Integrating Worker Differences into Workforce Planning

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ABSTRACT

Integrating Worker Differences into Workforce Planning

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In today's global and competitive market, manufacturing companies are working hard to improve their production system performance. Most companies develop production systems that can help in quality improvement, cost reduction and throughput time reduction. Manufacturing systems typically consist of different elements including production methods, machines, processes, control and information systems. Human issues are an important part of manufacturing systems, yet most companies do not pay sufficient attention to them. The majority of a company's improvement comes when the right workers with the right skills, behaviors and capacities are deployed appropriately throughout a company. Developing an integrated workforce planning system that incorporates the human being is a challenging problem. To achieve this goal, a multi-objective mixed integer nonlinear programming model is developed to determine the amount of hiring, firing, training, overtime for each worker type and the amount of the break for each worker. This thesis considers a workforce planning model including human aspects such as skills, training, workers' personalities, capacity, motivation, learning rates, and fatigue and recovery levels. This model helps to minimize the hiring, firing, training and overtime costs, minimize the number of fired workers with high performance, minimize the break time and minimize the average worker's fatigue level. The results indicate that the worker differences should be considered in workforce scheduling to generate realistic plans with minimum costs. This thesis also investigates the effects of human fatigue and recovery rates, and human learning rates on the performance of the production systems. Moreover, a decision support system (DSS) based on the proposed model is introduced using the Excel-LINGO software interfacing feature. It is shown that considering both technical and human factors together can reduce the costs in manufacturing systems and ensure the safety of the workers.

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LIST OF ACRONYMS

AP	-	Aggregate Planning
CPR	-	Cardiopulmonary Resuscitation
DSS	-	Decision Support System
HF	-	Human Factors
HR	-	Human Resources
LP	-	Linear Programming
MPS	-	Master Production Schedule
MRP	-	Material Requirements Planning
MET	-	Maximum Endurance Time
MIP	-	Mixed Integer Program
MILP	-	Mixed Integer Linear Program
MINLP	-	Mixed Integer Nonlinear program
OLE	-	Object Linking and Embedding
NIOSH	-	The National Institute for Occupational Safety and Health
VBA	-	Visual Basic for Applications
WP	-	Workforce Planning

LIST OF SYMBOLS

t - Index of planning period, $t=1, 2,\dots, T$

j,k - Indices of human skill levels, $j, k = 1, 2,\dots, S$

x,y - Indices of machine levels, $x, y = 1, 2,\dots, ML$

p - Index of personality attributes, $p= 1, 2,\dots, P$

s - Index of tasks, $s =1, 2,\dots, TS$

h_{jpt} - Cost of hiring a p - level worker with skill level j in period t (\$/worker)

f_{jpt} - Cost of laying off (firing) of a p - level worker with skill level j in period t (\$/worker)

tr_{kjpt} - Cost of training a p - level worker from skill level k to skill level j in period t (\$/worker)

sr_{jpt} - Salary of a p - level worker with skill level j at regular time in period t (\$/worker)

so_{jpt} - Hourly rate of a p - level worker with skill level j at overtime in period t (\$/worker-hour/period)

A_{jt} - Available regular working hours of a worker with skill level j for each person in each period t (hours/ period),

AOT_{jt} - Available overtime working hours of a worker with skill level j for each person in each period t (hours/ period)

C_{jp} - Capacity of a p -level worker with skill level j for each person in each period

Op_x - Opportunity to work on machine level x in each period

R_{jpx} - Readiness (willingness) of p -level workers with skill level j to work on machine level x

D_{jt} - Demand for skill level j in period t (worker-hours/period)

ss_{kj} - =1 if training from skill level k to skill level j is possible; or 0 otherwise

ws_{jx} - =1 if working on machine level x with skill level j is possible; or 0 otherwise

INP_{jpx} - Initial productivity level for worker p - level workers with skill level j working on machine level x

LE_{jpx} - Individual learning constant for worker p - level workers with skill level j working on machine level x

INW_{jpx} - Initial number of p -level workers with skill j required to be assigned to machine level x (workers)

V_{jptx} - = 1 if a p - level worker with skill level j can work on machine level x in period t; or 0 otherwise

PO_{jptx} - The output performance from a p - level worker with skill level j working on machine level x during time t

M - A big number

m - Number of cycles during a whole period of work

w_z - Positive weights that reflect the decision maker's preferences regarding the relative importance of each goal, $z = 1, 2, 3$

$goal_C$ - Desired cost level

$goal_B$ - Minimum amount of unproductive time

$goal_F$ - Minimum fatigue level can be achieved

W_{jptx} - Number of p - level workers with skill level j required to be assigned to machine level x in period t (workers)

H_{jptx} - Number of p - level workers with skill level j hired and assigned to machine level x in period t (workers)

L_{jptx} - Number of existing p - level workers with skill level j who are assigned to machine level x in period t-1 and they are laid-off in period t (workers)

Y_{kjptyx} - Number of p - level workers who were assigned to machine level y and then are trained from skill level k to skill level j and assigned to a higher machine level x in period t (workers)

OT_{jptx} - Overtime hours of p - level workers with skill level j in period t (worker-hours/period)

E_{jpx} - Difference between the initial productivity INP_{jpx} and the maximum productivity (Pr)

Pr_{jptx} - Productivity if a p - level worker with skill level j does work on machine level x during time t (based on time-constant leaning model; $0 \leq Pr_{jptx} \leq 1$)

PO_{jptx} - The output performance from a p - level worker with skill level j working on machine level x during time t

TI_{jptsx} - Time p - level workers with skill level j spend on task s on machine level x during period t (worker-hours/period)

B_{jptsx} - Break time of p - level workers with skill level j following task s on machine level x during period t (worker-hours/period)

Q_{jptx} - = 1 if p - level workers with skill level j cannot be fired during period t because they are received training in the same period t; or 0 otherwise

U_{jptx} - = 1 if p - level workers with skill level j cannot be fired during period t because they are hired in the same period t; or 0 otherwise

d_C^+, d_C^- - The positive and negative deviation from $goal_C$

d_B^+, d_B^- - The positive and negative deviation from $goal_B$,

d_F^+, d_F^- - The positive and negative deviation from $goal_F$.

CHAPTER 1 INTRODUCTION

The research described in this thesis is concerned with the integration of human factors into production planning of manufacturing systems. It investigates the importance of including human factors within planning models to provide more realistic and accurate plans for manufacturing companies. This chapter discusses the production planning problem and the solution techniques that can be used towards this end. Also, the need for the integration between production planning and human factors is described. The objectives and the structure of the thesis are outlined at the end of this chapter.

1.1 Production Planning

In today's global market, customers have become more demanding and seek more variety, lower cost, and superb quality. In this competitive environment, companies develop efficient production systems that contribute towards continuously increasing customer satisfaction. Production plans are developed in order to produce the right amount of products at the right time so that the production time and costs are minimized or the contribution to profit is maximized.

Production planning is the process of determining how much production will occur in the next planning horizon in order to satisfy demand. It determines expected inventory and workforce levels, and other resource requirements. Most manufacturing planning systems are becoming more complex in order to improve the productivity and the flexibility of the production operations. Managers in a production system can make different types of decisions that depend on the planning horizon. There are three types of planning horizons: long, medium, and short. A long-term planning horizon, or strategic planning, has a long-range impact on the direction of the production system. It covers a horizon of two to ten years. The decisions made by top management might involve capacity, product, supplier needs and quality policy. Medium-term planning covers a period from six months to two years. It gives more detailed decisions than the strategic decisions. Determining work force levels, production rates, projected inventory levels, outsourcing and subcontracting and quality costs are examples of the tactical decisions made by the middle management. Finally, a short-term planning horizon, or operational planning, covers any period from one day to six months and it involves the allocation of jobs to machines as well as parts movement on the shop floor (Hopp & Spearman, 2008).

Production planning covers all stages of production, from the procurement of raw materials to shipping the final product. It includes many activities such as capacity planning, bill of materials preparation, routing sheets preparation, demand planning, lead time estimation, manufacturing time estimation and more. It is performed to ensure that the task of delivering the product is done smoothly and in a timely manner at minimum total cost. The process starts with an aggregation of demand from market forecasts, capacity, and business planning. After developing the aggregate plan, it is disaggregated or broken down into specific product requirements and becomes the master production schedule (MPS). The MPS determines the quantity and timing of planned production, taking into account the on hand inventory, and customer orders. The MPS must be checked for feasibility using rough-cut capacity planning process. Then, the MPS is broken into a production schedule for each component of an end-item to develop the material requirements planning (MRP). The MRP is considered as the heart of the planning process. The three major inputs of the MRP system are MPS, inventory status records, and the bill of material. Outputs from the MRP process include planned-order schedules, order releases, changes, performance-control reports, planning reports, and exception reports. At this point, management must make detailed capacity requirements planning in order to check the feasibility of the MRP plan. The MPS and MRP are revised and updated regularly based on the situation on the production shop floor A detailed production plan determines how much and when to make each product or component. The goal is to match the production rate and the demand rate, so that the customer satisfaction is achieved. (Stevenson, 1999; Sipper & Bulfin, 1997).

1.2 Human Factors in Production Planning

Typically, human factors (HF) are considered too late in system design (Helander, 1999; Jensen, 2002; Neumann & Nedbo, 2009). There are specific challenges in integrating human issues into production planning, as for example, humans are adaptive, and it is difficult to quantify their characteristics. However, a research study has shown that 50-75% of implementations of modern manufacturing technologies were not successful (Clegg et al., 2002) because most companies failed to integrate HF into the production system. More specifically, if HF is considered at the early stages of the planning process, the management can develop more accurate production plans, leading to less production time and cost.

Much work has been done in the area of HF or ergonomics. However, most work in the area of production planning and scheduling has completely ignored the human aspects that are inextricably linked to the planning of production. As one of the main elements in production planning, human issues cannot be ignored without considerably reducing benefits of the production system. There are few reported research results related to HF incorporated in production planning. The advantages derived from integrating HF with production systems have been discussed (Udo & Ebiefung, 1999; Oborski, 2004). These benefits have been established through surveys and actual implementations. In highly competitive companies, integration of human aspects with production planning helps to increase productivity, reduce throughput times, and improve product quality. These findings present a significant research opportunity.

Human capital is the sum of the knowledge, experience, expertise, capability, capacity and creativity possessed by the individuals of an organization. Workforce planning is a systematic identification and analysis of what a company is going to need in terms of the size, type, and quality of workforce to achieve its strategic objectives. Workforce planning determines what workforce is needed to support production. It ensures having the right people at the right place at the right time to meet the company's employment needs. This includes planning for hiring new workers, firing extra workers, and training existing workers. Effective workforce scheduling is one of the most critical tasks affecting performance of manufacturing systems. It is important to assign the right job to the right person at the correct time. Also, it is very important to have a close match between workers' skills, attitudes and strength and his/her tasks he/she performs (for simplicity, we will use he/him hereafter). This needs an effective workforce scheduling system. This system aims to reduce waste in employing people, lessen uncertainty about current personnel levels and future needs, and avoid worker and skills shortages or surpluses by hiring the right workers in appropriate numbers.

In this thesis, a new model for workforce scheduling to support production planning is developed to achieve better production performance while reducing risks to operator health. Also, a decision support system (DSS) is developed to aid managers with the practical implementation of the model. A methodology of integrating HF into workforce planning is presented. A model that represents how a production system relates to human issues is developed. Finally, different solution methodologies for the model are provided. This thesis introduces a new integrated production planning framework based on the theoretical framework for worker performance modeling. The next section discusses the research objectives followed by a section on the proposed methodology for developing the model.

1.3 Problem Statement

In order to satisfy customer demand, it is imperative that the production process runs smoothly and efficiently. Hence, the production planning function can be complex due to several factors such as the number of products, worker's differences, the demand patterns, uncertainty, number of periods in the horizon, alternative processes, subcontracting, overtime, and inventory. Moreover, most managers find that existing production planning models fail to be implemented in real life (Byrne & Bakir, 1999) due to the fact that they neglect the consideration of human aspects, which can be a critical within a factory environment. Since the foremen frequently calculate delivery dates for a shipment based on their own planning without considering the actual transition times between manufacturing activities and the actual workers' performance, an increase in chaos on the shop floor may be noted.

