites with complex heavy machinery and equipment certainly contributed to the high number of construction injuries and fatalities. Moreover, Singh et al. (1999) concluded that the largely transient nature of the construction workforce made it very difficult to develop health promotion strategies.

C. Previous Solutions

From a managerial perspective, a transient workforce can be very beneficial to contractors. This is because temporary employment relieves the employer from providing benefits to the workers, which reduces cost. Moreover, the added flexibility of frequent hiring and firing minimizes unnecessary long term investments in the workforce (Camden 2003). Nonetheless, there are considerable difficulties in making intelligent hiring and firing decisions within the context of a transient workforce that exhibits high levels of absenteeism.

A number of strategies have been proposed to manage the transient workforce in the construction industry. Sargent et al. (2003) suggested several solutions to reduce voluntary quits and absenteeism. They concluded that providing safer site conditions, introducing incentive programs, and changing the definition of overtime were possible

solutions to combat high turnover rates. Cameron and Duff (2007) studied the effects of introducing specific strategies like goal-setting and training on-site to improve the workers' safety behaviors. They found that while goal setting improved the behaviors of workers, training provided no additional benefits. This proved that the workers were well aware of safety procedures, however to act in that way did not fit within the site culture. Therefore, it was concluded that while an ultimate solution was not yet clear, changes must be made to the company's culture itself to allow for better safety practices. However, such measures are difficult to implement unless there was a clear strategy behind them.

Providing optimization models and tools that deal with the allocation and employment decisions of transient workers seems to be the most suitable strategy for managing a transient workforce. This is confirmed by Assaf and Al-Hejji (2006) since they recommended optimizing the labor strategic decisions to improve the shortage and productivity of workers. Edwards (1983) suggested that a suitable workforce management strategy should consist of: (1) predicting the demand of workers, (2) predicting the supply of workers, and (3) optimally matching the supply and demand of workers.

The need to mathematically provide an optimization model for workforce management strategies has been noted in several studies. Sing et al. (2014) formulated a mathematical model that was capable of estimating the supply and demand of technicians in the construction industry. They used the triangulation technique by using qualitative and quantitative data. The data was collected by means of interviews and surveys done with contractors, design consultants, and quality control consultants

working in Hong Kong. They also used government and institutional reports to ascertain the validity of their models. Two models were formulated; one for the demand and one for the supply of technicians. The model was then tested to calculate the demand and supply of technicians in Hong Kong for the next 5 years. These models were developed for general, strategic planning use and hence they cannot be used operationally on individual construction projects.

Gomar et al. (2002) proposed a model that focused on the benefits of hiring multi-skilled workers. Those benefits included enhancing worker efficiency, prolonging worker employment duration, and decreasing indirect labor costs. The authors added that multi-skilled workers resulted in a better continuity of work in addition to improving quality. The model aimed at minimizing the total number of workers, the switching between tasks, and the hiring and firing decisions. The model was then run on different scenarios using data from a real case study. The results indicated that multiskilled workers were always preferred over single-skilled workers by the optimization model.

Srouf et al. (2006) developed a linear optimization model for workforce optimization that was based on CII's Tier II study that dealt with future improvements to the current workforce. Their linear model aimed at minimizing labor costs and meeting the demand of workers, through cross-training, proper workforce hiring, and utilizing multiskilled workers. The formulated model was tested on a case study of an industrial project with five different training and hiring scenarios. The results indicated that when compared with possible approaches taken by industry practitioners, the model provides cost savings of about \$30,000, and a benefit-to-cost ratio of 15:1.

Nonetheless, the problem with these models is that they are static, i.e. they are run once over the entire project timeline. This can pose several problems since any changes that occur during the construction phase cannot be taken into account. A better solution would be to have a model that could run at different times; covering different time horizons in the process. This would improve the applicability of such models as changes in the demand or supply of workers could be accounted for. Another problem is that these models assume that training facilities that can train workers in other skills are readily available. Most developing countries do not have such facilities, and consequently, multiskilled workers cannot be utilized in those countries. Contractors are, anyway, reluctant to train a worker who may leave to another project in the next day. Therefore, this shows that a static model that advises training workers and utilizing multiskilled workers does not always provide the optimal strategies.

In order to develop a more dynamic model, real data has to be collected on transient workers working in a developing country. Therefore, a survey was administered on site managers in the country of Lebanon in order to capture the characteristics of the workforce and the different uncertainties that affect workforce management. Chapters 4 and 5 present the methodology and the results of the survey.

CHAPTER IV

SURVEY METHODOLOGY

The findings in Chapters 2 and 3 provide valuable information to understand the characteristics of the construction workforce. However, these studies were done in countries which have a relatively low uncertainty, i.e. countries with a stable political situation and controlled labor pool. Workers in countries with a substantially higher uncertainty might not share some of those characteristics. Therefore, the country of Lebanon was a suitable option to study the different workforce characteristics that might exist in a country with no labor regulations and which is politically unstable. Based on the literature review, five hypotheses related to the workforce characteristics were specified. These are as follows:

1. The rate of absenteeism is higher for unskilled workers than skilled workers. [H1]
2. Working in longer shift schedules is associated with higher rates of absenteeism. [H2]
3. Projects with a high percentage of labor who have been working with the same company for long periods have lower absenteeism rates than projects with higher labor turnover. [H3]
4. High rates of absenteeism cause delays in the project. [H4]
5. Large projects have higher absenteeism rates than small projects. [H5]

Fieldwork was undertaken to investigate the characteristics of the Lebanese construction workforce and test these hypotheses. The methodology adopted in this study relies on a survey instrument which allows for collecting data from a large sample (Ling et al. 2012). The framework of Agarwal (2011) was followed in the design and administration of the survey. The first part of the survey (Q1 through Q9) aimed at quantifying and characterizing the workforce demographics. The second part (Q10 through Q17) focused on identifying the different uncertainties that could affect projects, and quantifying their effects on project performance. Several questions (e.g., Q11, Q12, and Q14) aimed at exploring the relationship between absenteeism and project schedule to validate the formulated hypotheses. Q10 was about the rate of absenteeism per week for unskilled, skilled, and foremen. Other questions (Q6, Q7) targeted the workshift schedule (the respondents had to give the number of working days and hours), and the percentage of unskilled, skilled, and foremen who were working for the same company for the past 9 months. We selected a period of 9 months as Wang, et al (2010) noted that a 35 week (9 months) timeframe is the time needed for construction workers to be considered long-term employees. Finally, a question about the project schedule (Q14) was asked to measure the effects that change orders or absenteeism might have on a project performance.

The target population was the construction managers/field engineers working on construction projects in Beirut. Beirut is the capital city of Lebanon with a population of 1.5 million and an area of 20 km². Most of the major construction projects in the country are situated in Beirut, and hence most of the construction workforce is centralized in the city. The questions in the survey were mostly of a continuous nature;

and therefore, the sample size calculations were based on this fact. The level of acceptable risk, alpha, was set at 0.1 and a 3 percent acceptable margin of error was chosen. Before calculating the sample size, the population size was estimated by using data from the “Order of Engineers and Architects” on the amount in m² of building permits in Beirut from March 2011 to March 2013 (2,256,805 m²) (Order of Engineers and Architects 2013). Then, this number was multiplied by a factor of 0.8 to account for the projects that were still not underway. To obtain an estimate of the number of projects that are currently underway, this number was then divided by 5,000 m² which represents a typical floor area of 500 m² multiplied by 10 (i.e., a ground floor, underground parking, and 8 floors). This is the average size of a new building project in Beirut. Hence, the population size was estimated to be about 361 projects assuming that every project has a construction manager and/or field engineer. Using the formulas suggested by Cochran (1977), the sample size was found to be 65. Since this number is greater than 5 percent of the estimated population, Cochran’s correction formula had to be used and the subsequent population size was found to be 54. To guarantee a fair geographical distribution of sites in the Beirut area, a total of 60 projects were surveyed. Figure 1A shows the location of Lebanon and figure 1B shows the surveyed sites. The Beirut area was divided into blocks, and the site visits were done at random.



Figure 1A: Lebanon

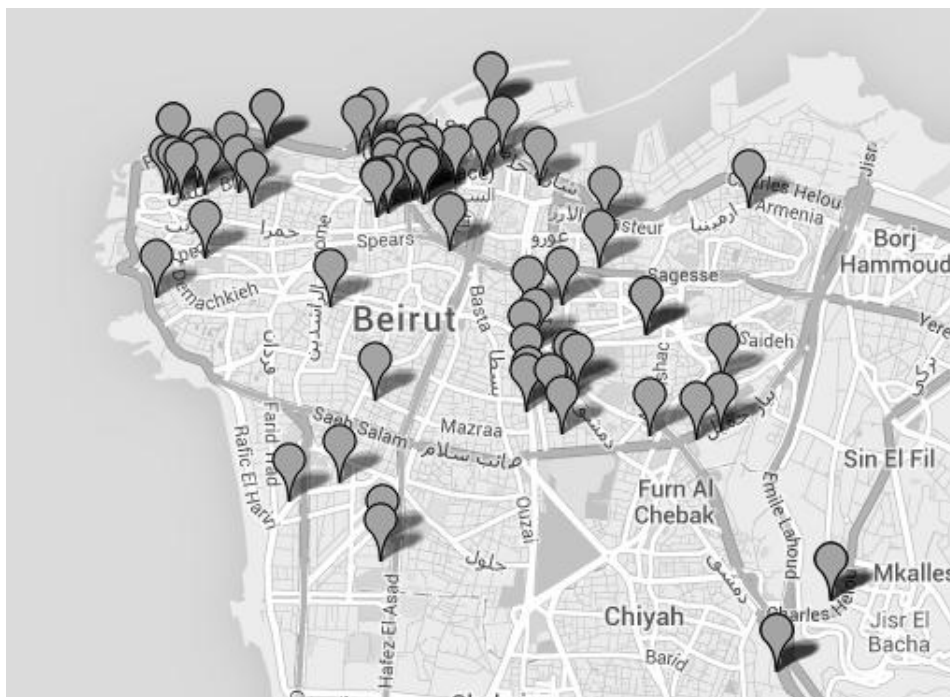


Figure 1B: Surveyed Site

The survey was conducted by means of personal interviews. This method was chosen because internet based surveys tend to have a very low response rate and suffer significant bias. Moreover, some of the respondents might have an inquiry about some of the questions; and therefore, it is essential that an interviewer be present. A telephone based survey was also infeasible since it is almost impossible to get the numbers of the sample population due to a lack of resources and information. A typical interview lasted anywhere from 20 to 60 minutes, depending on the availability and the attentiveness of the respondents. The interviewer would walk to the site and ask for the project/construction manager. If they were not available, then the interviewer would talk to the site engineers who were responsible for the site.

Before administering the survey to a full sample of construction sites, a pilot test was carried out with two experts from the construction industry. One of the experts was a senior construction manager with over 35 years of experience, who serves as an area construction manager for a prominent construction contractor. The other expert was a lead project engineer with 10 years of experience who works for another prominent contractor in Lebanon. The subjects provided some valuable insights on questions that seemed ambiguous or misleading. Based on the feedback, minor modifications were made to the survey.