On the other hand, traditional workforce scheduling tools are limited, given that they ignore worker differences. Rather than focusing on "head content", the attention is given to "head count", which prevents the flexibility of the resulting schedule with regards to the growing demand for fast changing business dynamics (Birch et al., 2003; Castley, 1996; Jensen, 2002). A key difficulty with existing models is the absence of the most important HF inherent in the production system such as personality, motivation, fatigue and learning curves. Also, most of the existing production planning models considers very few human factors and lacks clarification on the effects of disregarding the remaining human factors with regards to job performance and job satisfaction. As one of the main elements in a production system, human issues such as diverse workers personalities, motivation, capacities, fatigue rates and learning rates cannot be ignored without significantly reducing the benefits of the production system.

The consideration of HF in production planning potentially improves both injury risk and production performance (Neumann & Medbo, 2009; Udo & Ebiefung, 1999). Thus, the importance of integrating HF early in the production planning phase is illustrated in the way that early changes to the product and the work yield cheaper costs. Additionally, the omission of several HF may present severe limitation to many traditional models. As such, the research presented in this thesis aims to accomplish production planning that takes into consideration numerous human factors. Hence a realistic reflection of the actual work environment may be formulated and employed to ensure that workers perform their jobs in a safe and optimal way.

1.4 Research Objectives

The main objective of this thesis is to develop a model that can consider several human aspects in production planning for optimal performance. The model will be validated by introducing a validation methodology based on building the model gradually and the potential benefits of the model will be evaluated by introducing a real case study from an industrial company. This research aims to study how worker differences affect workforce planning and management decisions at tactical levels. The objectives of this dissertation research are:

- To develop a theoretical workforce planning framework for modeling the human performance and the production planning process. This will help other researchers to understand the ways in which different human factors may be incorporated into the production planning.

- To develop a mathematical model that considers human factors such as workers' skills, training, personalities, capacities, motivations, learning rates, and fatigue and recovery levels in order to generate realistic schedules.

- To build a Decision Support System (DSS) to assist mangers and other researchers in applying the proposed model into practice.

Our objective in the first phase of this research is to develop a theoretical framework to help to identify the most important human factors that affect human performance. First, a basic workforce planning model (WP) that considers only training and overtime programs under static demand conditions will be developed. Studying the use of worker flexibility through these factors will provide greater insights on the combined effect they have on the workforce planning decisions at both tactical management levels. The objective of this phase is to reduce the total regular and overtime salaries, hiring, firing, and training costs. We seek to study the effects of including training and overtime options in the WP model on the decision making process from the company's perspective.

The second phase of this research is geared towards optimizing the workforce related decisions while taking into account the individual differences among workers. These individual differences are mainly attributed to different people capabilities and limitations. Under these conditions of human differences, the development of an optimized WP turns out to be a challenging task. Hence, to achieve the companies' objectives, we need to develop efficient mathematical models that quickly react to workers' performance changes on a rolling horizon basis.

In the third phase of the thesis, the effects of fatigue, recovery, learning rates on workers' performance and workforce scheduling decisions are studied. Workers can improve their efficiency through repetitions of the tasks. Similarly, they can lose their efficiency if there is an interruption between successive assignments to the task. This research evaluates the effects of fatigue on workers' performance. Also, when one considers the effects of learning, the workforce decisions get more complicated. This research aims to find the best scenario for workforce scheduling depending on the workers needs, companies' objectives and rules.

In the last part of this research, the goal is to develop a decision support system (DSS) for workforce planning and scheduling to help companies use the model in their planning decisions. This software would serve the management, operations and planning levels of an organization and help to make decisions. It helps automate managerial processes and speeds up problem solving and decision making in an organization.

1.5 Research Methodology

The research methodology defines the sequence of activities to be carried out in order to achieve the research goals. The research will be initiated by developing a theoretical framework for modeling the human performance which contains information on different HF that affect performance. Simultaneously, the information required to support the proposed research will be collected based on various HF and the production planning literature. Then, a new mathematical model for a workforce planning process that considers HF will be developed. Next, different extensions to the problem will be introduced in order to consider the reality of the planning process. The functional relationships between different factors in the manufacturing context must also be identified, and human, technological, and organizational factors that affect production planning performance must be studied. Moreover, different methods for solving the proposed model will be suggested. To serve testing and validation purposes for the developed models, several problem instances with different degrees of complexity are prepared. The values of the input parameters are estimated from realistic data ranges so that the practicality of the developed models is ensured.

1.6 Thesis Organization

This research is organized as follows: Chapter 2 presents a literature review of HF and their relation to workforce planning. Chapter 3 discusses the HF modeling and production planning frameworks. Chapter 4 introduces a formal definition of the problem along with a mathematical formulation that addresses the various aspects of the workforce planning process. The initial model assumes that some human differences information is not available. Moreover, this chapter addresses the importance of incorporating the human differences into workforce planning process by considering personality and productivity in the model. It also addresses the importance of incorporating workers' learning issues in the same model. It provides some insights into the impact of some interrelated human factors on the workforce planning decisions under stable operating conditions. In Chapter 5, the effects of human fatigue and recovery on the performance of the production systems are investigated. In Chapter 6, a decision support system (DSS) based on the proposed model is introduced using the Excel-LINGO software interfacing feature in order to easily apply it in practice. Finally, Chapter 7 presents the conclusions and future research directions for this thesis.

CHAPTER 2 LITERATURE REVIEW

This chapter presents a comprehensive review of production planning models. The concept of HF and its relation with production processes is described. Also, the benefits of integrating HF with production planning are introduced. This review covers both traditional operations management topics and psychology science areas. In Chapter 3, the proposed workforce planning theoretical framework will be discussed.

2.1 Existing Research in Production Planning

Effective production planning processes are essential for success in manufacturing operations. There are numerous approaches that have been proposed for solving the production planning problem. Mula et al. (2006) review some of the existing literature of production planning under uncertainty. They found that simple production systems can be addressed using analytical or mathematical models. For more complex production systems, simulation and artificial intelligence can be used. Aghezzaf et al. (2010) presented three models for generating robust tactical production plans in a multi-stage production system, under product demand uncertainty. These models produced plans that achieve better trade-offs between minimum average cost and minimum cost variability. A hybrid fuzzy nonlinear programming model with different goal priorities has been developed for aggregate production planning decision-making problems (Jamalnia & Soukhakian, 2009). In their model, objectives priority, customer satisfaction and learning curve effects have been considered. Techawiboonwong et al. (2006) developed a new master production scheduling (MPS) model that considers temporary skills in production planning. They provided a framework for identifying the permanent and temporary workforce size so that the total workforce and inventory costs are minimized. However, most of the mathematical models for solving planning and scheduling problems fail to provide full support to planning and control functions (Buxey, 1989; Shobrys & White, 2000; MacCarthy et al., 2001).

In recent years, several research papers have highlighted the importance of interactions between some key HF and the production system and the need to incorporate organizational behavior issues in operations management (Bidanda et al., 2005; Aryanezhad et al., 2009). Previous research has determined that the worker assignment strategies, worker skills, training, communication, autonomy, reward/compensation system, teamwork aspects, and conflict management need special attention for companies implementing cellular manufacturing (Bidanda et al., 2005). Aryanezhad et al. (2009) developed a mathematical model to deal with a simultaneous dynamic cell formation and worker assignment problem. They discussed the importance of incorporating the human issues into traditional dynamic cell formation. In their model, they considered some human issues such as hiring and firing workers, training, salary and workers' skills. Moreover, they concluded that considering the learning curve and other human issues in the model would be a promising area of work in future research. Mazzola et al. (1998) developed a nonlinear mixed-integer programming model for solving the multiproduct production planning problem in the presence of workers' learning. However, Connelly and Gallagher (2004) provided an extensive literature review related to using temporary workers in master schedules. A comprehensive review of the literature on the HF of production scheduling is provided by Crawford and Wiers (2001).

On the other hand, researchers utilized mathematical models, heuristics and simulation to study the impact of some human aspects such as cross-training and learning curves on system performance. Stewart et al. (1994) developed four optimization models for different cross-training scenarios to assist managers in deciding optimum tactical plans for training and assigning a workforce according to the skills required by a forecasted production schedule. Felan and Fry (2001) investigated the concept of a multi-level flexibility workforce using simulation. The results indicate that it is better to have a combination of workers with high flexibility and workers with no flexibility rather than employing all workers with equal flexibility. Gomes da Silva et al. (2006) developed an aggregate production planning model that includes workers' training, legal restrictions on workload and workforce size. Jamalnia and Soukhakian (2009) have developed a fuzzy multi-objective nonlinear programming model for aggregate production planning problem in a fuzzy environment. Learning curve effects have been considered in formulating the model. Wirojanagud et al. (2007) used the general cognitive ability metric to model individual difference in efficacy of cross-training and worker productivity. Norman et al. (2002) proposed an MIP model for assigning workers to manufacturing cells in order to maximize the profit. The model considered both technical skills and human skills. Results indicate that the model provides better worker assignments than the one considering only technical skill. Previous research has used simulation as a powerful flexible tool to support production systems (Johtela et al., 2000; Kim & Kim, 2001). A simulation model can be used to handle many possible parameters and evaluate their effects on the production performance. It can consider virtually all types of technical constraints and test different configuration within the minimum time and cost.

Other researchers' developed frameworks and models that consider motivation, worker experience, workers' learning and forgetting, and fatigue rates in production systems. Azizi et al. (2010) considered workers motivation, learning and forgetting factors and workers' skills to measure employees' boredom and skill variations during a production horizon. Corominas et al. (2010) have taken into account learning curves and workers experience in modeling a scheduling problem. Learning is the process of acquiring experience, knowledge, and ability by a worker. According to learning curve theory the productivity of the worker increases with increase in experience due to learning effect. In the manufacturing sector, learning curves are extensively formulated to support workforce planning decisions. Learning has been considered in service workforce planning, and cellular manufacturing. Shafer et al. (2001) introduced an approach to measuring organizational learning wherein individual worker heterogeneity is modeled. Nembhard and Uzumeri (2000a) provided an important extension of this approach by incorporating both learning and forgetting into an individual-based model of productivity. In this model, both the learning and the forgetting components were shown to be preferred models among numerous candidate models (Nembhard & Uzumeri, 2000b; Nembhard & Osothsilp, 2001). Billionnet (1999) formulated the problem of scheduling a workforce assignment with different levels of worker qualifications in order to minimize labor costs. Jaber and Neumann (2010) developed a mixed-integer linear programming (MILP) model that describes fatigue and recovery in dual-resource constrained systems. The results obtained from their model suggest that short rest breaks after each task, short cycle times and faster recovery rates improve the system's performance. Fatigue may be defined as a physical and mental weariness existing in a person and harmfully affecting the ability to perform work. Worker fatigue can greatly impact system performance in terms of quality (Eklund, 1997). It can significantly affect human productivity (Oxenburgh et al., 2004). Inordinately long working hours and poorly planned shift work can result in employee fatigue.

As discussed above, the literature review demonstrated that most of the work on workforce planning and scheduling assumed that workers are identical. As far as the author is aware, incorporating HF such as personality, capacity, skill, training, learning, fatigue, productivity and motivation together into workforce planning has not been previously considered in the existing literature. Our research will contribute to the literature by extending existing models of service workforce planning and scheduling beyond current capabilities. Three objective functions are considered in the proposed model. They are: cost minimization, idle time minimization, and average fatigue minimization. In summary, ergonomics must be implemented concurrently with production planning in order to improve planning process performance.

2.2 Human Factors in the Context of Manufacturing Systems

Human factors, or ergonomics, has been defined as "the theoretical and fundamental understanding of human behavior and performance in purposeful interacting socio-technical systems, and the application of that understanding to the design of interactions in the context of real settings" (Wilson, 2000). During the last decades, ergonomics have shown little contribution in building production systems. Most business managers have accepted the idea that ergonomics are working as protectors of workers, rather than creators of systems (Dul & Neumann, 2009; Perrow, 1983). They generally associate ergonomics with health and safety issues rather than with effectiveness of organizations (Jenkins & Rickards, 2001). Typically ergonomics is considered too late in the production system development process, making most business decisions hard to change (Helander 1999; Jensen, 2002; Neumann et al. 2009). Perrow (1983) mentioned that the main problem is that HF specialists have limited influence and control within the organizational context. Also, they have no control of strategic resources and a weak network in and outside of the organization. However, it is shown that ergonomics can contribute to different company strategies and support the objectives of different business functions in the organization (Dul & Neumann, 2009). On the other hand, many ergonomics models have been developed without a clear understanding of how they could be implemented in a specific company (Butler, 2003; Hägg, 2003). Berglund and Karltun (2007) studied the effects of the human, technology and organizational aspects on the outcome of the production scheduling processes. Based on their study, schedulers need to consider uncertainty, their experience, problem solving, workers' differences, technical system limitations, the degree of proximity between employees and their informal authority. Jensen (2002) presents approaches and tools developed in the Scandinavian countries. He explained that the changes in the ergonomics role inside a company require understanding the organizational prerequisites. He proposed a political agent in order to complement the roles of an expert and a facilitator. He suggested developing studies on management of ergonomics and organizational development.

Previous literature on workforce management has addressed various issues such as worker differences and how much performance improvement can be gained (Barrick &

Mount, 1991; Hunter, 1986; Hunter et al., 1990; Kanfer & Ackerman, 2000; Ragotte, 1990; Wirojanagud et al., 2007). Penney et al. (2011) presented a comprehensive review that study the relationships between personality and job performance and provided directions for future research. Human performance is the accomplishment of a task by a human operator. Jones (1993) presented a model that highlights the four components of job performance manager controls. These components are selection such as skills, and personality, training, recourses such as people, machines, policies and finally motivation. People with high personality levels will be more motivated to perform well because they are confident they have the ability to do their job (Bono & Judge, 2003). Personality is a major force behind individual differences in behavioral tendencies. It influences job performance by determining whether an individual has a natural inclination for job duties whether a physical or cognitive job. It can be used by human resource professionals to evaluate job applicants and predict job performance (Rothstein & Goffin, 2006). Motivation is generally the most accepted mediator of personality dimensions and job performance relationship (Erez & Judge, 2001). Hackman and Oldham (1976) proposed a model that studies the interaction among three variables which affect the job design: personal psychological state, jobs characteristics, and individual's attributes that determine his response for a challenging work. Blumberg and Pringle (1982) developed a model that can link between worker motivation and productive performance. In their paper, they suggested that expected work performance of individuals is determined by three factors: Capacity, Opportunity and Willingness. General cognitive ability (GCA), defined as the ability to process information, was used to model individual differences to predict job performance in all jobs (Hunter, 1986). Kroemer et al. (2001) mentioned that many attributes, conditions, and reactions affect the person's performance. Examples of these factors are task type, task quantity, task environment, person's capability and attitude.

Thus, the problem here seems to be systemic and there is an obvious need to integrate ergonomics processes into the organization early so that underlying principles can be incorporated. There are many reasons for not considering human issues early into production planning. Helander (1999) discussed seven common reasons for not considering ergonomics early into production system development process. Some of these common objections to ergonomics are many users think that ergonomics is for the design of chairs and ergonomics is only common sense, that the research in ergonomics is too abstract to be useful, and that people are adaptive, so there is no need for ergonomics and the technical system should be designed first before considering ergonomics. Bidanda et al. (2005) mentioned that the major reason is that human issues are typically difficult to quantify. However, none of these are valid reasons to not consider HF early in the production process.

There are specific challenges in integrating human issues into production planning because people differ from one another. In reality, there is a tremendous variability in individual capabilities. This makes most production system designs ignore the effects of the human differences. Buzacott (2002) studied the impact of worker differences on the production system since individual differences can result in substantial loss in throughput. On the other hand, Broberg (2007) has pointed out that HF tools to integrate ergonomics into the design process are not known by engineers. Some tools for handling HF in planning are creating digital human models, integrating ergonomics into predetermined motion time systems and integrating ergonomics into discrete event simulation (DES). However, DES has been considered to be an appropriate tool that can incorporate human aspects at the earliest planning stage for optimal performance (Neumann & Nedbo, 2009). Some ideas on how to integrate human performance modeling with discrete event simulation in assembly lines are suggested (Siebers, 2004; 2006). Due to the variation in human performance, there is a need for non-deterministic models of worker performance. Dul and Neumann (2009) provided a conceptual framework to help ergonomists in research, education and practice to understand how to support the strategic objectives of a company. This framework helps ergonomics experts to focus on ergonomics with business performance rather than ergonomics with occupational health and safety.

Given that a portion of the literature review presents aspects of general human factors, a critical literature research was then conducted to identify possible human factors that may affect their work performance. The literature search was carried out in a variety of areas, including production planning, human factors, human resource management, and psychology. A method of screening was carried out by assessing many theoretical work performance models in contrast to three criteria: general relevance to production planning, literature consistency and factors measurability. The investigation of these factors is based on the theoretical framework of Baines et al. (2005), which has identified the majority of the human factors that cause variations in human performance metrics. In effect, the Baines et al. (2005) framework has allowed for the identification of high ranked human factors affecting performance such as shift pattern, cognitive ability, personality, work teams, training, job rotation, job satisfaction, noise level, and skill levels. These factors, in addition to motivation, had been previously identified by Jones (1993) as the factors that affect job performance. Most current literature did not consider individual differences. Since, the majority of modern literature fails to consider individual differences, this research attempts to incorporate workers' differences to workforce planning and assignment through the introduction of worker personality factors into the production planning.

From the papers mentioned above, it can be concluded that the human factors that are important in manufacturing are as shown in Table 2.1 below.

Table 2.1: List of Manufacturing and Human Factors

#	**Item**	#	**Item**
1	Worker Training	7	Worker Recovery
2	Worker Type and Personality	8	Worker Productivity
3	Worker Intelligence	9	Worker Motivation
4	Worker Skills	10	Worker Capacity
5	Worker Fatigue	11	Worker Availability
6	Worker Break	12	Learning Curve Effects

2.3 Comparison Among Approaches

Several researchers proposed different solution methods for the production planning problem. This section gives an overview comparison among different researchers who studied the production planning at its different levels.

The literature on production planning models that consider the human aspects was also surveyed. It was found that many quantitative models on aggregate planning, master scheduling and material planning including optimization, heuristics, and simulation have been developed (Campbell & Diaby 2002; Chu, 1995; Gomes da Silva et al., 2006; Jain & Palekar, 2005; Jamalnia & Soukhakian, 2009; Lee, 1990; Leung & Chan, 2009; Nam

& Logendran, 1992; Pradenas & Peñailillo, 2004; Torabi et al., 2010; Wang & Liang, 2004, 2005). Figure 2.1 shows some of production planning attributes that are used in recently published articles. The goal of this thesis is to develop a model that includes the HF listed in Table 2.1 to fill the gaps and weaknesses of the current approaches.

However, some necessary extensions to the current model should be done in order to reach the completeness of the production planning problem. First, other human factors could be considered such as worker experience, and temporary workers. Second, fuzzy cost parameters and uncertain demand should be considered because some information such as demand, workers, machines costs, and objective functions is incomplete or unpredictable. Finally, in practical production planning systems, many functional areas in a company that yield an input to the production plan have conflicting objectives governing the use of the organization's resources.

Items →	1	2	3	4	5	6	7	8	9	10	11	12
Aggregate Planning												
Gomes da Silva et al. (2006)	C	C										
Jamalnia and Soukhakian (2009)												C
Workforce Planning												
Wirojanagud et al. (2007)	C		C	C				C			C	
Ulusam Seçkiner et al. (2007)		C										
Cellular Manufacturing												
Aryanezhad et al. (2009)	C			C				C			C	
Norman et al. (2002)	C	C		C				C				
Scheduling												
Azizi et al.(2010)		C		C					C			C

Figure 2.1: Attributes used in Recently Published Articles

Where: C: Considered.

Building a model that minimizes costs, customer service, changes in production rates, changes in work-force levels and utilization of plant and equipment can be applicable to the real world.

CHAPTER 3 HUMAN FACTORS

The Board of Certification in Professional Ergonomics (BCPE) in North America defines ergonomics or human factors as "A body of knowledge about human abilities, human limitations, and other human characteristics that are relevant to design". In an industrial workstation, the human interacts closely with machines, the environment and possibly other people. Consequently, more attention must be given to the human characteristics, abilities, and limitations in the planning of production systems in order to generate a robust production plan that can be flexible, feasible and realistic.

Despite increasing industrial mechanization, workers are still needed to deal with various situations on the shop floor. This chapter describes human capabilities and limitations. Then, the differences between human and machines are presented. Finally, theoretical frameworks for modeling the human performance and the production planning process are introduced.

3.1 Human Limitations

People are the most important asset in any organization. They differ in their performance and behaviors at work because they have different limitations and capabilities. These limitations are associated with various physical, psychological, physiological and psychosocial aspects. When designing for a human, there is a need to understand their capabilities and limitations. Humans are an interesting paradox in terms of their information processing skills. They have serious limitations on the amount of information they can process. However, many factors limit human performance such as physical and psychological capabilities which can vary from one person to another. The person's capability is further limited by his or her muscular strength. Table 3.1 illustrates the human factors that describe human limitations at work.

Table 3.1: The Human Factors That Describe the Human Limitations At Work.

Category	**Human Factors**
Physical	Reach Lifting ability Capacity Skeletal features Sensory features Energy level
Physiological	Illness Drugs and medications effects Fatigue and oxygen supply Environmental contaminants Alcohol effects Time zone adjustment Aging and circadian rhythm
Psychological	Individual ability variations Aptitude Knowledge Interests Personality Memory Motivation
Psychosocial	Cultural Context Group pressures Individual risk-taking

3.2 People and Machines

Many decades ago, people produced products by hand. However, with the advent of the Industrial Revolution, many machines have been invented in order to increase production rates and improve the quality of products. In general, many non-predictable activities can be given to a human because he explains, judges and decides appropriate actions based on his intelligence and experience. Machines still have a long way to go before they can match humans in terms of perception, reasoning and memory. Table 3.2 shows a comparison between people and machines in terms of various attributes.

Table 3.2: A Comparison Between People and Machines (Kroemer et al., 2001)

Attribute	**Machine**	**Human**
Speed	Much more superior	Comparatively slow
Power	Consistent and as large as designed	Comparatively weak. About 1.5 kW for 10 seconds, less than 150 W during a working day
Consistency	Ideal for consistent, repetitive, routine tasks	Not reliable, subject to fatigue
Information Capacity	Multi-channel	Mainly single channel
Memory	Ideal for literal reproduction and short term storage	Better for principles and strategies and long term storage but easily distracted
Reasoning Computation	Deductive, fast and accurate, but poor error correction	Inductive, slow and inaccurate, but good at error correction
Sensing	Specialized, narrow range. Good at quantitative assessment. Poor at pattern detection	Wide energy ranges, some multi- function capability
Intelligence	None	Can anticipate, learn, deal with expected and unpredicted events
Decision Making	Dependent on program and sufficient inputs	Can decide even on the basis of incomplete and unreliable information
Perceiving	Copes poorly with variations in written/spoken material. Susceptible to noise	Copes well with variations in written/spoken material. Susceptible to noise
Creativity, Emotion	None	Creative and emotional
Flexibility	Relatively inflexible	Adaptable and flexible
Communication	Cannot communicate except through complex electronic systems	Can communicate with each other

However, the determination of which activities should be assigned to humans and which to machines is based on the nature of the situation, the complexity and the demands without comparing attributes one by one. On the other hand, when there are many routine and repetitive tasks such as performing complex calculations and storing huge amounts of information, machines should be applied to relieve humans for more important tasks such as planning, judgment, learning, adapting to variations, etc. Finally, many manufacturing systems (e.g. automobile manufacturers) need human and machine integration; production lines have robots and computers to build heavy car frames and assembly departments need human involvement to assemble and package the final product.