CHAPTER V

SURVEY RESULTS AND ANALYSIS

Data was collected from 60 construction sites. The data entry was done in SPSS (SPSS Inc.). The results were then divided into two parts: descriptive stats and hypotheses testing data. Descriptive stats aimed at presenting the Lebanese construction workforce characteristics in terms of demographics, longevity of work, wages, and training. The second part quantified the effect of project uncertainties on the project schedule, and it also targeted exploring the relationship between different workforce characteristics and project uncertainties. The detailed results are presented in the following sections.

A. Descriptive Stats

Table 1 shows the characteristics of the respondents, all of whom are Lebanese nationals. The vast majority of the respondents are site engineers, construction managers, or project managers. More than half of the respondents had 10 or more years of experience in the construction industry (average is 13 years). Almost all of the respondents were males. This reflects the reality of the construction industry in Lebanon which is still dominated by a male majority.

Most of the surveyed projects were in superstructure or finishing phases (45% and 33% respectively). This is an expected result given that a typical 1.5 to 2.5 year residential project spends 2 to 4 months in excavation and shoring, another 2 to 4

months in substructure construction, 8 to 12 months in superstructure construction, and 6 to 10 months for finishing and commissioning.

Table 1: Demographics Characteristics of Respondents

Description	Frequency	Percentage
Interviewee Designation		
Project Manager	23	38
Site Engineer	24	40
Construction Manager	12	20
Assistant PM	1	2
Gender		
Male	59	98
Female	1	2
Experience (years)		
Up to 10	28	47
11-20	22	37
>20 years	10	16

Figure 2 shows the demographics of the local construction workforce. Almost 98% of the unskilled and 90% of the skilled workforce is non-Lebanese Arabs, mainly from the neighboring country, Syria. However, 77% of the foremen are local, which means that higher positions are usually given to Lebanese nationals. Foremen are treated as regular employees by the contractors, and hence receive benefits such as healthcare and housing expenses. It is interesting to note that these figures are similar to those found in a recent study of the building construction workforce in Texas where 81% of the workers were reported as Hispanic or Latino (Workers Defense Project 2013). A large number of those workers come from the neighboring country of Mexico.

On average, unskilled workers are paid \$18 to \$19 per day while skilled workers are paid \$30 to \$31 per day. Daily wages range from \$24 to \$48 depending on the skill type of the worker. For example, elevator mechanics receive about \$48 per day

while carpenters receive \$35 per day. On average, Foremen are usually given a monthly salary of about \$1,500. Some of the foremen working in small projects get as little as \$600. An interesting comparison to be made here is between the wages in Lebanon and the United States (US). A skilled carpenter, for example, working in the US receives \$18 per hour or about \$144 per day (Srour et al. 2006).

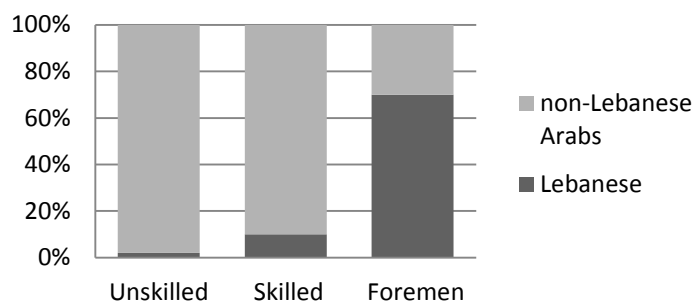


Figure 2: Workforce Demographics

The trades involved in the surveyed projects are those most commonly found in residential building projects; trades usually found in industrial and heavy/civil projects are very rare. There were no welders or pipefitters. Only 7 percent of the respondents used traffic operators and 47 percent did not have any fencing specialists. An overwhelming majority of the contractors did not offer any training to their workforce. A mere 3 percent offered basic safety training for their workers. This can be attributed to the fact that there are limited training opportunities in Lebanon, and most of the workers learn their trades while helping the skilled workers, i.e. on-job training. Interestingly, the lack of formal schooling found among the Lebanese workforce is consistent with the residential construction workforce of Texas where 85% had a high school or lower level of education (Workers Defense Project 2013).

B. Hypothesis Testing

To test the first hypothesis [H1], the following question was asked to the respondents: *On average, what percent of the workforce is absent per week?* This was asked for both unskilled and skilled workers. The answers corresponded to the percentage of workers that were absent (both excused and unexcused) during the week. The absenteeism rate for unskilled workers had a mean of 7% compared to 4% for skilled workers. A paired t-test was undertaken to determine if there was a difference between absenteeism percentages for the skilled and unskilled workers. The pairing between unskilled and skilled workers' absenteeism percentages was done on the basis of the construction sites to control for site-based variability. The difference variable in the paired samples t-test had a mean of 3 and a standard deviation of 4.3. The results of the paired sample t-test indicated a *t*-value of 5.4 which is greater than 2.0 (with a sample of 60 and a confidence level of 95%) and a *p*-value equal to 0.000, making the two variables statistically different. This confirms the hypothesis that absenteeism rates are higher for skilled workers than for unskilled workers. A possible explanation is that unskilled workers are usually perceived as "more dispensable", and therefore have a higher chance of getting an excused absence. Foremen have a very low absenteeism rate (0.6%) due to their vital role in construction (the work cannot commence if the foremen are absent). Interestingly, the absenteeism rates in Lebanon are lower than that in other parts of the world. For example, Alberta, Canada, has an average absenteeism rate of 15% (Salehi Sichani et al. 2011). One possible reason for this difference might be that workers in Lebanon are mostly foreign and likely to be at the mercy of economic need.

Most contractors are very strict with absenteeism, particularly for skilled workers, with several respondents noting that they fire workers if the absence is not excused.

The respondents were also asked to rank the different factors that might increase absenteeism. Figure 3 shows the average relative importance of each factor, 5 being the highest effect and 1 the lowest effect.

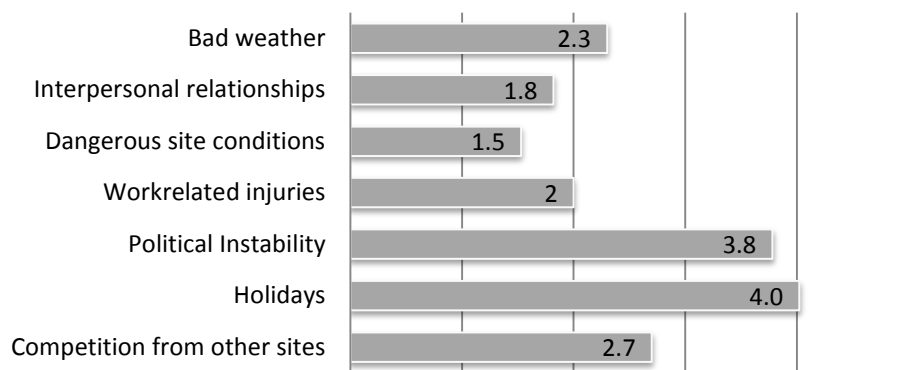


Figure 3: Factors Affecting Absenteeism

As shown in Figure 3, holidays and political instability have the highest effect on absenteeism. Despite the threat of being fired for unexcused absenteeism, it is common for workers to be absent during holiday times – whether paid or not. It is also interesting to note that the external factors to the project (e.g., bad weather, political instability, holidays, and competition from other sites) have the highest effect while internal factors (e.g., interpersonal relationships, dangerous site conditions) have a relatively low effect on absenteeism.

The respondents were also asked to estimate the predictability of unskilled labor shortages on a 5 point scale, 1 being predictable and 5 being unpredictable, over 3 periods namely daily, weekly, and seasonally. The averages of the daily and weekly

predictability were almost identical (2.7) while the average seasonal predictability was much higher than the other two (3.5). This is an expected result as it is difficult for a contractor to forecast shortages 3 or 4 months into the future especially when factors affecting absenteeism are mostly external.

The second hypothesis [H2] that was tested was that projects that have longer work schedules have higher absenteeism rates than other projects. The respondents were asked to *specify the shift schedule that is used on site (the number of working days and hours)*. The answers to this question were discrete since respondents had to choose from a set of choices: 7 working days (12, 10, or 8 hour shift), 6 working days (12, 10, or 8 hour shift), or 5 working days (12 or 10 hour shift). A bivariate Spearman's rank correlation was carried out since the data of work shift schedule was discrete rather than continuous. The Spearman correlation coefficient was positive for both skilled and unskilled workers (0.155 and 0.195 respectively); however, the p-values (0.237 for skilled and 0.136 for unskilled) were greater than 0.05 which indicated that the results were not statistically significant. This could be due to the fact that both skilled and unskilled workers receive overtime for any extra hours of work beyond the standard 8 hour shift. Therefore, most of those workers prefer to receive extra wages and hence they avoid being absent.

The third hypothesis [H3] was that projects that employ workers for long periods have lower absenteeism rates than projects who frequently fire and recruit workers. The specific question was: *Of the current workers what percentage has been working with your company for more than 9 months?* A bivariate Pearson correlation analysis was used between the longevity of work percentage and the absenteeism rate.

The Pearson correlation factor was found to be -0.41 for unskilled workers with a p-value of 0.001 indicating significance and -0.14 for skilled workers with a p-value of 0.283 which indicates that it is not significant. Therefore, there is a significant negative correlation between the number of unskilled workers who work for more than 9 months and absenteeism rates whereas there does not seem to be any significant correlation between job tenure and absenteeism for skilled workers. This might be because unskilled workers are less likely to endanger their job and are less likely to work for a competitor if contractors are offering a high level of job security. However, skilled workers are usually employed for longer periods (on average 75% of skilled workers worked for more than 9 months in the company), and hence have a relatively high job security which prevents them from being absent.

A question was also asked about the project schedule: *Currently what is the difference between the planned schedule and the actual schedule for your project?* The majority of the respondents (62%) stated that their projects were on schedule. This information was used in order to test [H4] to check if there is any correlation between absenteeism rates and the project schedule performance. Again a bivariate Spearman's rank correlation was used because the data on the project schedule was discrete. The Spearman correlation coefficient was positive for both skilled and unskilled workers (0.183 and 0.333, respectively). However, only the p-value for the unskilled workers (.011) indicated that the correlation between absenteeism and the project schedule is significant. That is, projects which are behind schedule have higher rates of absenteeism among their unskilled workers. On the other hand, the correlation of skilled absenteeism with project schedule performance is not statistically significant. This information is

interesting because usually projects that suffer from skilled rather than unskilled labor shortages are behind schedule. One potential reason for this result is the reliability and robustness of the original project schedule. If the original schedule was not realistic (e.g., aggressive) and/or did not account for contingencies, then the project is bound to face some delay regardless of the degree of uncertainty in worker availability. It may also be a case that project delay is a symptom of more general project mismanagement to which the workers may be responding. For example, if the project delay results in a delay in paying the unskilled workers, they may abandon the primary site for a better managed site. Alternatively, there might be some level of bias in the responses as many of the respondents might have felt that the project schedule question was asking for sensitive information that was an evaluation of their work.