3.3 Human Performance Modeling Framework

Many theoretical frameworks relating human factors and performance have been developed (Lewin, 1935; Miller & Swain, 1987; Dahn & Laughery, 1997; Bonney et al., 2000; Toriizuka, 2001). Many existing frameworks are quite general in natural. Recently, a theoretical framework for modeling human performance has been developed by Baines et al. (2005). The framework identifies the thirty key human factors and performance measures for worker behavior based on four criteria: general relevance, specific relevance, robustness and measurability. These factors provide a comprehensive picture of the factors that are to influence a worker performing production planning activities. The key factors are divided into two categories: personal factors and environmental factors. The personal factors range from intelligence factors such as the individual's personality, and biographic characteristics to the work attitude in the workplace such as age, gender, and marital status which can be easily obtained from personnel records. On the other hand, the environmental factors can be the organizational factors such as shift patterns, training, and job rotation and the physical characteristics of the workstation such as noise, ventilation and lighting levels. Research studies indicate that certain environmental factors beyond the employee's control play a stronger role in influencing his or her job performance (Porter & Lawler, 1968).

The first step of the research was to identify human factors which are most likely to cause variation in human performance. While human factors can be found in a variety of areas, including manufacturing management, psychology, ergonomics, physiology, health and safety, organizational studies, industrial relations, and human resources management, they are divided into four categories for the purpose of this research: individual factors, environmental factors, job factors, and organizational factors.

3.3.1 Individual Factors

Individual factors are divided into four major categories: cognition, personality, biographic, and work attitude. Schmidt and Hunter (1998) mentioned that cognitive ability and experience (i.e. opportunity to learn) are the most valid predictors of job performance. They conducted empirical research about the validity of various individual measures for predicting future job performance. Similarly, they found that personality, biographic data and job knowledge has been used in theories of job development. However, personality traits (e.g. conscientiousness) can lead to higher job knowledge which causes higher levels of job performance (Barrick & Mount, 1991; Hurtz & Donovan, 2000; Salgado, 2002; Tett et al., 1991). Personality can be defined as the sum of physical, mental, emotional and social characteristics possessed by a person that uniquely influences his cognitions, motivations, and performance in any environment. On the other hand, there are some limitations to the previous research. Firstly, individual factors' correlations have not been studied well. Also, some factors have been ignored, such as lifestyle and adaptability because they are difficult to measure or they do not affect manufacturing system performance.

3.3.2 Environmental Factors

The human body interacts with its environment. The working environment should be safe and predictable. The design of the working environment has a direct effect on people's performance. Research indicates that environmental factors have a significant influence on worker performance (Hatch, 1987; Sullivan, 1990). Environmental factors are room temperature, humidity, lighting, noise, indoor air quality, and vibration. Exposure to extreme workplace temperatures can result in heat stress or cold stress. Passons (2000) describes the effects of temperature and humidity on job performance. Another significant factor that affects performance is lighting. Poor standards of lighting can cause visual fatigue and serious accidents. However, increasing the level of illumination results in smaller and smaller improvements in performance until performance level is off (Bennett et al., 1977). Some recommended illumination levels for use in interior lighting design for different tasks and worker characteristics are available (Sanders & McCormick, 1993). Quebec's Regulation Respecting Occupational Health & Safety specifies minimum illumination levels for different environments (Editeur officiel du Québec, 2011). In addition, Gawron (1982) studied the effects of noise on performance. Although high noise levels pose serious threats to the hearing, the effects of noise on general performance are not clear-cut. Workers prefer doing their jobs in clean environments. For example, there is evidence that carbon monoxide lowers physical work performance strongly (Scheff et al., 2000). Also, vibrations have major effects on human comfort, health, and performance (Griffin & Lewis, 1978; Jones, 1992). On the other hand, there is still little research that studies the effects of mechanical vibrations on the person's mental activities and decision-making abilities (Kroemer et al., 2001).

3.3.3 Job Factors

The nature of the work undertaken can clearly affect job performance. Several factors associated with the job nature include schedule, duration, job intensity, technique, and posture. For example, Henning et al. (1997) studied effects of exercise breaks and schedule on productivity. Also, the effects of exercise intensity and task difficulty on human cognitive processing have been studied (Kamijo et al., 2007). Similarly, the working technique is important in conserving energy and in providing varied use of different muscle groups. Finally, studying the working posture is important to determine the best way the worker can perform the job effectively For example, working in a standing position may be better than working in a sitting position because it helps the worker to move about and vary the load on individual muscle groups and facilitate circulation.

3.3.4 Organizational Factors

People generally work in groups and these groups form the main structure of an organization. There are many factors of organizations which influence the way people behave at work. These factors include shift patterns, work teams, hierarchical structure, communication, training, maintenance, job rotation, and diversity. Akerstedt and Landstorm (1995) studied the effects of shift work on productivity. Also, team work effects have been studied by Dunphy and Bryant (1996). However, lack of communication is commonly a contributor in accidents. The effects of the communication direction on job performance and satisfaction have been examined by Goris et al. (2000). Organizational hierarchy has been widely studied (Woodward, 1965). The hierarchy usually consists of a singular/group of power at the top with subsequent levels of power beneath them. Also, empirical studies have been done on the effects of employer-provided training on the productivity growth within companies (Barrett & Connell, 2001). In addition, job rotation strategy increases employees' motivation and satisfaction and decreases fatigue and boredom (Bhadury & Radovilsky, 2006; Miller et al., 1973). Azizi et al. (2010) presented a new methodology to implement job rotation plans in manufacturing systems.

3.3.5 Measures of Human Performance

The task of managing and measuring human performance is complex and can be a difficult challenge. Human performance can be expressed in different ways. The indicators of the human factors can measure how the person affects the manufacturing system or how the manufacturing system affects the person. Human performance indicators can be rather objective or subjective. Objective indicators can be measured directly, such as productivity or quality, whereas subjective indicators are based on the planner's judgment such as loyalty or satisfaction. Human performance can be critical in production planning efficiency. Some human performance indicators are difficult to measure.

Key performance indicators must reflect the organizations' goals, they must be the key to its success, and they must be measurable. It is important to define consistent performance indicators and set up a way to measure them. Table 3.3 shows a list of human performance indicators and their definitions. However, while all human performance measures should be considered due to their influence on the output of the production planning process, it is critical to limit them to those factors essential to the organization reaching its goals and keep them small just to keep everybody's attention focused on achieving the same performance indicators. In this thesis, some human performance indicators that are listed in Table 3.3 will be added to the proposed model step by step in order to consider the technical and the human issues in the planning process without facing any difficulties in finding the solution for the proposed model. For example, we can build a multi-objective model that can reduce the cost, reduce the workers' turnover rate and reduce the total activity time concurrently.

Table 3.3: Indicators of Human Performance within a Manufacturing Environment (Siebers, 2004)

Objective	Dependability Distribution	Unexpected interruptions to the task completion
	Activity Time Distribution	Time taken to complete a specific single task or range of tasks
	Error Rate Distribution	Frequency of unintentional task completion faults
	Reliability Distribution	The ability of a person to perform and maintain its functions in routine circumstances for a specified period of time
	Absenteeism Rate	Informal absence from work
	Accident Rate	Frequency of hazardous events attributable to human error
	Staff Turnover Rate	Number of employees who leave and replaced over a given period
Subjective	Stress Rate	Any influence that disturbs the natural equilibrium over a given period
	Fatigue Rate	Weariness resulting from bodily (or mental) exertion
	Job Satisfaction	Sense of inner fulfillment and pride achieved when performing a particular job
	Conflict Size	A clash, struggle, or trial of strength involving two or more persons or groups

3.3.6 Formation of the Human Performance Modeling Theoretical Framework

In the previous section, the human factors that are most likely to influence a person carrying out production tasks were listed. Figure 3.1 illustrates the proposed framework derived from Baines et al. (2005) and Jones (1993) models. The factors range from the individual, environmental, job to organizational factors.

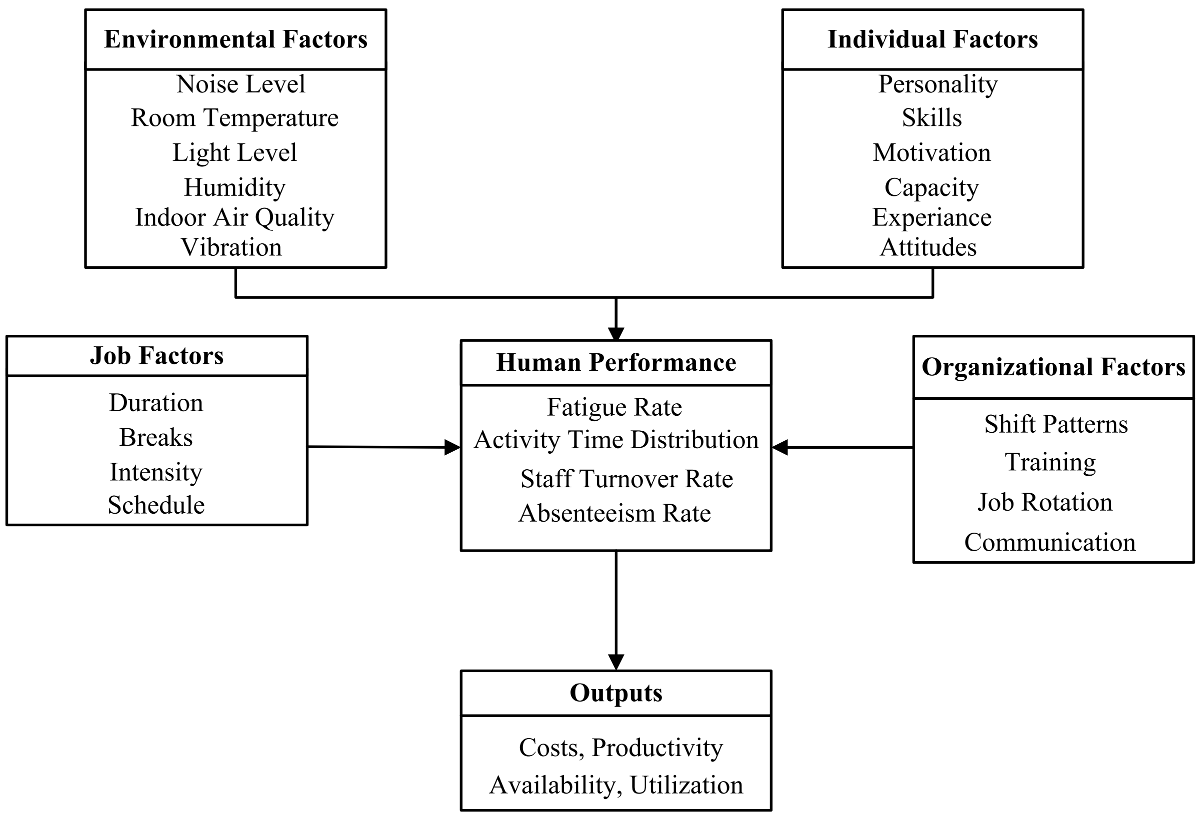

Figure 3.1: The Theoretical Framework for Modeling Human Performance

The key factors shown in the framework provide a comprehensive picture of the factors that are most likely to influence a person carrying out production tasks. However, it is essential to consider a small number of factors in modelling the human performance in the manufacturing system because it is difficult to measure all of the factors and make the framework workable in practise. In this research, fatigue rate, working breaks and staff turnover rate are introduced as part of the general objective function that leads to minimize cost and increase productivity. However, in order to link the framework of the human performance with the production planning process, we need to build a production planning framework that helps to classify the human factors into different planning levels. The production framework is presented in next section.

3.4 Formation of the Production Planning Theoretical Framework

A production planning problem exists because there are limited production resources and decisions must be made as to how to model their capacity, workers' behavior, and costs. Also, the production function contains uncertainty, such as uncertain demand, lead times and unexpected human or machine breakdown. For instance, lead times are a consequence of the load on the system together with random effects arising from problems of quality, reliability of the machines and processes, deliveries, people and the demand. However, companies frequently adopt simultaneously the contradictory strategies of varying load while fixing the quoted lead time. This may be one reason why many plans are unrealistic. Thus, production planning should respond effectively to internal and external changes by providing a faster response and better control of resources and delivery performance.