The last hypothesis [H5] states that larger projects have higher rates of absenteeism. To assess this hypothesis, the respondents were asked to estimate the size of the project as expressed by the total built-up area. A bivariate Pearson correlation indicated that there was a positive correlation between the size of the project and absenteeism rates (0.361 for skilled and 0.156 for unskilled), however only skilled absenteeism was statistically significant with a p-value of 0.005 whereas the p-value for unskilled was 0.233. This can be explained by referring to the crew sizes in construction projects. As the project size increases, crew sizes are bound to be higher, and consequently this can affect absenteeism. If the crew size was sufficiently large, then a worker might feel more at ease or less responsible because there is sufficient number of workers to cover for his/her absence. However in smaller projects (particularly small residential type projects), the crew sizes are small and relatively

constant through the construction phase. Moreover, there usually exists one or two workers for each trade and hence if one worker was absent, the entire project might be delayed. This puts more responsibility on workers operating in small crews and therefore makes them less prone to be absent. This is not applicable for unskilled workers because those types of workers are easily replaced and usually operate in different job crews throughout the construction phase. Consequently, this makes them easier to replace in case of absence, and because of this, unskilled workers are not less likely to show up to work in smaller projects.

CHAPTER VI

MODEL FORMULATION

The survey results presented in Chapter 5 show that a highly transient workforce has significant special characteristics. As demonstrated by the survey results, the Lebanese construction workforce comprised mostly of foreign workers, exhibits interesting characteristics relative to absenteeism, thus, forcing construction site managers to hire and fire frequently. Also, internal project factors like working conditions and interpersonal relationships seem to have a small effect on the workers' absenteeism. In order to manage a workforce with such characteristics, a decision making tool is needed to assist decision makers in making optimal labor-related decisions on a frequent basis. There is an abundance of literature on models that try to optimize strategic workforce management decisions. However, the problems of a transient workforce and uncertainties in the construction industry are rarely incorporated into these kinds of models. Furthermore, most of the existing models assume that the demand profile in a project is fixed for the entire construction phase, which is rarely the case. Therefore, this study aims at using mathematical modeling techniques to assist decision makers in making operational decisions dynamically for a transient workforce. Because of the workers' temporary nature of employment, decision makers have to hire and fire workers frequently; the proposed model can be run as frequently as necessary for periods that match the foreseeable demand. For example, due to demand variations, it is common to make hiring decisions every 4 to 12 weeks (Lattouf et al. 2014). Hence, the proposed model is a useful tool for optimizing the

hiring and firing decisions dynamically. Uncertainty factors, like absenteeism and limited supply of workers, are also incorporated into the model. In addition, the model distinguishes between skilled and unskilled workers as these two types of workers have significantly different characteristics.

The model was formulated as an integer linear programming (ILP) model. More specifically, it takes the form of an assignment model in which we must assign groups of workers with various skills to work in specific time periods without exceeding the availability of the workers while meeting the demand for workers. The following sections describe the decision variables, parameters, objective function, and constraints of this model.

A. Decision Variables

The model includes the following decision variables:

1. u_{it} : the number of unskilled workers affiliated with skill i to hire in time t
2. m_{it} : the number of unskilled workers affiliated with skill i to fire in time t
3. z_{it} : the number of unskilled workers affiliated with skill i working in time t
4. s_{it} : the number of skilled workers from available work pool with skill i to hire in time t
5. h_{it} : the number of skilled workers with skill i to hire from outside work pool in time t (Sometimes, decision makers might not be able to hire from the available market. Hence, they might have to spend extra money to hire workers from another site, or to get workers from outside the country)
6. n_{it} : the number of skilled workers with skill i to fire in time t
7. k_{it} : the number of skilled workers with skill i working in time t

The first five decision variables deal with the hiring and firing decisions respectively. Therefore, they are important to personnel who are responsible for the

hiring and firing of workers. In Lebanon, those responsible for such decisions are typically the foremen. The last two decision variables are typically used by site management since they represent the worker assignments (i.e. what each worker is supposed to work on in a specific period).

B. Parameters

The model includes the following input parameters:

1. DU_{it} : the demand for unskilled workers affiliated with skill i in time t
2. DS_{it} : the demand for skilled workers with skill i in time t
3. hc_i : hiring cost of a skilled worker with a skill i from available work pool.
4. hs_i : hiring cost of a skilled worker with a skill i from outside available work pool.
5. hcu_i : hiring cost of unskilled worker affiliated with a skill i
6. fs_i : firing cost of a skilled worker with a skill i
7. fsu_i : firing cost of unskilled worker affiliated with a skill i
8. wu_i : weekly wage of unskilled worker affiliated with skill i
9. ws_i : weekly wage of skilled worker with skill i
10. $Z0_i$: Number of unskilled workers affiliated with skill i available at start of planning
11. $K0_i$: Number of skilled workers with skill i available at start of planning

C. Objective Function

The main aim of this model is to minimize all labor related costs while meeting the labor demand profile over the course of the planning period. This includes any hiring and firing costs, in addition to the wages incurred, which is typically the largest component. The objective function consists of the following five terms:

1. The cost that will be incurred to hire skilled workers with skill i in time t from available work pool.

$$\sum_{i=1}^i \sum_{t=1}^t [hc_i * s_{it}]$$

2. The cost that will be incurred to hire skilled workers with skill i in time t from outside available work pool

$$\sum_{i=1}^i \sum_{t=1}^t [hs_i * h_{it}]$$

3. The cost that will be incurred to hire unskilled workers affiliated with skill i in time t

$$\sum_{i=1}^i \sum_{t=1}^t [hcu_i * u_{it}]$$

4. The cost that will be incurred to fire skilled workers with skill i in time t

$$\sum_{i=1}^i \sum_{t=1}^t [fs_i * n_{it}]$$

5. The cost that will be incurred to fire unskilled workers affiliated with skill i in time t

$$\sum_{i=1}^i \sum_{t=1}^t [fsu_i * m_{it}]$$

6. The incurred wages on site:
 - a. By unskilled workers affiliated with skill i

$$\sum_{i=1}^i \sum_{t=1}^t [wu_i * z_{it}]$$

- b. By skilled workers with skill i

$$\sum_{i=1}^i \sum_{t=1}^t [ws_i * k_{it}]$$

D. Constraints

The constraints of the model are as follows:

1. Availability constraints:

- a. $z_{it} \geq u_{it} + (z_{it-1} - m_{it})$, $t \in (1, 2, \dots, n)$ represents a set of constraints to make sure that the model does not assign more unskilled workers affiliated with skill i in time t than the available pool
- b. $z_{it} \geq u_{it} + (Z0_i - m_{it})$, $t \in (0)$ same as constraint 1a but during first week of planning the number of unskilled workers affiliated with skill i who are available from previous week is equal to $Z0_i$. This constraint is needed because the number of workers at time zero cannot be calculated by the model; it has to be input by the user
- c. $k_{it} \geq s_{it} + h_{it} + (k_{it-1} - n_{it})$, $t \in (1, 2, \dots, n)$ set of constraints to make sure that the model does not assign more skilled workers with skill i in time t than the available pool
- d. $k_{it} \geq s_{it} + h_{it} + (K0_i - n_{it})$, $t \in (0)$ same as constraint 1b but during first week of planning the number of skilled workers available from previous week with skill i is equal to $K0_i$

2.Meeting the demand:

- a. $DU_{it} \leq (z_{it-1} - m_{it}) * \text{Unskilled Availability factor} + u_{it}$: set of constraints to make sure that the demand for unskilled workers DU_{it} is met. The availability factor represents the fraction of workers hired in previous weeks that are not absent. This is not applicable for newly hired workers since it is illogical for them to be absent.
- b. $DS_{it} \leq (k_{it-1} - n_{it}) * \text{Skilled Availability factor} + s_{it} + h_{it}$: set of constraints to make sure that the demand for skilled workers DS_{it} is met. The availability factor represents the fraction of workers hired in previous weeks that are not absent. This is not applicable for newly hired workers since it is illogical for them to be absent.

3.Hiring capacity of skill i

$$s_{it} \leq \text{Available work pool of skill } i$$

This constraint provides an option for the decision makers if they have enough data to confirm that there is an upper limit on the number of skilled workers with skill i to hire (e.g. there is a skilled labor shortage).

4. Firing constraints:

- a. $m_{it} \leq z_{it-1}$: A constraint on the number of unskilled workers that can be fired. The number of unskilled workers affiliated with skill i to fire in time t cannot be more than the number of unskilled workers available from last week
- b. $n_{it} \leq k_{it-1}$: A constraint on the number of skilled workers that can be fired. The number of skilled workers with skill i to fire in time t cannot be more than the number of skilled workers available from last week

The reason behind these constraints is to ensure that the model does not fire and hire workers from the same skill simultaneously (especially if the hiring and firing costs are set to zero).

CHAPTER VII

MODEL DYNAMICS

The developed model is coded in C++ using Microsoft's Visual Studio and solved using the GUROBI solver (Gurobi Optimization, Inc. 2014). The demand data can be extracted from an excel file provided by the user. All the decisions are output into excel files that can be easily interpreted by the user. To test the capabilities of this model in a dynamic setting, we run it across different planning and forecast horizons. The following subsection describes the horizons over which the model is run.

A. Planning and Forecast Horizons

The planning horizon refers to the period of time over which the model's output decision are to be implemented. In other words, it represents the number of weeks over which the model's estimated hiring, firing, and allocation decisions are to be made. The length of the planning horizon depends on the length of time for which the plan is intended to be used. Figure 4 shows the planning horizons that were tested.

These were:

- i. Planning horizon equal to 12 weeks [Entire 12 week phase of the project planned]
- ii. Planning horizon equal to 4 weeks [Entire 12 week phase of the project divided into 3 planning intervals]
- iii. Planning horizon equal to 2 weeks [Entire 12 week phase of the project divided into 6 planning intervals]

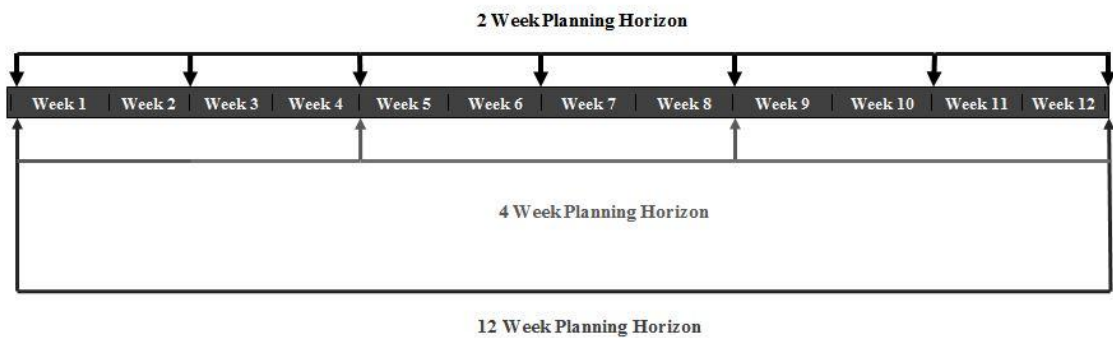


Figure 4: Planning Horizons

The forecast horizon refers to the period of time over which the project's demand data is known with certainty. The length of the forecast horizon depends on the availability of accurate information about the demand of labor. This means that the decision maker has to identify the exact demand data for the selected forecast horizon. For instance, if a user chooses to plan for 4 weeks, then a planning horizon of 4 weeks is chosen. However, the length of the forecast horizon will depend on the accuracy of the demand data that the user has at the start of planning; if a decision maker has accurate demand data for the entire 4-week planning horizon, then a forecast horizon of 4 weeks is used. However, if the decision maker has accurate demand for the first two weeks of planning and estimated demand for the last two weeks, then a forecast horizon of 2 weeks is used. This introduces the notion of running times, which correspond to the number of times the model is run during a specific planning horizon. In this example, the decision maker has to run the model twice during the 4-week planning period in order to get the optimal decisions. This is because the demand data for the last two weeks is estimated, i.e. not accurate. Figure 5 shows the forecast horizons and the running times that were used in this study. At the top of the axis, we have a planning

horizon of two weeks, a forecast horizon of 1 week, and the model is run every week;
on the lower axis, the planning horizon is four weeks, the forecast horizon is two weeks,
and the model is run every two weeks.