Developing a production framework model potentially gives a better understanding of the relationship between variables in the production system. Production planning can be partitioned into three layers: strategic, tactical, and operational. These three echelons have different scopes and planning horizons and are subject to varying intensities of uncertainties. Strategic decisions determine the required capacity, specify the quality policy, identify the customer needs, and select the product-markets and product mix. Tactical plans determine the size of the workforce, production rates, inventory levels, and quality levels. At the operational level, management allocates jobs to machines on a day-to-day basis, determine the amount of overtime and subcontracting and specify the delivery dates. Figure 3.2 shows a general framework for the production planning process.

Human factors are often considered as separate from the production planning process. However, human resources are a company's most valuable assets and it is essential to consider the human factors through the planning process to find out the human effects on planning performance. The first step of integrating human factors in the production planning process is to link it to the three planning levels: strategic, tactical, and operational.

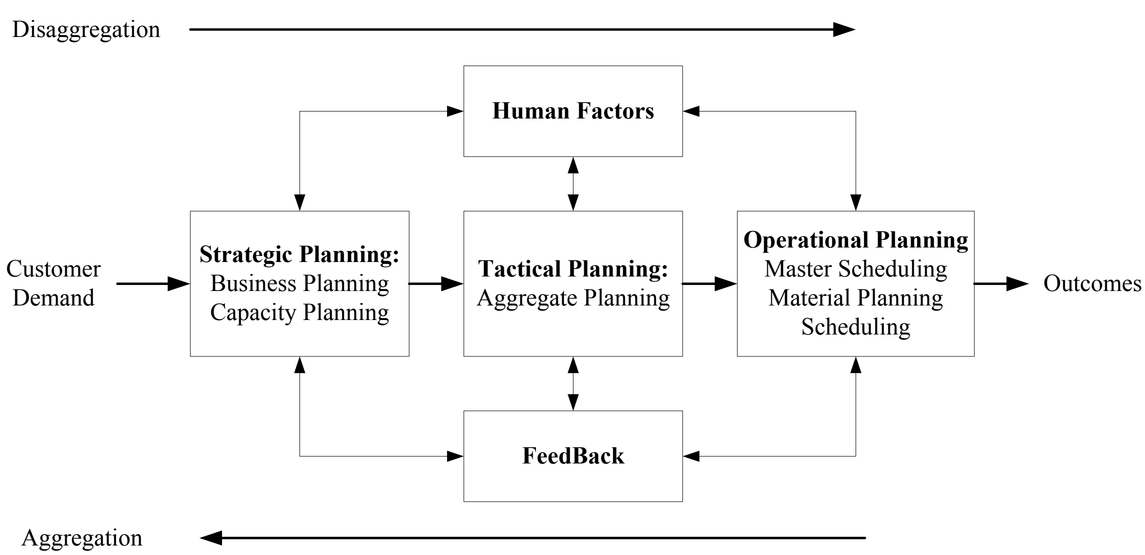

Figure 3.2: Production Planning Process Framework

The approach of linking human factors to the production planning stages seems to be a way to improve the impact of the ergonomists in the world of business. In this approach, the organizational factors are considered as the input to all of the planning levels; strategic, tactical and operational, individual factors and the job factors affect both the tactical and operational stages, and finally the environmental factors affect the operational planning. Strategic planning is an organization's process of defining its strategy and direction. It makes all the employees work for the same purpose and aims to reduce uncertainty and coordinate the efforts of organizational members. However, organizational factors, such as communication, hierarchical structure, teamwork, have significant effects on the quality of strategic planning process. For example, high centralization of organizational structure reduces the quality of the strategic planning. One type of strategic planning is capacity planning. Capacity planning is the process of determining the maximum amount of work that a company is capable of completing in a given period of time to satisfy the changing demands for its products.

In addition, the tactical planning level is affected by organizational, individual and job factors. It is developed to translate the strategic plan to an operational plan. Aggregate planning is considered as a tactical plan that tries to find the best cost compromise between production and workforce costs. This plan is used to change the workforce levels to cope with fluctuating demand. For example, management needs a plan to decide how many and what type of workers to add, train, or remove and when to subcontract in order to meet production needs. Many human issues influence the feasibility of the plan such as human skills, the cognitive ability, and training. Finally, operational planning is affected by individual, job and environmental factors. It covers detailed staffing schedules, shift systems and lot sizing. It is important that the operations planners understand human capabilities and limitations in the plan to avoid exceeding limits of human performance. A more detailed framework that shows the interrelations between the human factors and the planning process is illustrated in Figure 3.3.

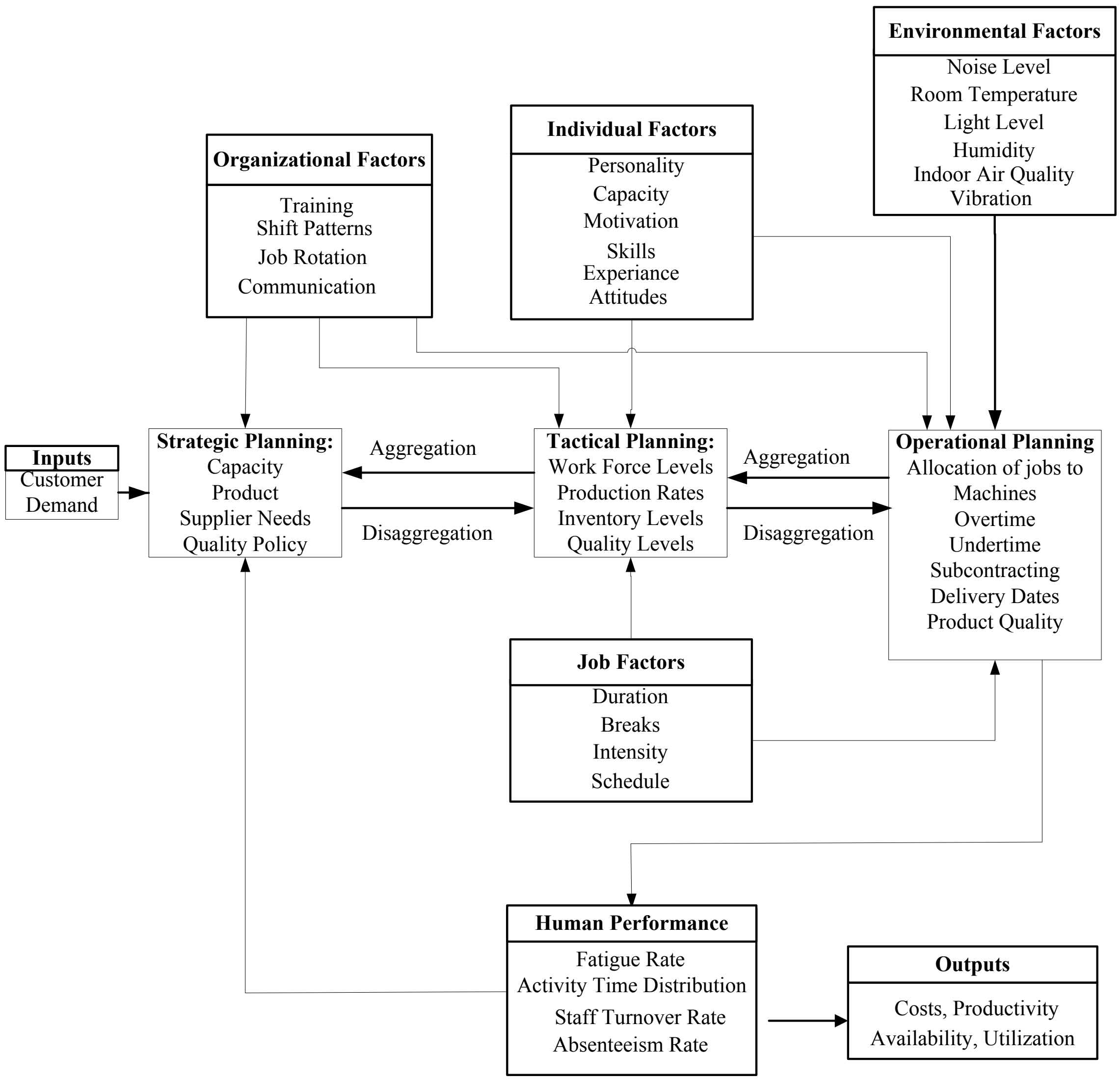

Figure 3.3: Detailed Production Planning Process Framework

In this thesis, workforce planning will be studied in more detail because many important decisions regarding human factors are made during this planning stage. Also, the workforce planning module occupies a central position in the production planning hierarchy. Moreover, it is generally easier to consider a planning problem that can fit with the three different planning levels based on the time horizon. Workforce planning problem can be modified to be strategic, tactical or operational based on the management decisions. This research addresses the problem of workforce planning at the tactical level. The next section provides the workforce planning problem modeling to illustrate the human factors-planning integration.

3.5 Workforce Planning Framework

Workforce planning is the critical link between the business strategy and Human Resources (HR) strategy. There are three types of workforce planning: operational, tactical and strategic. Strategic workforce planning is broader and longer term than tactical and operational workforce planning. Strategic Workforce Planning should take into account the projected loss of knowledge through employee exits and the projected knowledge requirements for sustaining and progressing the business. Knowledge requirements may include new skills, new roles, or documentation of key workforce personality. Operational workforce planning involves the systems and processes adopted and evolved to enable strategic workforce planning through the production of the evidence required for executive decision-making on workforce matters. Workforce planning determines the resource (labor) capacity a company will need to meet its uncertain demand over a long, intermediate or short time horizon.

As shown in the figure, the WP is used to determine the workforce levels of a company, performance and strategies for workforce transition on a finite time horizon. The main objective is to reduce the total overall cost to fulfil customer demand. It seems that the framework contains many factors that are difficult to be modelled from the first attempt. However, considering a few factors at first and then increasing the number of the factors in the model is the strategy selected for building the right model. In the first trial, the following human factors are considered: worker skills, and worker training. Then, worker personality, motivation and capacity are introduced. These factors are selected because they are the most valid predictors of work performance. In the next model extension, worker fatigue, and recovery are discussed. Finally, learning curves are presented to show the dynamic nature that characterizes any human behavior. Figure 3.4 shows the proposed workforce planning framework. However, it is critical to develop a model that can consider human factors occurring in the real world.

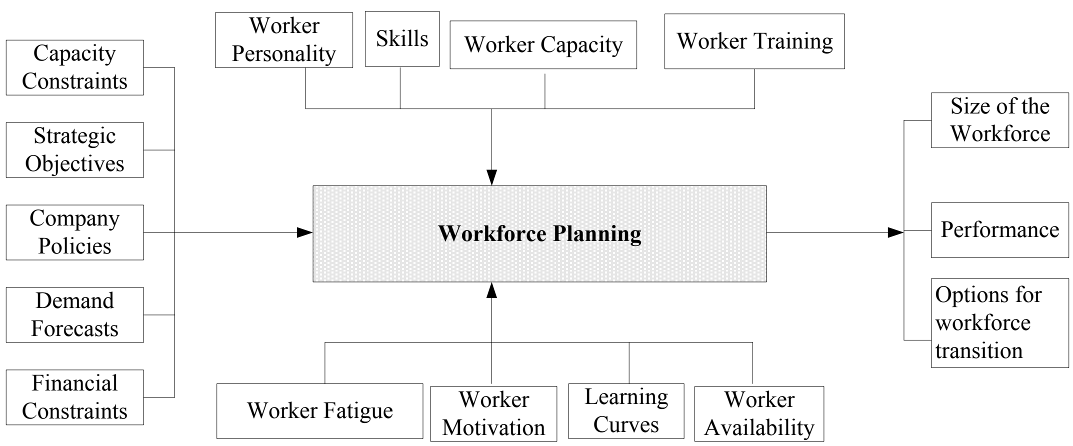

Figure 3.4: Workforce Planning Framework

CHAPTER 4 MODEL A: EFFECTS OF WORKERS' DIFFERENCES ON PLANNING DECISIONS

In this research, we present two mathematical models in terms of time horizon and human factors characteristics. This chapter introduces Model A, which incorporates personality, motivation, capacity and learning curves. This model investigates the effects of workers' differences on planning decisions on a weekly basis. It discusses the impact of learning curves on the productivity of the workers and the total performance of production. In the next chapter, Model B is introduced; it integrates fatigue and recovery rates with Model A and discusses the effects of these factors on the planning decisions on a daily basis. Sensitivity analyses are performed on the models.

4.1 Problem Definition

In this chapter, we assume that we have a manufacturing company that has different machines types, which are grouped into several machine levels depending on their complexity. We assume that we have three machine levels; machine level one contains machines that are easy to operate by operators with low skills level, machine level two requires an intermediate skills level and finally machine level three is the most complicated level that needs a high level of human skills. The company produces several products on different machine types based on the products' routing sheet. Also, we assume that we have flexible routing, which means that every operation of products can be processed on more than one machine with different processing times. Worker flexibility has been considered in order to reduce the manufacturing system variability. It can be achieved by using overtime, training, and temporary workers assignment.

In each period, workers can be trained in order to improve only their skill level. In many cases, training is better than firing and hiring new workers. It is assumed that the training period is zero, which means that the worker is productive as soon as he is trained. Layoffs are never easy and do incur a human cost. When the company has a high percentage of layoffs, the loyalty and motivation to the company will be decreased. Also, most companies use labour laws and contracts to control the firing of workers. However, hiring new workers sometimes affects the performance of the present workers because they need to be trained to the same level of the previously fired workers. It is assumed that all workers have initial productivity to start their work at the first period depending on their capacity, motivation and working conditions. One of the best ways to increase profits for a company is to increase productivity. As time passes by, workers become more productive.

On the other hand, performance measures quantitatively tell us something important about the products and services that organizations produce. They are tools to help understand, manage, and improve what companies do. They can be represented by single dimensional units like hours, dollars, number of errors, number of CPR-certified employees, etc. In this chapter, the objective function is to minimize the total costs resulting from the hiring, firing and training, and over time in dollars. Costs and workforce performance can be critical in production planning efficiency. However, in order to satisfy the total demand of each period, we are interested in determining:

1. How many workers to assign to each machine level in each period?
2. How many workers, with which skill levels to hire or fire in each period?
3. How many workers to train from lower skill level to higher one in each period?

4. How many hours a worker with specific skill and personal level can work in overtime?
5. What level of performance of the workers should be achieved?

4.1.1 Measuring the human factors

In this thesis, we will adapt the theoretical model developed by Blumberg and Pringle (1982) for measuring the expected performance of the workers. They suggested that expected work performance of individuals is determined by three factors:

1. Capacity: the ability to perform a task based on skill, age, health, knowledge, energy level, and intelligence.
2. Opportunity: factor beyond a person's control, such as tools and material availability, working conditions, policies and payment rules.
3. Willingness: the inclination to perform a task affected by attitude, personality, task characteristics, job status and feeling of equity.

The physical characteristics of the workers such as strength are taken into account through the term "Capacity", which is the ability to do a physical task. However, the strength of motivation formula is not in its exactness but in its structure. Riggs (1987) suggested ways for quantifying the factors that model the motivation formula on a zero-to-one scale. Previous research supported the modeling approach of individual differences (Waldman & Spangler, 1989).

Workers are grouped according to different human skills and personalities. Each worker has at least one skill level and can be assigned to certain machine levels. Various personal traits can make up a human being. They are the endowments of human character (personality traits). They are grouped within the categories of an individual's miscellaneous attributes and skills. Personal attributes include worker calmness, clarity of thoughts, constructiveness, creativity, dynamics, education, efficiency, energy, focus, health, intelligence, integrity, knowledge, organization, relationship with others, responsibility, and desire to seek improvement.

The field psychology describes personality in terms of five personality traits, namely openness, conscientiousness, extraversion, agreeableness, and neuroticism. Each person has some degree of each of these traits. These traits are defined as follows: openness is the degree to which a person is curious, intellectual, and creative. Conscientiousness refers to the degree to which a person is organized and dependable. Extraversion is the degree to which a person is outgoing, and sociable. Agreeableness is the degree is the degree to which a person is sensitive, kind and calm. Neuroticism refers to the degree to which a person is anxious, and moody (John & Srivastava, 1999).

Personality tests are common in psychology (John, 2000; Queendom.com, 2012). Several of these tests are used to assess personality traits such as openness (e.g. creativity) conscientiousness (e.g. organization), extraversion (e.g. energy), agreeableness (e.g. relationship with others), and neuroticism (e.g. calmness). The grouping of individuals with similar characteristics into personality levels contributes to reducing the variability of individual profiles. Thus, through the use of a 0-100% scale, the personality levels have been divided into three levels: level 1 indicating the lowest level, level 2 indicating the middle level, and level 3 indicating the highest level. Since this thesis relies on the measurement of personality levels through percentile score, Level 1 indicates the range from 0 to 33.3rd percentile, level 2 indicates the range from 33.4th to 66.6th percentile, and level 3 indicates the range from 66.7th to 100th percentile. Thus, Individuals with high scores on conscientiousness tend to be responsible, organized and mindful of details, whereas people with low scores on openness tend to have less curiosity and interests that are considered traditional. The assignment of weights to each personality dimension allows the manager to categorize the worker into a specific personality level. In effect, these weights may be determined based on the company's view of the most vital personality trait.

Assuming neuroticism dimension has been removed, since it has shown that is it inversely related to performance (Barrick & Mount, 1991). If a company has a desire to test a new worker and to identify his personality level, the identification would be made that four personality dimensions are vital for the prediction of the worker's performance, and would thus be used as the selected hiring criteria. To gauge the potential employee's personality level, the company may examine openness, conscientiousness, extraversion, and agreeableness. These criteria are measured through the use of a unique personality test using 0-100% scale; in which 0 is the worst or least desired outcome for each criterion and 100 is the best or most desired outcome for each criterion. The relative importance of each criterion is considered by assigning different weights in order to reflect the relative value of moving from the best to worst on the scale. If the worker is to score 60% on openness, 80% on conscientiousness, 40% on extraversion, and. 70% on agreeableness, it may be assumed that the weights 0.20, 0.6, 0.1, and 0.1 are assigned to the following criteria: openness, conscientiousness, extraversion, and. agreeableness, respectively. The final weighted average score of the worker is calculated as follows: 0.20(60)+0.6(80)+0.1(40)+0.1(70)=71%. Based on this final overall score, this worker has high personal attributes and would be categorized into personality level 3. Conversely, worker skills may also be evaluated in a similar manner.

Interval scale method was used to measure the capacity, motivation and opportunity factors (Riggs, 1987). The first step is to define the criterion. This is done by identifying the ideal state that can best satisfy the criterion. First, one of the objective metrics that can be used to measure the capacity is endurance: low endurance level (0 to 33.3rd percentile), medium endurance level (33.4th to 66.6th percentile), and high endurance level (66.7th to 100th percentile). Second, one of the metrics that can be used to measure the willingness is personality level zones: low personality level (0 to 33.3rd percentile), medium personality level (33.4th to 66.6th percentile), and high personality level (66.7th to 100th percentile). Third, one of the metrics that can be used to measure the opportunity factor is working conditions such as noise level, and ventilation: low working environment level (0 to 33.3rd percentile), medium working environment level (33.4th to 66.6th percentile), and high working environment level (66.7th to 100th percentile). The test should be applied many times for the same worker and working environment to calculate average values. The ideal state is defined by recognizing the superior personal abilities or working conditions that fit the machine level and set to be 100%. Next, the least desirable state is identified and set to be 0%. Any worker can be tested and compared to the best and worst situation. If the worker is very close to the perfect number, the rating may be 95%.

No meaningful measurement is possible without a criterion. To measure the endurance level, many factors should be considered in identifying the criteria such as age, gender, muscle type and task nature. These criteria and standards can be found in human factors journals (Garg & Ayoub, 1980; Snook & Irvine, 1969; Volkov & Volkov, 2004). Work motivation defined as willingness to work was measured using Sjoberg and Lind's (1994) 12-item scale. The criterion can be the reliability of the worker, which means the worker should give same output on repeated testing. In evaluating the noise level, a researcher can use the noise criteria for acceptable working environments. These criteria and standards are suggested by the National Institute for Occupational Safety and Health (NIOSH). Even though it is possible to measure the variables qualitatively, a researcher should use the objective measure to represent the factor. For example, it is possible to measure quantitatively the following metrics: endurance or intelligence, motivation, and ventilation or noise level to define capacity, willingness, and opportunity dimensions, respectively.

4.1.2 Assumptions

1) The values of all parameters are certain over the planning horizon.
2) Cost of hiring, firing and training workers are known and deterministic for each skill level and personal capabilities.
3) The availability of all workers is assumed to be equal to 80% by considering daily breaks, since workers are typically allotted an hour and half for a lunch break and other interruptions (e.g. coffee drinking, bathroom break, etc.), Therefore, approximately 0.8 refers to the percentage of a worker's total available time for which is found from dividing the time a worker is actually available by the total available working time (e.g. (8-1.5)/8)). Also, A_{jt} is the maximum available regular working time in hours per time period (e.g. 8 hours/day).
4) The number of worker skill levels is equal to the number of machine levels.

5) Capacity and willingness of the workers are increased as their skills and personalities levels increased.
6) Productivity of the worker is derived from the time-constant learning equation. Since the learning curve has an upper limit, the productivity has a maximum limit as well.

4.2 Model A Development

The model developed is mixed integer non-linear programming model (MINLP) that allows for a number of different staffing decisions (e.g. hire, train, fire and overtime) in order to minimize the sum of hiring, firing, training and overtime costs over all periods. In presenting the model, special notations and symbols are used and presented followed by the model solution (for complete list, see page xii).

Indices:

t - Index of planning periods, $t=1, 2,\ldots, T$

j,k - Indices of human skill levels, $j, k = 1, 2,\ldots, S$

x,y - Indices of machine levels, $x, y = 1, 2,\ldots, ML$

p - Index of personality attributes, $p= 1, 2,\ldots, P$

Model Parameters:

h_{jpt} - Cost of hiring a p - level worker with skill level j in period t (\$/worker)

f_{jpt} - Cost of laying off (firing) of a p - level worker with skill level j in period t (\$/worker)

tr_{kjpt} - Cost of training a p - level worker from skill level k to skill level j in period t (\$/worker)

sr_{jpt} - Salary of a p - level worker with skill level j at regular time in period t (\$/worker)

so_{jpt} - Hourly rate of a p - level worker with skill level j at overtime in period t (\$/worker-hour/period)

A_{jt} - Available regular working hours of a worker with skill level j for each person in each period t (hours/period),

AOT_{jt} - Available overtime working hours of a worker with skill level j for each person in each period t (hours/period)

C_{jp} - Capacity of a p -level worker with skill level j for each person in each period; $0 \leq C_{jp} \leq 1$

Op_x - Opportunity to work on machine level x in each period; $0 \leq Op_x \leq 1$

R_{jpx} - Readiness (willingness) of p -level workers with skill level j to work on machine level x; $0 \leq R_{jpx} \leq 1$

D_{jt} - Demand for skill level j in period t (worker-hours/period)

ss_{kj} - = 1 if training from skill level k to skill level j is possible; or 0 otherwise

ws_{jpx} - =1 if working on machine level x with p-worker of skill level j is possible; or 0 otherwise

INP_{jpx} - Initial productivity level for worker p - level workers with skill level j working on machine level x; $INP_{jpx} = C_{jp} \times Op_x \times R_{jpx}$

LE_{jpx} - Individual learning constant for worker p - level workers with skill level j working on machine level x

INW_{jpx} - Initial number of p -level workers with skill level j required to be assigned to machine level x (workers)

V_{jptx} - =1 if a p - level worker with skill level j can work on machine level x in period t; or 0 otherwise

M - A big number

Continuous Decision Variables:

W_{jptx} - Number of p - level workers with skill level j required to be assigned to machine level x in period t (workers)

H_{jptx} - Number of p - level workers with skill level j hired and assigned to machine level x in period t (workers)