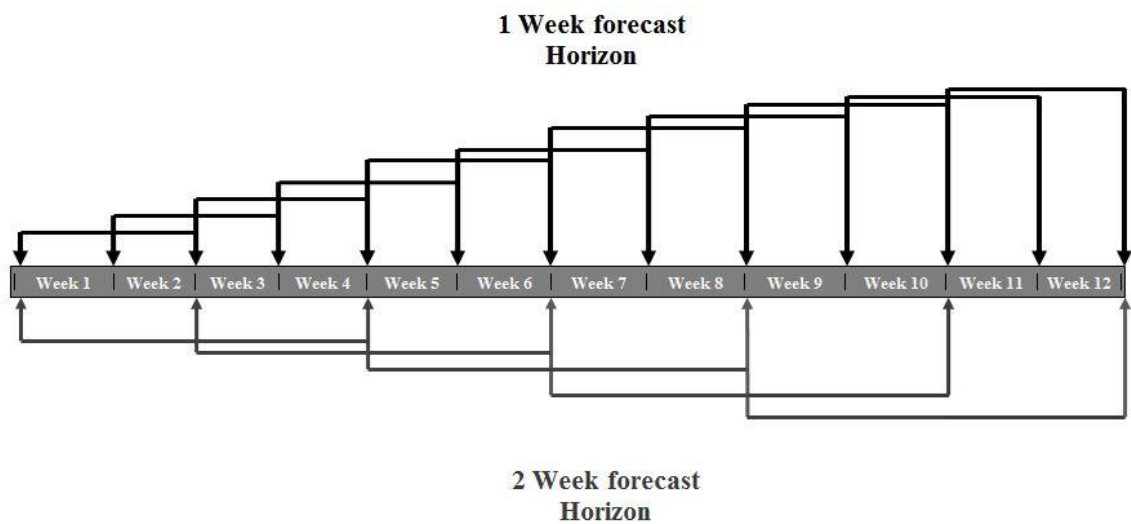


Figure 5: Forecast Horizons and Running Times

B. Input and Scenarios

To explore the relative merits of various planning and forecast horizons, we require demand data, both actual and forecasted, across several weeks of a large construction project. In order to obtain this data, we gained access to an ongoing commercial tower project located in Beirut, Lebanon. The finished tower will have 52 floors and 7 basements, with an average floor area of 1,100 m². The total built up area is 66,000 m², making it one of the biggest construction projects in the country in terms of height and area.

The types of workers selected for this study were steel fixers, carpenters, equipment operators, concrete workers, and electricians. Those represent the primary trades found in building construction. A survey done by Lattouf et al. (2014) on

construction sites in Lebanon indicated that most skilled workers were hired on a seasonal basis (approximately 12 weeks), and the majority of unskilled workers were hired on a monthly or weekly basis. Therefore, demand data were calculated for a period of 12 weeks since this was equal to the average hiring period of skilled workers, and consequently it was long enough to verify the effectiveness of the model. The calculations were done based on the project's resource allocations which were obtained from the Primavera schedule. Due to the unavailability of precise data on the number of workers working in a specific week, the numbers were calculated by extracting the amount of work that had to be done in a given week and then dividing this number by the average productivity of the work crews. The following equation illustrates this.

$$\text{Demand for week } t = \frac{\text{Amount of work for week } t}{\text{Average productivity of workers}}$$

It is interesting to note that the management in this project was very interested in calculating the productivity of work crews on site, and hence the figures should provide an accurate estimate for productivity. Moreover, the initial number of workers at the start of planning was assumed to be zero for all the skills.

Although the contracting company in charge of the case study project does not recognize any hiring and firing costs for workers, it was assumed that a penalty equal to the weekly wage of workers was incurred for each hired or fired worker. This amount was selected as an estimate of:

1. Worker's orientation costs. Newly hired workers should have a small orientation about the project and the company. Moreover, some companies have mandatory safety orientation programs
2. Safety tools and small equipment. Newly hired workers are typically given a safety helmet and safety boots as part of the country's safety requirements

3. Frequent firing can cause low morale and lower productivity among workers

The project manager estimated the absenteeism rates for skilled and unskilled workers at 10% and 15% respectively. This represents the percentage of workers who are absent on any given day per week. There was no upper limit on the number of skilled workers that could be hired at any given time.

The model is tested using two different scenarios. Scenario I assumes a standard demand of workers in the entire project's investigated phase. This is equal to the demand specified in the project's baseline resource allocation schedule. Scenario II uses a dynamic demand in which changes occur at specific times, during which the demand of workers in that specific week is lower than the standard demand by half (due to delays, material shortage, etc.). Figure 6 shows an example of the difference between the standard and dynamic demand profiles for steel fixers. A change in plan led to less demand of workers at times 3, 6, and 10. Section II of appendix shows the standard and dynamic demand for the other skills.

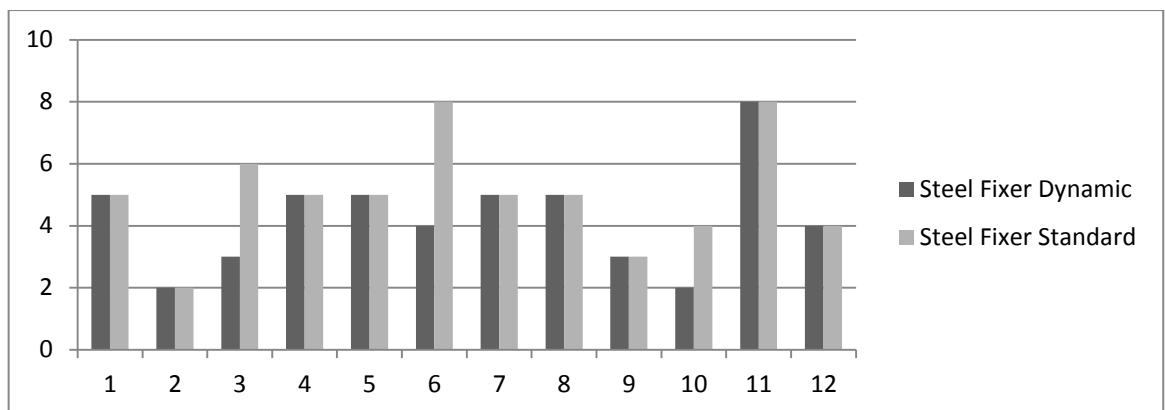


Figure 6: Standard vs. Dynamic Demand

Table 2 summarizes the tests that were carried out.

Table 2: Scenario Testing

Scenario		12 weeks			4 weeks			2 weeks														
		Forecast Horizon	Running Times	Case	Forecast Horizon	Running Times	Case	Forecast Horizon	Running Times	Case												
I		12 weeks	Once	Case 1.1	2 weeks	Once	Case 2.1	4 weeks	Once	Case 1.2	2 weeks	Once	Case 2.2	2 weeks	Twice	Case 2.4	2 weeks	Once	Case 1.3	1 week	Twice	Case 2.5
		12 weeks	Once	Case 2.6	2 weeks	Once	Case 2.1	4 weeks	Once	Case 2.7	2 weeks	Once	Case 2.2	2 weeks	Twice	Case 2.4	2 weeks	Once	Case 2.3	1 week	Twice	Case 2.5
II				Case 2.6			Case 2.1			Case 2.7			Case 2.2			Case 2.4			Case 2.3			Case 2.5

The model was tested on different cases. Scenario I had three cases and Scenario II had seven cases. The cases in Scenario I refer to the three planning horizons that were used. Case 1.1 is the 12-week planning horizon, Case 1.2 is the 4-week planning horizon, and Case 1.3 is the 2-week planning horizon. The forecast horizon was kept equal to the planning horizons in all cases. Hence, the model was run once in the 12-week forecast horizon, three times in the 4-week forecast horizon, and 6 times in the 2-week forecast horizon. This was done in order to reveal the effects of the planning horizon on the final decisions and the labor costs. The benefit of testing the model with such cases includes investigating the advantages and disadvantages of long term vs. short term planning horizons.

Scenario II was tested on seven cases. The demand data for each case was different because it was assumed that changes in the project's resource allocation schedule could only be done two weeks in advance for Cases 2.1 through 2.5, which was indicated by site management. However, it was assumed that a "clairvoyant" could actually inform the decision makers on all the demand changes at the start of the project for Cases 2.6 and 2.7. Hence, the 12-week forecast horizon was used for the 12-week planning horizon; similarly the 4-week forecast horizon was used for the 4-week forecast horizon. The model was not able to recognize any demand changes in Case 2.1. Demand changes in Weeks 6 and 10 were accounted for in Case 2.2, while changes in Weeks 2, 6, and 10 were accounted for in Cases 2.3, 2.4, 2.5, 2.6, and 2.7. This was done in order to demonstrate the importance of having a dynamic model with variable planning and forecast horizons, since current models that deal with labor decisions can only be used before the start of the project. Consequently, changes in the demand and

other uncertainties in the project cannot be taken into account. Hence, these scenarios show the impact of these changes on the decisions and the labor costs.

Figure 7 shows the planning and forecast horizons relative to the points in time at which the model is run. Looking at the running horizons, one can see the effect of the forecast horizon, where the hashed lines indicate the use of inaccurate demand data in planning. For example, case 2.1 uses an accurate demand for the first two weeks only, and an estimated demand is used to the other ten weeks, making the probability of making inaccurate decisions quite high.

Table 3 provides an example of running the model twice over the 4-week planning horizon using a 2-week forecast horizon for the skilled steel fixers (Case 2.4). During the first week, the model is run to provide decisions for the next 4 weeks (weeks 1, 2, 3, and 4). The demand data for the first 2 weeks is accurate, since, as mentioned previously, the demand for the forecast horizon must be actual rather than forecasted. However, it is estimated for Weeks 3 and 4 (by using the demand data from the baseline resource allocation schedule). This means that the proposed decisions for the first two weeks are optimal, but they may not be accurate for Weeks 3 and 4. Hence, the model is run again in Week 3 (also for the next 4 weeks), but now the demand data for Weeks 3 and 4 has become precise. Consequently, the decrease in the demand in Week 3 is incorporated, and this reduces the total labor costs as the demand decreases from 6 to 3. Similarly, changes in Weeks 6 and 10 were also accounted for.

The model was run for 30 instances for all the cases. The first instance represented the actual demand data that was collected from the project's resource allocation schedule, while the other 29 instances were randomly generated by using a

uniform distribution ranging from lowest demand to highest demand for each skill. This was done in order to statistically analyze the results.

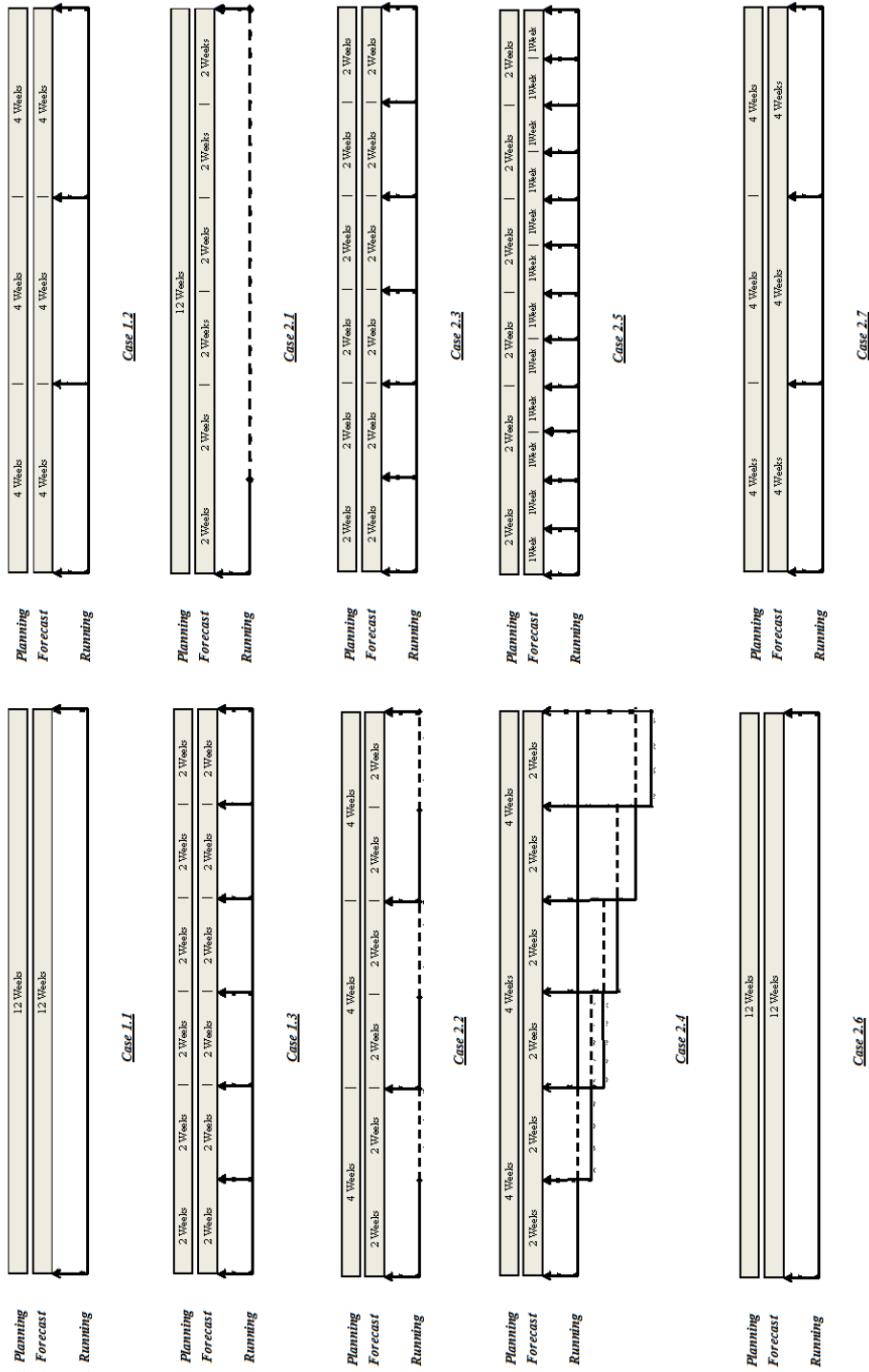
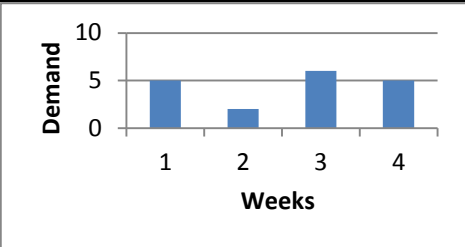
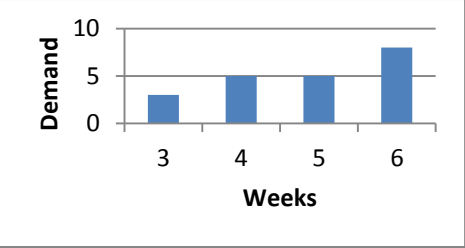
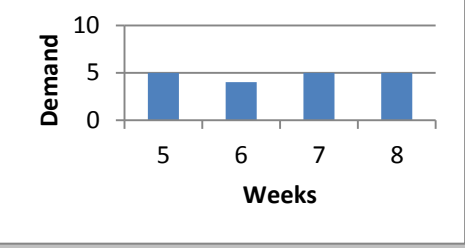
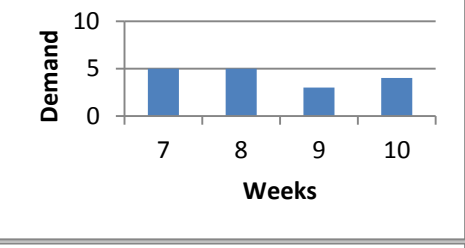
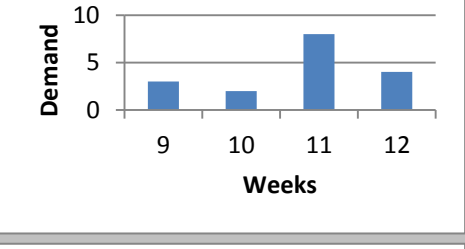
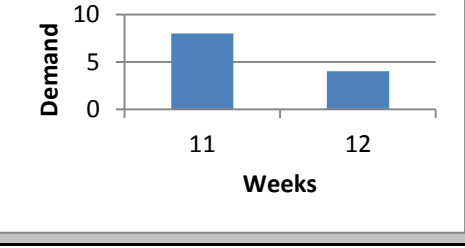


Figure 7: Illustration of Dynamic Horizons

Table 3: Forecast Horizon Example

<i>Week</i>	<i>Event</i>	<i>Model's Demand Input</i>
1	Run model for 4 weeks	
2	Apply decisions from first run	
3	Run model for 4 weeks	
4	Apply decisions from second run	
5	Run model for 4 weeks	
6	Apply decisions from third run	
7	Run model for 4 weeks	
8	Apply decisions from fourth run	
9	Run model for 4 weeks	
10	Apply decisions from fifth run	
11	Run model for 2 weeks	
12	Apply decisions from sixth run	

C. Setting the Parameters

In order to measure the effects of absenteeism and the hiring and firing costs, a sensitivity analysis was done on the base case (12-week planning horizon, 12-week forecast horizon) using the demand from the project's resource allocation schedule. The percentage change in cost was measured as absenteeism increases from 0% (Low) to 10% (Moderate) and finally to 20% (High). This range was selected because according to Lattouf et al. (2014) absenteeism in the Lebanese construction industry varies from 0 to 20%. The percentage change was calculated based on an average cost of \$177,100 (Moderate Absenteeism). Figure 8 shows the results. This shows that a high absenteeism can increase total labor costs by as much as 10%; while strategies that decrease or even eliminate absenteeism can reduce costs by up to 10%.

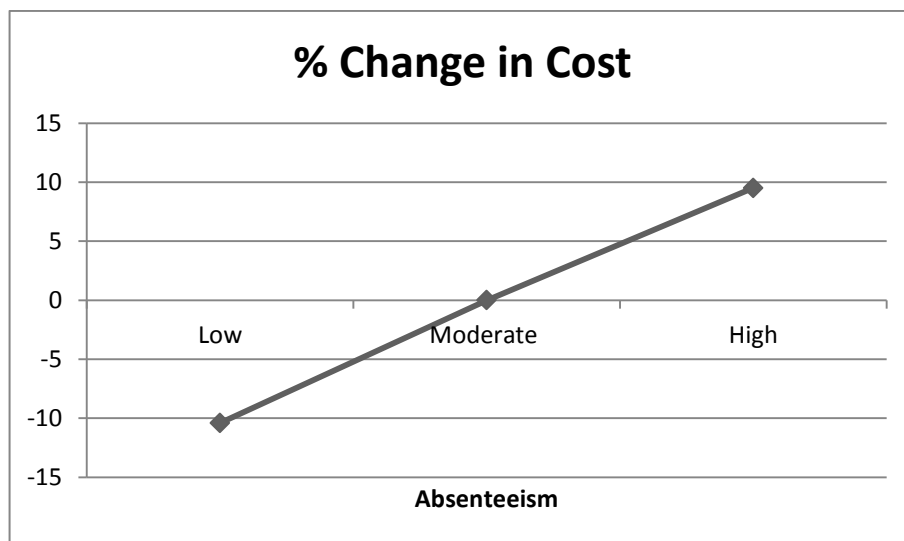


Figure 8: Absenteeism and Labor Costs

Figure 9 shows the total hiring and firing decisions made for each level of absenteeism. The graph indicates that as absenteeism increases, hiring decisions tend to

be more frequent and higher numbers of workers are hired every week. This is because high absenteeism means that there are fewer workers from the previous week, and hence more workers have to be hired in order to make up this shortage. However, firing decisions are relatively the same across the different levels of absenteeism except in Week 3. This can be explained by the fact the absenteeism will only effect the number of workers that are hired since the model tries to balance the supply and demand of workers. Hence, the number of workers that are going to be fired will only depend on the demand, not the absenteeism.



Figure 9: Absenteeism and the Number of Hiring and Firing Decisions

The hiring and firing costs were also varied to study their effects on the total labor costs. Hiring and firing costs were set at \$0 in the first case, a weekly wage in the second case, and twice the weekly wage in the third case. Figure 10 shows the relationship between the net numbers of hiring and firing and their relative costs. The number of hiring and firing tends to decrease as hiring and firing costs increase. This is because retaining workers, even if they are not needed, is more economically feasible than firing them and then hiring other workers in the consequent weeks. Therefore, overstaffing is economically feasible only if hiring and firing costs are higher than the workers' weekly wages.



Figure 10: Hiring and Firing Costs

C. Results

The data analysis was done in SPSS (SPSS Inc. 2013). Table 4 shows the mean value of labor costs plus/minus the standard error.