L_{jptx} - Number of existing p - level workers with skill level j who are assigned to machine level x in period t-1 and they are laid-off in period t (workers)

Y_{kjptyx} - Number of p - level workers who were assigned to machine level y and then are trained from skill level k to skill level j and assigned to a higher machine level x in period t (workers)

E_{jpx} - Difference between the initial rate of INP_{jpx} and the maximum rate of productivity (Pr), where $E_{jpx} \le C_{jp}$

OT_{jptx} - Overtime hours of p - level workers with skill level j in period t (worker-hours/period)

Pr_{jptx} - Productivity if a p - level worker with skill level j does work on machine level x during time t (based on time-constant leaning model; $0 \le Pr_{jptx} \le 1$)

PO_{jptx} - The output performance from a p - level worker with skill level j working on machine level x during time t

Binary Decision Variables:

Q_{jptx} - = 1 if p - level workers with skill level j cannot be fired during period t because they are received training in the same period t; or 0 otherwise

U_{jptx} - = 1 if p - level workers with skill level j cannot be fired during period t because they are hired in the same period t; or 0 otherwise

4.2.1 Objective Function and Model Constraints

Minimize:

$$Z = \sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{j=1}^{S}\sum_{x=1}^{ML}\left(Sr_{jpt} \times W_{jptx} + h_{jpt} \times H_{jptx} + f_{jpt} \times L_{jptx} + so_{jpt} \times OT_{jptx}\right) + \sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{j=1}^{S}\sum_{k=1}^{S}\sum_{x=1}^{ML}\sum_{y=1}^{ML}\left(tr_{kjpt} \times Y_{kjptyx}\right)$$

Subject to:

$$D_{jt} = 0.8 \times A_{jt} \times \left(\sum_{p=1}^{P}\sum_{x=1}^{ML} \mathrm{Pr}_{jptx} \times W_{jptx}\right) + \sum_{p=1}^{P}\sum_{x=1}^{ML} OT_{jptx} \qquad \forall j,t \qquad (1)$$

$$W_{jptx} = W_{jpt-1x} + H_{jptx} - L_{jptx} + \sum_{\substack{k=j-1 \\ k=y}}^{S}\sum_{y=x-1}^{ML}\left(Y_{kjptyx}\right) - \sum_{\substack{k=j+1 \\ j=x}}^{S}\sum_{y=x+1}^{ML}\left(Y_{jkptxy}\right) \qquad \forall j,p,t,x \qquad (2)$$

$$Pr_{jptx} = INP_{jpx} + E_{jpx}\left[1 - exp\left(-\frac{\sum_{i=1}^{t} V_{jpix}}{LE_{jpx}}\right)\right] \qquad \forall j,p,t,x \qquad (3)$$

$$PO_{jptx} \le V_{jptx} \times Pr_{jptx} \qquad \forall j,p,t,x \qquad (4)$$

$$OT_{jptx} \le AOT_{jt} \times W_{jptx} \qquad \forall j,p,t,x \qquad (5)$$

$$\sum_{\substack{k=1 \\ k>j}}^{S}\sum_{y=1}^{ML} Y_{jkptxy} + L_{jptx} \le W_{jp,t-1,x} \qquad \forall j,p,t,x \qquad (6)$$

$$W_{jptx} \le M \times V_{jptx} \qquad \forall j,p,t,x \qquad (7)$$

$$L_{jptx} \le M \times ws_{jpx} \qquad \forall j,p,t,x \qquad (8)$$

$$H_{jptx} \le M \times ws_{jpx} \qquad \forall j,p,t,x \qquad (9)$$

$$Y_{kjptyx} \le M \times ws_{kpy} \qquad \forall j,k,p,t,x,y \qquad (10)$$

$$Y_{kjptyx} \le M \times ws_{jpx} \qquad \forall j,k,p,t,x,y \qquad (11)$$

$$Y_{kjptyx} \le M \times ss_{kj} \qquad \forall j,k,p,t,x,y \qquad (12)$$

$$\sum_{k=1}^{S} \sum_{y=1}^{ML} Y_{kjptyx} \times L_{jptx} = 0 \qquad \forall j,p,t,x \qquad (13)$$

$$H_{jptx} \times L_{jptx} = 0 \qquad \forall j,p,t,x \qquad (14)$$

$$W_{jptx}, H_{jptx}, L_{jptx}, Y_{kjptyx} \ge 0 \qquad \forall j,k,p,t,x,y \qquad (15)$$

Constraint (1) shows that the total available worker hours is equal to the number of hours required for each skill in each period. Constraint (2) guarantees that the available workforce in any period equals workforce in the previous period plus the change of workforce in the current period. Constraint (3) is necessary to determine the production rate for worker (*j, p*) on machine level x during period t, which depends on the worker's experience performing tasks on that machine level. The current formulation is based on log-linear learning, and it is assumed that the worker's learning function for a particular machine level is only related to the worker's initial productivity level for that machine level and how much time the worker has spent performing that task on this specific machine level. This constraint makes this problem nonlinear and this particular formulation a challenge to solve. Constraint (4) ensures that the total output, *PO*, is always less than or equal to the productivity of the workers. Constraint (5) ensures that the overtime workforce available should be less than the maximum overtime workforce available in each period. Constraint (6) ensures that the total number of workers who are assigned to machine level x in period t-1 and now fired or trained for upper skill levels should not be greater than the number of workers required in previous period. Constraint (7) ensures workers are used at specific machine level in a certain period if and only if they are able to work in this particular level. Constraint (8) ensures that workers can be fired if and only if the assignment is possible. Constraint (9) denotes that workers can be hired if and only if the assignment is possible. Constraint (10) Training for better skills is possible if and only if the previous assignment is possible. Constraint (11) ensures that training for better skills is possible if and only if the latter assignment is possible. Constraint (12) ensures that training for better skills is possible if and only if training to that skill is possible. Constraint (13) guarantees the workers who are trained for skill level j should not be fired in the same period. This constraint contains a nonlinear formula that can be transferred to a linear term with the help of a binary variable as follows:

$$\sum_{k=1}^{S}\sum_{y=1}^{ML} Y_{kjptyx} \le M \times Q_{jptx} \qquad \forall j,p,t,x \qquad (16)$$

$$L_{jptx} \le M(1-Q_{jptx}) \qquad \forall j,p,t,x \qquad (17)$$

$$Q_{jptx} \in \{0,1\} \qquad \forall j,p,t,x \qquad (18)$$

Constraint (14) ensures that either hiring or firing workers occurs but not both. Also, this constraint has a nonlinear that can be transformed into linear one in the same way as the previous constraint, as follows:

$$H_{jptx} \le M \times U_{jptx} \qquad \forall j,p,t,x \qquad (19)$$

$$L_{jptx} \leq M\left(1 - U_{jptx}\right) \qquad \forall j,p,t,x \qquad (20)$$

$$U_{jptx} \in \{0,1\} \qquad \forall j,p,t,x \qquad (21)$$

Finally, constraint (15) is the non-negativity constraint.

4.3 Computational Results

To illustrate the model proposed in this chapter and assess the effect of workers` differences on total costs and workforce plan, simple examples are presented in this section. Insights on the effect of various human factors on workforce planning decisions are presented. Different scenarios are tested to show the impact of personality levels and performance on workforce decisions.

4.3.1 Comparison of Two different Models

The first step to demonstrate model validation is to do model verification by checking for obvious errors or units inconsistency. This process can be done by solving the equations right. A practical example from Sipper and Bulfin (1997) is adapted. The authors provided a case study regarding the development of Precision Transfer Inc.'s different strategies of aggregate planning that makes a variety of gears. In fact, data for the past year indicates that a worker is able to produce, on average, four gears per day. At the beginning of each month, new workers can be hired at a cost of $450 per worker, and existing workers can be fired at a cost $600 per worker. Additionally, workers are paid $120 per worker per day. Available to work for 21, 20, 23, 21, 22, and 22 days in each month, all workers are paid for eight hours of labour per day and there are currently 35 workers employed for Precision. Moreover, it is assumed that the company does not carry inventory and each month we produce exactly the amount demanded. Also, we assume that workers have 100% productivity and they cannot take any kind of breaks. Individuals are hired when the need for workers is greater than the number of available workers. Also, individuals are laid-off once the number of available workers exceeds its need. Through the assumption that Precision has a zero inventory plan, the exact amount needed is produced per period, similarly to the just-in-time philosophy. Indeed, previous studies show 75% of the current companies select this strategy or modified chase option, since it improves a company's overall cash flow situation (Buxey, 2003). As such, two differing problems instances with different sizes are solved through the use of the proposed model. It is also assumed that the company hires workers with solely skill 1 as well as personality 1, and that workers can be hired for two period planning horizon. Hence, Table 4.1 illustrates calculations for a zero-inventory plan presented by Sipper and Bulfin (1997). Alternatively, Table 4.2 demonstrates the input parameters and generated results from or proposed model without considering overtime, training, personality, productivity, motivation, capacity, availability and fatigue options. The number of workers needed for a month is calculated as follows:

$$\text{Workers Needed} = \frac{\text{Demand/month}}{\text{days/month} \times \text{units/worker/day}}$$

Based on the input data provided, a worker can produce 4 gears per day and there are 21 working days in January. Workers needed to satisfy January's demand are equal to 2760/ (21*4) = 32.86 workers. Through this problem, it is assumed that there is no overtime. The workers required are equivalent to 32.86 workers * 8 hours/day * 21 days/month = 5520 worker-hours/month. The results of both of the problems are generated as shown in Table 4.1 and 4.2, respectively.

Table 4.1: A Production Plan Taken from Sipper and Bulfin (1997)

		January	February
Days, P1		21	20
Units/worker, P2	= 4*P1	84	80
Demand (units), P3		2,760	3,320
Workers needed, P4	= P3/P2	33	42
Workers available, P5		35	33
Workers hired, P6	= Max (0, P4-P5)	0	9
Hiring cost, P7	= 450*P6	0	4,050
Workers laid off, P8	= Max (0, P5-P4)	2	0
Lay-off cost, P9	= 600*P8	1,200	0
Labor cost, P10	= 120*P1*P4	83,160	100,800
Units produced, P11	= P3	2,760	3,320
Total cost ($), P12	= P7+P9+P10	84,360	104,850

Table 4.2: A Workforce Plan Generated from the Proposed Model A

		January	February
Hours Availability, A_{1T}	= P1*8	168	160
Demand (workers hours/period), D_{1T}	= 2*P3	5,520	6,640
Workers needed, W_{11T1}	= P3/P2	32.86	41.5
Workers available, INW_{11T}		35	32.86
Workers hired, H_{11T1}	= Max (0, W_{11T1}-INW_{11T})	0	8.64
Hiring cost, h_{11T}*H_{11T1}	= 450*H_{11T1}	0	3,888
Workers laid off, L_{11T1}	= Max (0, INW_{11T}- W_{11T1})	2.14	0
Lay-off cost, f_{11T}*L_{11T1}	= 600*L_{11T1}	1,284	0
Labor cost, sr_{11T} * W_{11T1}	= 120*P1*W_{11T1}	82,807	99,600
Total cost ($), Z	= 450*H_{11T1}+600*L_{11T1}+120*P1*W_{11T1}	84,092	103,488

In the first problem, the laid-off workers is equal to 2.14 workers (35 workers available – 32.86 workers needed) and the total costs are equal to 214 workers * $600/worker = $1284. Since this plan solely assumes an integer number of workers, the numbers are rounded up from 32.86 to 33 workers. However, if the fractions are not rounded up to the nearest integer numbers, then Problem 2 produces improved results to those found in Sipper and Bulfin (1997). Thus, in this problem, we assume that the number of workers used, hired, or fired is real numbers. If, as shown in Table 4.2, 32.86

workers rare needed for January, then the fraction may be converted to the equivalent number of hours' worth in hours through the multiplication of the total availability of the worker, which is equal to 0.86 workers * 168 hours/month = 144 worker-hours/month. Consequently, we can see the results are close to the ones found in literature, without taking into account other human factors.