Table 4: Results (All figures are in \$k± Standard Error)

Demand	12 weeks		4 weeks		2 weeks	
	Forecast Horizon	Running Times	Forecast Horizon	Running Times	Forecast Horizon	Running Times
Standard	12 weeks	Once	2 weeks	Once	4 weeks	Once
	2 weeks	Once	4 weeks	Once	2 weeks	Twice
Dynamic	12 weeks	Once	2 weeks	Once	4 weeks	Once
	2 weeks	Once	4 weeks	Twice	2 weeks	Twice

1. Scenario I: Standard Demand, Planning Horizon Equal to Forecast Horizon

The results show that the mean cost was lowest in case 1.1 (\$183,200 compared to \$183,900 and \$184,800 for case 1.2 and 1.3 respectively). This is expected because having a wider view of the demand schedule could lead to retaining workers rather than firing them since the wages incurred would be lower than hiring costs in the future. However, the p-value of the one way ANOVA was 0.49, indicating that there was no significant difference between the costs incurred using the three planning horizons. This means that using longer planning periods does not guarantee more savings than short forecast periods.

2. Scenario II: Dynamic Demand

a. Forecast Horizon Shorter than Planning Horizon

The mean labor costs were \$183,200 for case 2.1, \$177,100 for case 2.2, and \$177,200 for case 2.3. The one way ANOVA test indicated a p-value of 0.000 which proves that the means of the three planning horizons were statistically different. Furthermore, a Tukey HSD post Hoc test was carried out in order to compare each case with the other two. This showed that the results of case 2.2 and 2.3 were not statistically different (p-value=0.998), while the results of case 2.1 was statistically different from those in 2.3 (p-value=0.000) and the 2.2 (p-value=0.000). These results demonstrate that running the model over the entire project timeline can be risky since any changes that occur during the construction phase are not taken into account. Furthermore, the negligible difference between the results of cases 2.2 and 2.3 points toward the fact that even though one of the variation orders was not taken into account, retaining the

workers rather than firing them proved to be an equally viable decision. This is because the wages incurred can be equal or even lower than the firing and hiring costs of the extra workers if the changes in the demand are of short durations.

b. Forecast Horizon Shorter than Planning Horizon and Frequent Running Times

The mean labor costs were \$173,400 for case 2.4, and \$173,900 for case 2.5. A paired sample t-test was carried to check if there was any significant difference between the two populations. The p-value was 0.000 indicating that the two means were different. This means that using a 4-week planning horizon is a better option to use if a forecast horizon of 2 weeks is used and the model is run twice. This is because a wider planning range allows the model to check the variations in the demand further into the future. As opposed to case 2.2, the model was able to foresee the variation order in week 4 in the 4-week planning horizon, because when the model was run again at week 2, the user had to specify accurate demand data as opposed to data from the baseline resource allocation schedule, making it possible for the user to perceive the variation in the demand in week 3.

It is also interesting to note that the results of those two cases were compared with cases 2.2 and 2.3, since the demand profiles used were the same but running times were different. The paired sample t-test indicated a p-value of 0.000, indicating a statistical significance. The mean value of labor costs for cases 2.2 and 2.3 was \$177,150 compared to \$173,650 for cases 2.4 and 2.5. The reason for this difference is that running the model more frequently and with short forecast horizons leads to more savings in the labor costs as any changes in the demand are accounted for. For example,

a 2-week forecast horizon run in the context of a 4-week planning horizon effectively gives the optimal decisions for the first 2 week while also taking into account the changes in the demand for the other 2 weeks, making the decisions more optimal.

c. Clairvoyant

The mean labor costs were \$173,300 for Case 2.6 and \$173,800 for Case 2.7. The p-value of the paired sample t-test was 0.000 indicating that the two means were different. The 12-week forecast horizon run in the context of a 12-week planning horizon gave the lowest cost in this case study. This is because it was assumed that all the demand changes were known from the start, and this led to the model using accurate demand and forecasting the demand variations across the entire project horizon. However, this is not practical in reality since it is very hard to know the demand changes across the entire project timeline at the start of the project. Also, running the 2-week forecast horizon in the context of the 4-week planning horizon proved to be very close to the optimal solution (0.06% difference). It is also interesting to mention that Case 2.4 gave better results than Case 2.7 (0.23% difference). This is because even though it was assumed that all the demand changes were known beforehand in Case 2.7, decisions made for Week 3 for example, are made while looking at the next two weeks only. In Case 2.4, the decisions made for Week 3 are made while looking four weeks into the future due to the frequent running of the model. Therefore, future variations in the demand are more likely to be identified in Case 2.5.

CHAPTER VIII

CONCLUSIONS AND EXTENSION FOR FUTURE WORK

This study investigated, using a survey research design, the demographics and the different uncertainty factors that affect a transient workforce in a developing country. Five hypotheses were formulated and tested. A paired sample t-test was conducted to identify significant differences in traits between skilled and unskilled workers. Pearson and Spearman correlation factors were used to check the relationship between absenteeism and the different factors studied. The levels of absenteeism were found to be related to several factors, namely level of skill, tenure of work, and the project size. According to the collected data, absenteeism of skilled workers does not seem to have a significant effect on the project schedule, but this may be due to the prevalence of bias associated with the survey question on project schedules.

Most importantly, the survey indicated that a highly transient workforce has several special characteristics which necessitates the need of particular tools that can help in managing such a workforce efficiently. Therefore, an integer linear programming model was developed to provide optimized hiring, firing, and allocation decisions to managers. The model was applied on a case study involving a large commercial building project in Beirut. Two different scenarios were tested. Different combinations of forecast and planning horizons were used in order to evaluate the different practices that might be applied in the real world. The findings indicated that the key to getting optimal decisions lies in the interplay of planning horizons, forecast horizons, and running times. Using a long planning horizon could be risky especially since changes in

the demand were not taken into account. Moreover, running the model twice using a 2-week forecast horizon in the context of a 4-week planning horizon was the optimal solution to use when demand changes were hard to forecast. The cost difference between the apriori solution and this case was an insignificant 0.06%. This is because it could provide more insights to the model, and using a two week forecast horizon lead to a more accurate demand profile. Of course, this cannot be generalized on any project. This is because the model depends on the project's labor demand profile. Namely, if the user develops a good resource allocation schedule that minimizes demand variations and uncertainties, then a longer forecast horizon can be used; while having a risky project and a poor schedule makes a short forecast horizon more favorable.

The proposed model can provide many benefits. For example, the model's output can act as a guide to the decision makers to make the optimal hiring, firing, and staffing decisions under different forecast horizons. This is very important as inaccurate strategic workforce decisions can prove to be very costly to construction projects. For example, a large commercial project in Beirut with a total built up area of 45,000 m² suffered a huge loss because of problems related to workforce management. This is because for a time period of six months, several construction activities were put on hold due to several reasons (e.g. lack of approved shop drawings, lack of approved materials, delays in preceding activities, etc.). Consequently, the demand of labor was supposed to be lower than expected, as the amount of work to be performed had decreased. However, the site management did not take any action in that regard, and the labor demand profile was not changed. Subsequently, many workers were idle during their working hours due to the extra supply of labor. The impact of this decision was not

immediately recognized; but six months later senior management found that the cost per unit of production (especially m³ of concrete) was above the norm. To verify this observation, they benchmarked the current cost to previous projects. The results were clear; the cost per unit of production was much higher compared to the data. Top management performed some corrective measures which included firing many extra workers that were not needed. The cumulative loss was approximately \$80,000 per month (\$480,000 total). This case shows the significance of optimized workforce strategic decisions and the huge losses incurred because of improper decisions. The proposed model can be an indispensable tool used by site managers to eliminate those kinds of problems.

Other benefits include the model's ability to handle several forecast and planning horizons. This is vital to projects with demand profiles that tend to vary considerably because of the complex nature of project. The model can also be used to study the increased costs of higher than expected absenteeism and variable demand profiles. This is especially important to contractors since the total labor costs can be estimated before the start of the project. Also, variability in the costs can be used to set the contingency allowance if high absenteeism or big variations in the demand are expected. Finally, the model can be a valuable tool to determine if overstaffing is economically feasible since retaining workers can occasionally be cheaper than firing workers who are not needed and then hiring workers later on when the demand is high. This is especially true when the hiring and firing costs of workers are high compared to the wages paid.

Nevertheless, there are several limitations in this study. The survey results are self-assessed by the respondents i.e. no actual on-site assessment is attempted by the research team. Therefore, the research team cannot validate the data against documented measures in the projects that are investigated. Also, several respondents refused to share some information that they thought were critical and hence the results might not adequately represent all the projects that were studied. The proposed model also has several limitations. For example, it cannot be used to measure the effects of underestimating absenteeism. This is because this element affects the project schedule rather than the labor costs, and hence the model is not capable of measuring that effect. The values of the model's parameters are self-assessed by the users i.e. they cannot be measured by the model. Therefore, if the users do not have methods to accurately measure absenteeism rates or the demand of workers for example, the model can give inaccurate results. Also, the model does not take into account the productivity of workers. Newly hired workers might have lower productivity than other workers because of several factors such as learning curves. The model was also formulated based on survey results from construction projects in Beirut. These tend to be big projects and consequently the model might not be applicable to small scale projects like private villas. This is because the workforce in this type of project does not usually change; which means that hiring and firing decisions are very rare.

A model that focuses on accurate methods to estimate the productivity of workers could be incorporated into the current proposed optimization framework. This would make the model more accurate as newly hired workers, for example, could be assigned a lower productivity than previously hired workers. Moreover, methods to

accurately estimate the demand of workers in different skills from the quantity of work can also prove to be very valuable. This is because any changes in the quantity of work can automatically be converted into demand changes without the need to manually estimate the changes for each skill. These additions can greatly enhance the validity of the proposed model.

APPENDIX

A. Survey Sample

Job Title

Years of Experience

1. Which of the following most closely matches the type of project that you are currently working on?

- Residential Building Commercial Building Heavy/Infrastructure Industrial

2. What phase is the project currently in?

- Shoring-Piling-Excavation Substructure Construction Superstructure Construction Finishing

3. How many workers are on site today?

Unskilled: _____ Skilled: _____ Foremen: _____

4. What is the percentage of over-staffing* for the workers listed above?

Unskilled: _____

Skilled: _____

Foremen: _____

* Over-staffing is when you allocate more workers than needed for flexibility reasons or to account for uncertainty with regards to worker productivity or the risk of workers not showing up onsite on a particular day

5. What are the demographics of the workers? (Estimate the percentage of each nationality, Total of rows must add up to a 100%)

Skill Level	Lebanese	Arabs(Non-Lebanese)	Southeast Asia (India, Pakistan...)	Other	Total
Unskilled	___%	___%	___%	___%	<u>100%</u>
Skilled	___%	___%	___%	___%	<u>100%</u>
Foreman	___%	___%	___%	___%	<u>100%</u>

6. Longevity of work

Of the current unskilled workers what percentage has been working with your company for more than 9 months?

_____%

Of the current skilled workers what percentage has been working with your company for more than 9 months?

_____%

Of the current foremen what percentage has been working with your company for more than 9 months?

_____%

7. Please specify the shift schedule that is used on site (working days – hours). Use S for the summer season, W for the winter season, and B if both seasons have the same shift schedule

-
- 7 working days- 12 hours a day
 7 working days- 10 hours a day
 7 working days- 8 hours a day
 6 working days- 12 hours a day
 6 working days- 10 hours a day
 6 working days- 8 hours a day
 5 working days- 12 hours a day
 5 working days- 10 hours a day
 If other specify: _____

8. Please select from the list below the relevant trades on site across the whole project:

-
- Brick layer Carpenter Painting & Decoration HVAC*
 Plumbing/Sanitary Electrician Elevator Mechanic Excavator
 Fencing Tiling Equipment Operator
 Laborer Insulation Masonry
 Pipe fitter Plastering Roofing
 Scaffold Stonework Steel fixer
 Traffic operations Other _____

* HVAC refers to Heating, Ventilation, and Air Conditioning.

9. Please specify according to the chosen trades (Q8), the corresponding costs

Trade	Level	Wage(\$/day)	Overtime Payment(\$/hour)	Overtime Frequency (Once a week, once a month ...)	Hiring Costs /Additional Costs (e.g., housing...)
	Unskilled				
	Skilled				
	Foreman				

10. Absenteeism*

On average what percent of the unskilled workforce is absent per week?

_____ %

On average what percent of the skilled workforce is absent per week?

_____ %

On average what percent of the foremen is absent per week?

_____ %

**Absenteeism is the failure to appear at work*

11. On a scale of 1 to 5, 1 being absolutely agree, and 5 being absolutely disagree, Rate your level of agreement with the following statements.

The frequency of <i>unskilled labor</i> shortage is predictable from <u>day to day</u>	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
The frequency of <i>unskilled labor</i> shortage is predictable from <u>week to week</u>	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
The frequency of <i>unskilled labor</i> shortage is predictable from <u>season to season</u>	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5

12. On a scale of 1 to 5, 1 being no effect and 5 being highest effect, rate the effect of the following factors on absenteeism.

	No Effect				Highest Effect
Competition from other sites	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
Holidays	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
Political Instability	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
Work Related –Injuries	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
Dangerous site conditions	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
Inter-Personal Relations	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5
Bad Weather	<input type="checkbox"/> 1	<input type="checkbox"/> 2	<input type="checkbox"/> 3	<input type="checkbox"/> 4	<input type="checkbox"/> 5

13. How frequent are variation orders on site?

Once per week
 Once every other week
 Once a month
 Once every other month
 Once a year

14. Currently what is the difference between the planned schedule and the actual schedule for your project?

Ahead of schedule by _____ weeks
 On Schedule

Behind Schedule by _____ weeks

15. Who is in charge of recruiting workers?

Crew leader Foreman Construction/Project Manager Engineer Human Resources Other _____

16. When is hiring performed?

Unskilled

On a Daily Basis On a Weekly Basis On a Monthly Basis On a Seasonal basis On a Yearly Basis

Skilled

On a Daily Basis On a Weekly Basis On a Monthly Basis On a Seasonal basis On a Yearly Basis

Foreman

On a Daily Basis On a Weekly Basis On a Monthly Basis On a Seasonal basis On a Yearly Basis

17. Other than On-Job training does your company offer any training?

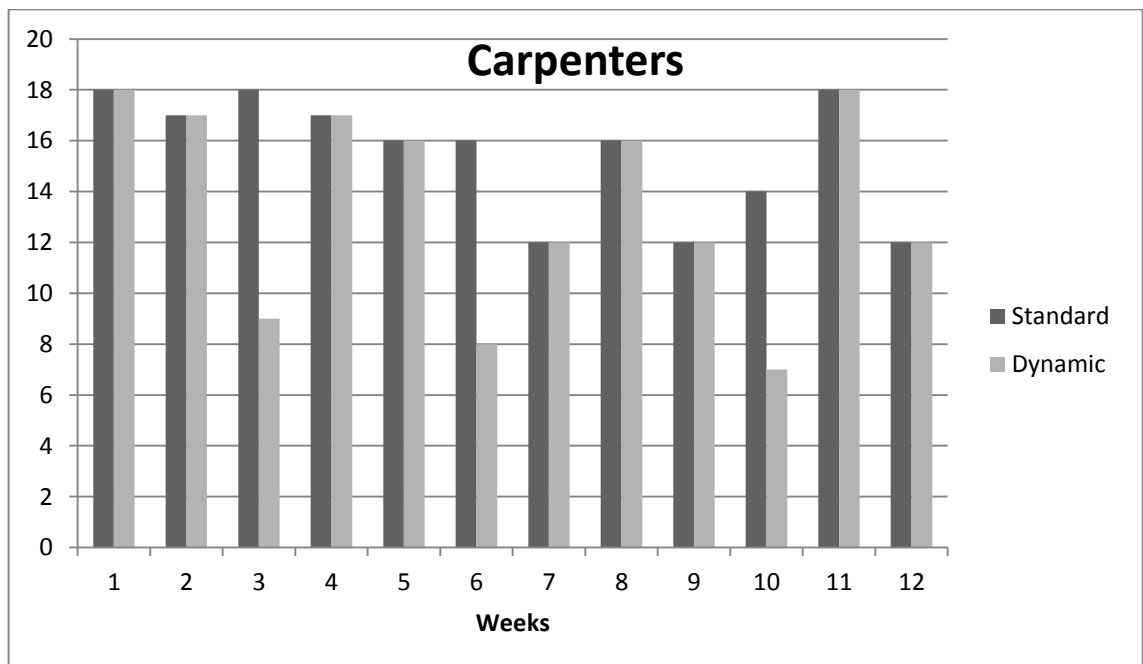
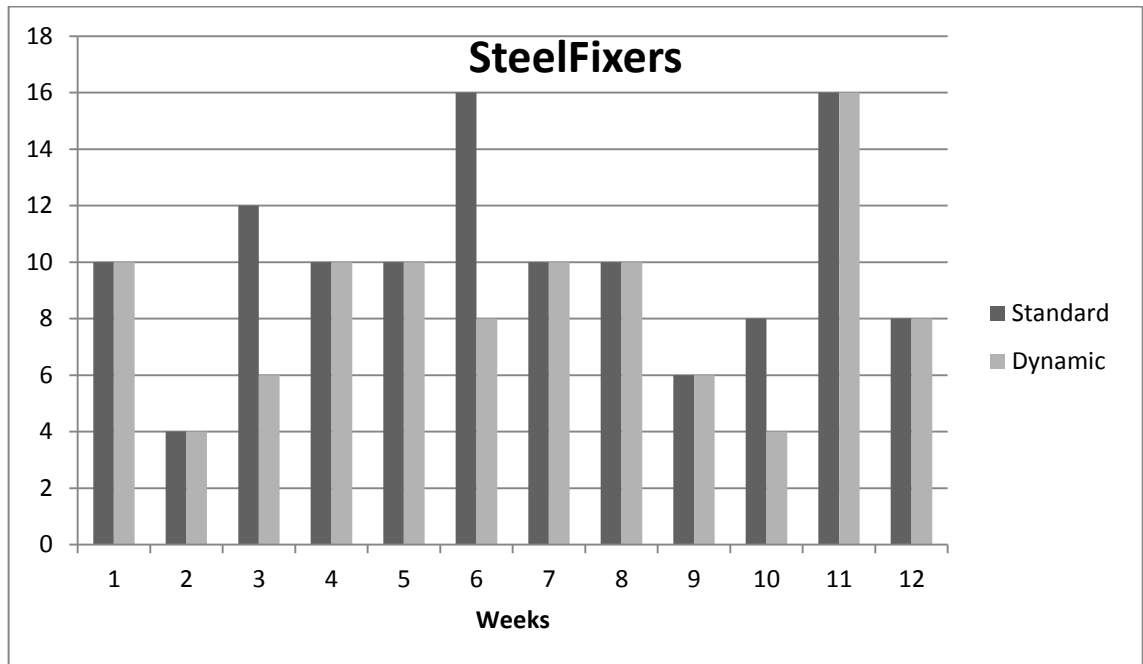
Unskilled No Yes, please specify the type of training and duration:

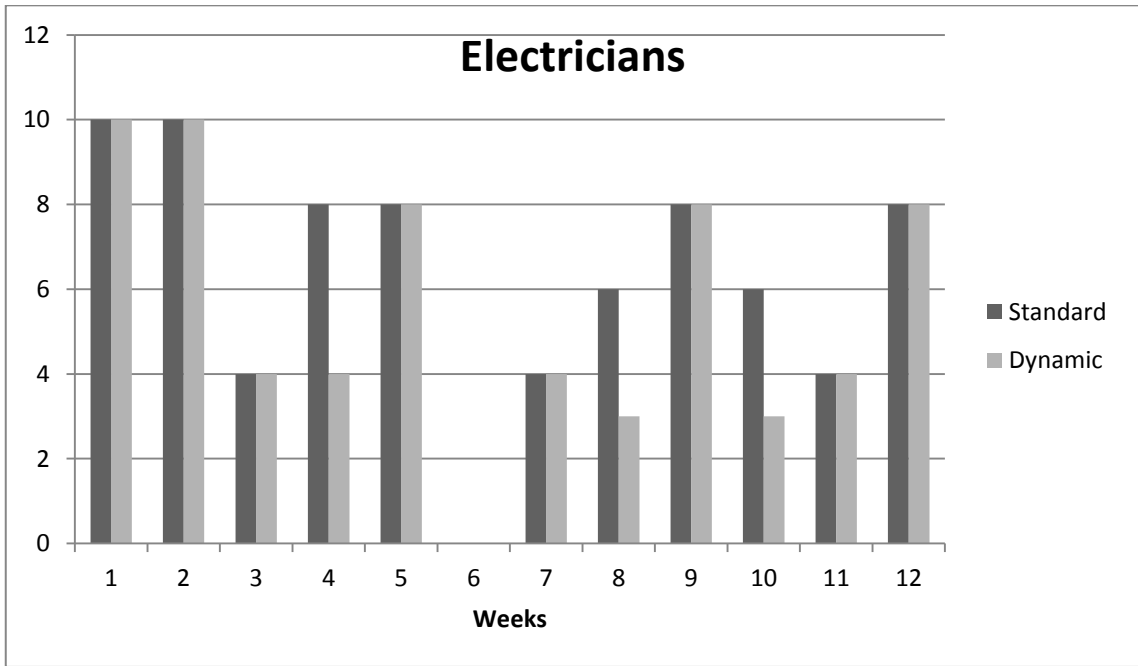
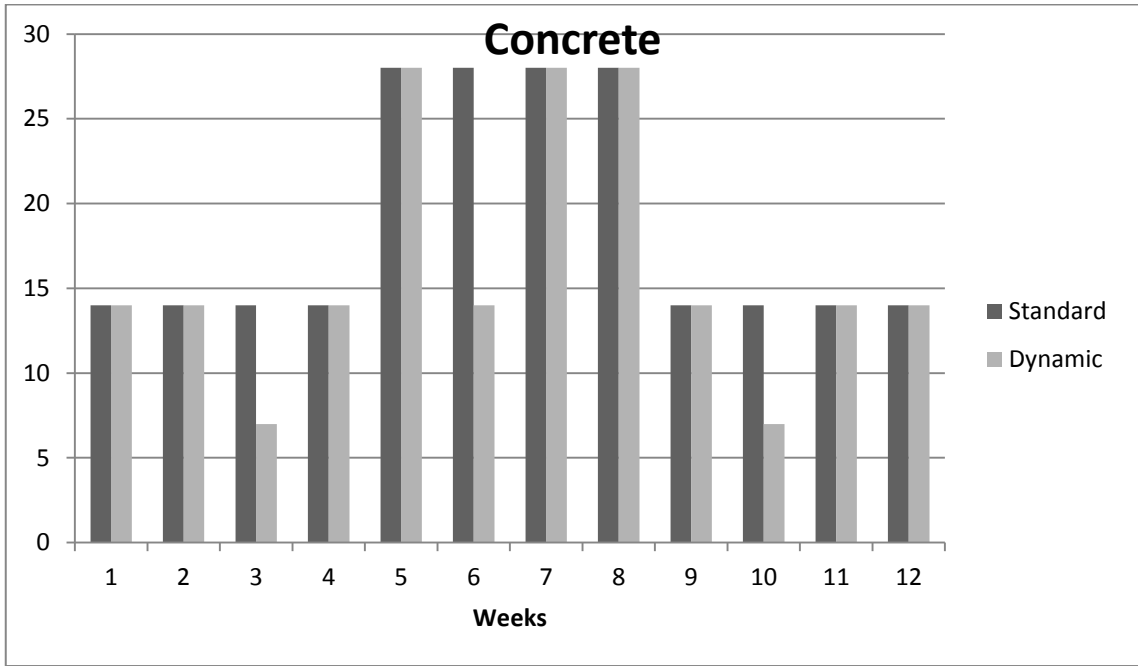
Skilled No Yes, please specify the type of training and duration:

Foremen No Yes, please specify the type of training and duration:

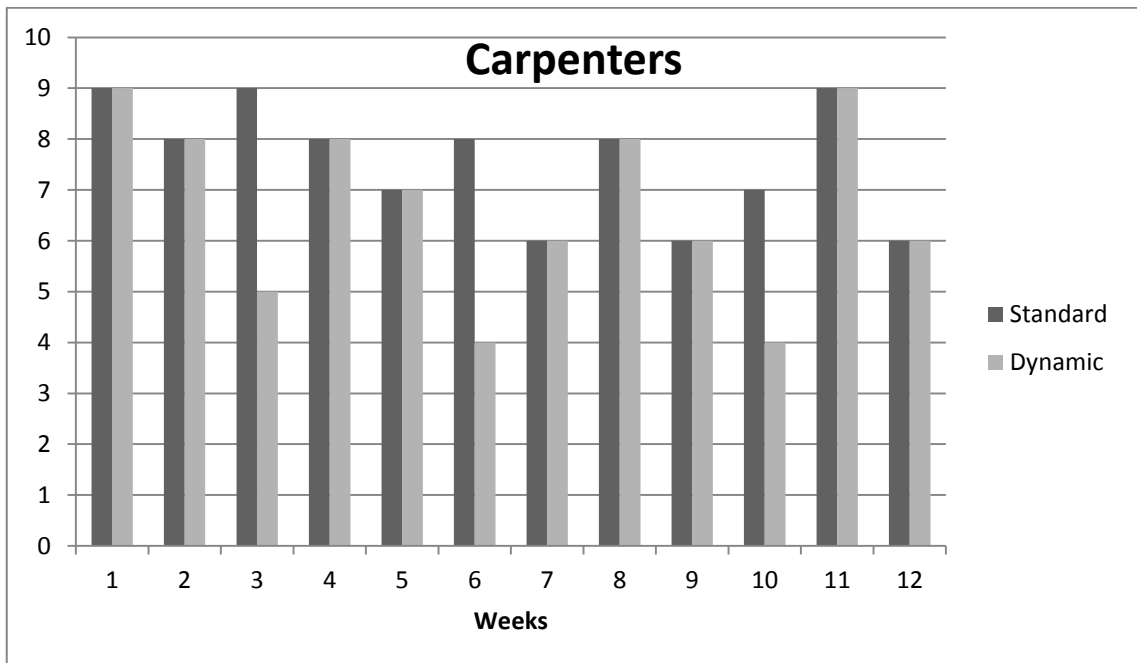
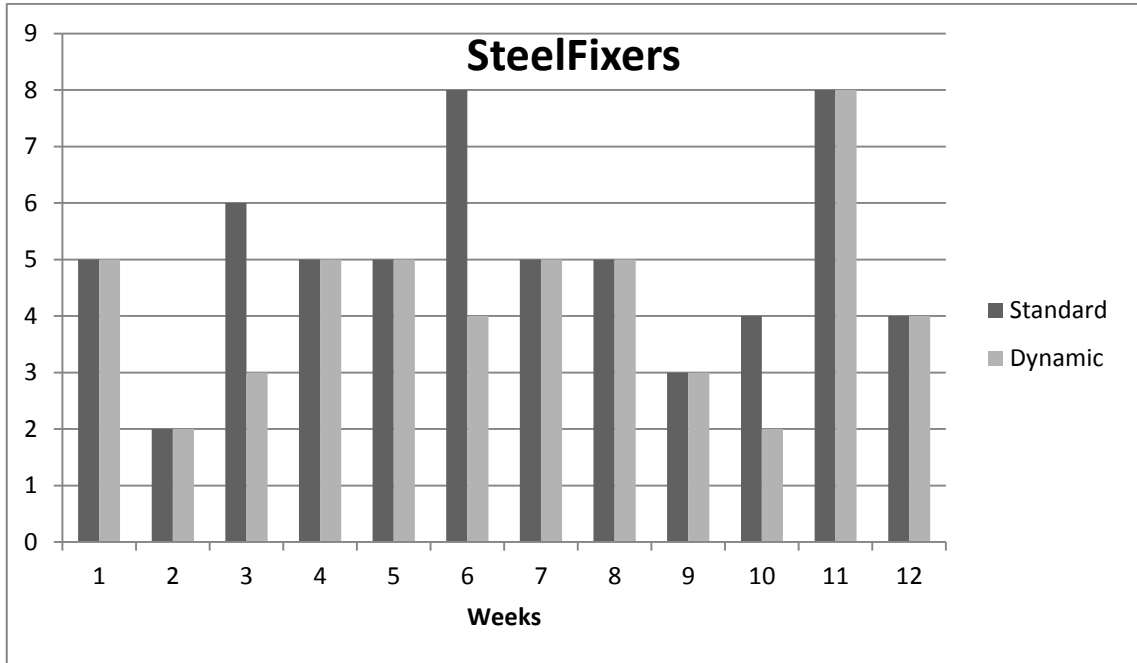
B. Standard vs. Dynamic Demand Profiles

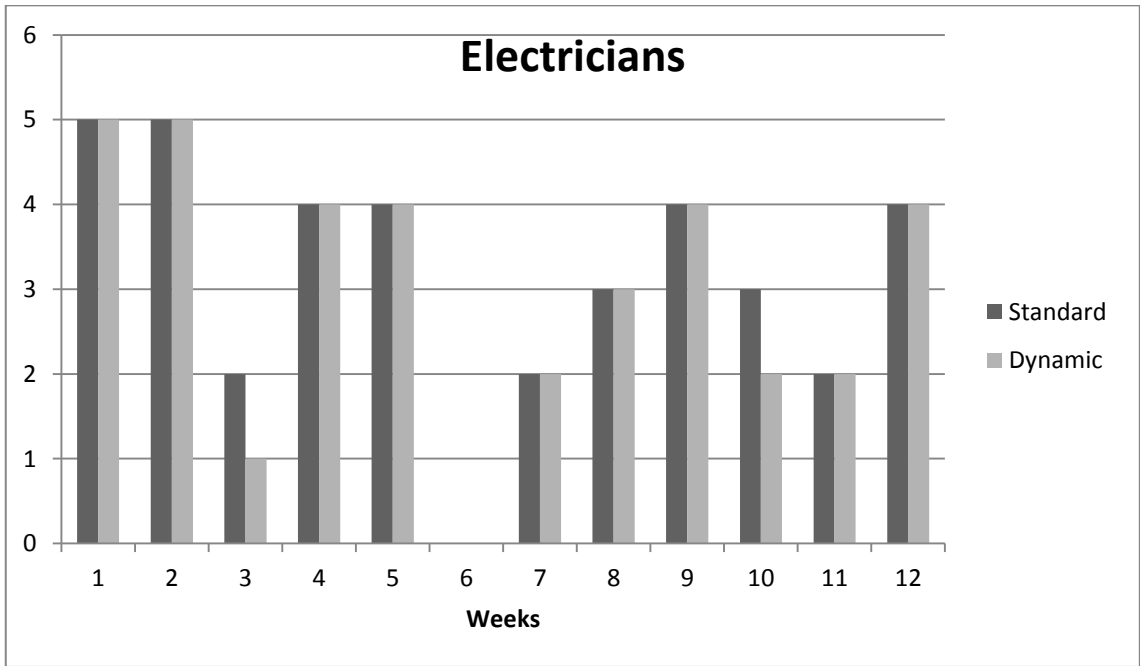
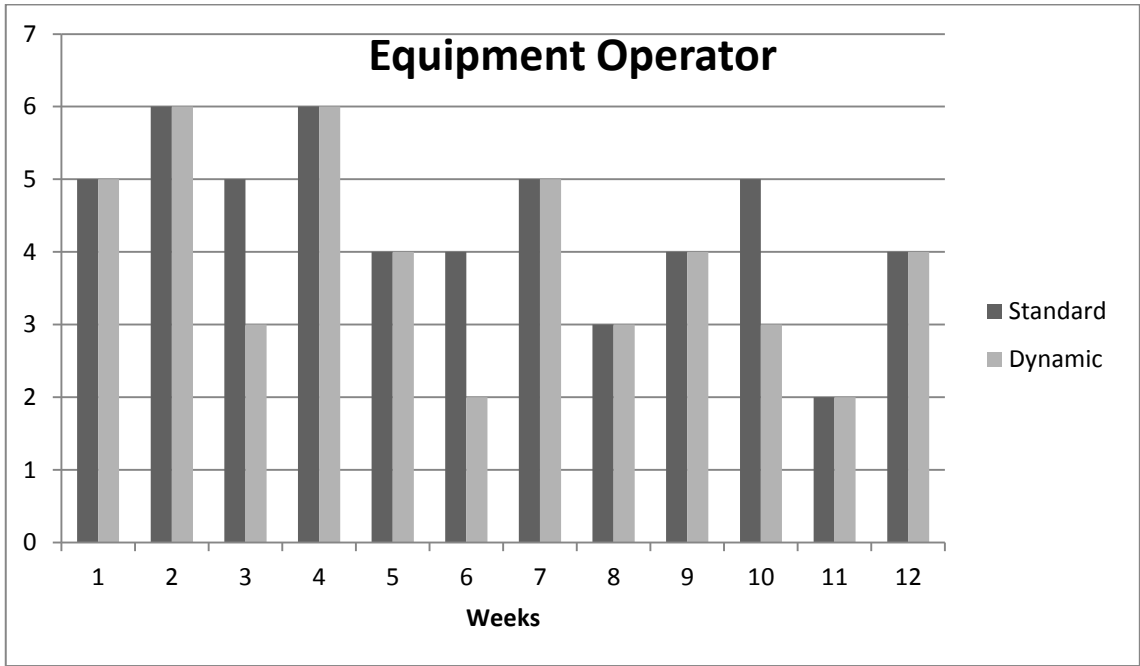
1. Unskilled





2. Skilled





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