4.3.2 Model Limitation

Solving larger trails is particularly challenging if the variables are integers. However, my model mostly uses real variables and the larger trials may be solved in a reasonable time as shown in Table 4.3. To ensure that the software is able to generate results within a reasonable timeframe, six different examples with diverse dimensions are shown in the Table below. These examples are derived from the input data from the previous case study. Any changes in these input data will result in a modification of the solution. It can be seen that if the problem size is increased, the results can be generated after running the model for a long time. Additionally, the fact that the majority of the variables are integers indicates that it is difficult to obtain a solution within a reasonable time using off-the-shelf optimization software. Therefore, the development of a solution algorithm may be a promising area for future work.

Table 4.3: Six Different Examples with Different Dimensions

	Variable	Periods	Skills	Number of Variables	Number of Constraints	Optimality	Total Costs	Time (sec)
1	Real	6	3	2979	1171	Global	2,402,554	1
2	Integer	6	3	2979	1171	Local	2,404,226	360
3	Real	6	6	29,619	4150	Local	5,043,800	5

4	Integer	6	6	29,619	4150	Local	5,052,844	1200
5	Real	6	10	197,425	10,936	Local	8,175,000	300
6	Integer	6	10	197,425	10,936	None	-	-

On the other hand, if the number of workers used, hired, fired, and trained are assumed to be integer variables, then an increase in the solving time of the model will be noted. Furthermore, global optimal solution would potentially fail to be reached. According to the results illustrated in Table 4.3, the current plan LP relaxation obtained from LINGO 13.0 for the first problem has a total cost of $2,402,554. In comparison, the rounded local optimal solution of the second problem is $2,404,226. The cost of the solution from the second problem, in which the variables are assumed to be integers, is 0.07 percent above the first problem solution, thus meaning that the results are similar.

4.3.3 Model Validation

The process of testing and improving a model to increase its validity is commonly referred to as model validation. It ensures that the proposed model can be used in a real word system with confidence and demonstrate that all the approximations to reality incorporated in the model do not affect the quality of the results. In general, changing the values of the parameters to see whether the output of the model behaves normally can be used as a reasonable approach for model validation.

The establishment of the objective function allows each term in the equation to be evaluated separately by multiplying the term of interest by 1 and all other terms by 0. As a result, validation is carried out term by term. With regards to each term's validation, a set of input values with a known solution is chosen. Whilst the model is used to evaluate the solution, the model solution is compared with the known solution.

The first step solely evaluates hiring and firing. If the number of people required in a given period is larger than the available workforce, then the number of individuals hired should be equal to the number of individuals required minus available workforce. Similarly, if the available workforce is larger than the number of workers required, the number of workers fired is the difference between available and required workforce. Consequently, the next stage also takes into account the skill level. In effect, a comparison is conducted at each level. In all scenarios, the model results are shown to be identical to the known solution.

The second step exclusively evaluates training. To evaluate this, the total number of people required is identical to the available workforce. However, in this case, the number of workers in a particular skill level differs from the available workforce in the same skill level. In the event that a surplus in the lower skill-level and a shortage in the higher skill-level occur, a sufficient amount of individuals are trained for the higher skill-level. If it is impossible to fill the openings of one skill level with workers from a lower skill level, the necessity arises for new workers to be hired. Similarly to step 1, different sets of input workforce data with known required outputs have been used and the model results are the same as the known outputs.

The third step solely evaluates overtime. If the workforce available during regular time is insufficient to satisfy the demand, then the expected solution excludes any hiring or layoffs. Instead of increasing the workforce size, the model has chosen to use overtime option. Thus, as opposed to increasing the size of the workforce, the chosen model utilizes the alternative of overtime.

The forth step considers the cost of hiring and firing, overtime as well as training. If the cost of training is high, while the cost of hiring and firing is low, then the model's results recommend hiring and firing, instead of training. Likewise, in the event of low training costs are high hiring and firing costs, then training is recommended. To validate this part of the model, the specification of the cost data allows preference to be supplied for either training or hiring and firing. Consequently, the model results were once again identical to the expected and known output results.

4.3.4 Numerical Example

A company produces its products to fulfil known demand along an 8-week planning horizon. The hiring, and firing costs are assumed to be higher for higher skill levels. Also, it is assumed that the worker is available for 40 hours a week (160 hours per month) at regular time and he is available for 10 hours a week (40 hours per month) at overtime. However, it is assumed that a worker is not productive during daily breaks that are assumed to last for a constant 1.5 hours a day. Moreover, it is assumed that worker motivation depends on his skills and personality. Worker willingness to work is increasing as machine level is increasing over the planning period. Input data are shown in Appendix C, Tables C.1 to C.7. The known demand of worker skills in worker-hours in each period is summarized in Table C.1. Table C.2 shows workers' availabilities. Table C.3 shows the available workforce at period zero. Table C.4 shows the cost of training from skill level to another skill level in each period. Willingness to perform on each machine level for every personality level in each period is illustrated in Table C.5. Salaries, hiring costs, lay-off costs, overtime costs and workers' capacities are shown in Table C.6. Learning parameters for each worker type are illustrated in Table C.7. Using the input data presented the model consists of 3961 variables and 1819 constraints and the global optimal solution for the problem can be obtained using LINGO 13.0 software within one minute of program running. This software uses Global solver to search until the global optimum is confirmed. The Global solver converts original non-convex, nonlinear problem into several convex, linear sub-problems. Then it uses the branch- and bound technique to search over these sub-problems for global solution (LINDO Systems INC., 2012). The computer that is used to solve the model has a 2.13 GHz Intel Core processor, I3 CPU, and 4GB RAM. The total costs are $1,669,220.

Results from the proposed model are shown in Table 4.4. In this chapter, many human factors such as workers' training, skills, overtime, workers' availabilities, workers' capacities, workers' personalities, workers' learning and workers' motivation are considered to show the importance of including these factors at the early planning stages. However, the results from the model offer staffing decisions on what, how and when to hire, fire and train. Also, the number of worker-hours during regular time and overtime is determined.

Table 4.4: Resulting Weakly Workforce Plan

			W1	W2	W3	W4	W5	W6	W7	W8
		Demand (workers)	**100**	**50**	**100**	**70**	**65**	**100**	**65**	**100**
Worker Skill 1	P1	Workers used on level 1	0	0	0	0	0	0	0	0
		Workers hired on level 1	0	0	0	0	0	0	0	0
		Workers fired from level 1	0	0	0	0	0	0	0	0
		Workers trained to level 2	40	0	0	0	0	0	0	0
		Overtime hours	0	0	0	0	0	0	0	0
		Productivity, %	36	41	46	50	53	56	59	62
	P2	Workers used on level 1	0	0	0	0	0	0	0	0
		Workers hired on level 1	0	0	0	0	0	0	0	0
		Workers fired from level 1	0	0	0	0	0	0	0	0
		Workers trained to level 2	0	0	0	0	0	0	0	0
		Overtime hours	0	0	0	0	0	0	0	0
		Productivity, %	50	57	63	68	73	77	80	83

	P3	Workers used on level 1	103.7	68.6	90.3	82.3	72.4	80	66.9	76.2
		Workers hired on level 1	103.7	0	21.7	0	0	7.6	0	9.3
		Workers fired from level 1	0	0	0	8	9.9	0	0	0
		Workers trained to level 2	10	35.2	0	0	0	0	13.1	0
		Overtime hours	1037	0	9038	0	0	800	0	762
		Productivity, %	65	73	80	85	90	94	97	100
		Demand (workers)	**110**	**100**	**110**	**100**	**100**	**80**	**100**	**80**
Worker Skill 2	P1	Workers used on level 1	0	0	0	0	0	0	0	0
		Workers used on level 2	40	0.9	0	0	0	0	0	0
		Workers hired on level 1&2	0	0	0	0	0	0	0	0
		Workers fired from level 1&2	0	39.1	0	0	0	0	0	0
		Workers trained to level 3	30	0	0.9	0	0	0	0	0
		Overtime hours	400	0	8.6	0	0	0	0	0
		Productivity, %	54	62	69	74	79	83	86	89
	P2	Workers used on level 1	0	0	0	0	0	0	0	0
		Workers used on level 2	10.2	10.2	10.2	10.2	10.2	10.2	4.3	4.3
		Workers hired on level 1&2	0	0	0	0	0	0	0	0
		Workers fired from level 1&2	0	0	0	0	0	0	0	0
		Workers trained to level 3	9.8	0	0	0	0	0	5.9	0
		Overtime hours	101.7	101.	101.7	23.9	0	0	42.8	42.8
		Productivity, %	64	73	80	86	91	95	97	99
	P3	Workers used on level 1	0	0	0	0	0	0	0	0
		Workers used on level 2	58.7	93.9	93.9	93.9	92.5	71	74.4	74.4
		Workers hired on level 1&2	38.7	0	0	0	0	0	0	0
		Workers fired from level 1&2	0	0	0	0	1.3	21.5	0	0
		Workers trained to level 3	0	0	0	0	0	0	9.7	0
		Overtime hours	587.1	163.	345.5	0	0	0	651.9	0
		Productivity, %	80	88	93	96	97	98	99	99.9
		Demand (workers)	**120**	**90**	**120**	**90**	**100**	**60**	**100**	**60**
Worker Skill 3	P1	Workers used on level 1	0	0	0	0	0	0	0	0
		Workers used on level 2	0	0	0	0	0	0	0	0
		Workers used on level 3	60	60	60.9	60.9	60.9	60.9	60.9	60
		Workers hired on level 1,2&3	0	0	0	0	0	0	0	0
		Workers fired from level 1&2	0	0	0	0	0	0	0	0.9
		Overtime hours	600	0	608.6	0	255	0	608.6	0
		Productivity, %	73	84	90	94	97	98	99	100
	P2	Workers used on level 1	0	0	0	0	0	0	0	0
		Workers used on level 2	0	0	0	0	0	0	0	0
		Workers used on level 3	39.8	33.5	33.5	33.5	33.5	0	5.9	0
		Workers hired on level 1,2&3	0	0	0	0	0	0	0	0
		Workers fired from level 1&2	0	6.4	0	0	0	33.5	0	5.9
		Overtime hours	398.3	0	146.2	0	0	0	58.9	0
		Productivity, %	80	88	93	96	98	98.9	99.9	100
	P3	Workers used on level 1	0	0	0	0	0	0	0	0
		Workers used on level 2	0	0	0	0	0	0	0	0

Workers used on level 3	10	10	10	0.1	0.1	0	9.7	0
Workers hired on level 1,2&3	0	0	0	0	0	0	0	0
Workers fired from level 1,2&3	0	0	0	9.9	0	0.1	0	9.7
Overtime hours	100	0	0	0	0	0	97.1	0
Productivity, %	93	97	99	99.6	99.8	100	100	100

The results show that hiring, firing and training of workers are varied between all personality levels depending on hiring, firing or training costs and performance levels. We can notice that hiring and firing decision variables are not binary decisions because they are defined to determine the number of workers hired or fired in a particular period. The demand element determines the number of workers hired. Rather than being an integer value, the number of workers calculated is a real one. This is due to the fact that demand is represented in terms of worker's hours per period required, as well as his work for a certain number of hours per period. Note that the difference between integer and linear programming is also addressed in subsection 4.3.2, which shows that the total costs using real variables are about the same as when using integer variables (the costs using integer variables is a little higher because the number of workers is rounded up to the next integer value). Moreover, linear programming is a useful workforce planning tool and it is make sense keep the model simple and understandable. Given that the analysis period is a week consisting of five working days, if a worker's first day is on a Wednesday, then he counts as 2/5 =0.4 of a worker for that week. This fraction may also be achieved by hiring a part-time worker or working overtime.

It is generally assumed that workers are identical. This research shows that workers' performance can be used to model workers' differences and to predict hiring, firing and training workers. Table 4.4 shows the number of workers hired, fired and trained in each period for different personality level. From the Table, it can be seen that most of the workers hired have high personality level. Performance is a critical factor in hiring, layoff and training decisions. However, if initial settings are modified, the results are likely to be different. On the other hand, we see that hiring and cross-training highly depends on productivity factors, salary and training costs. The highest level personnel are shown to be more attractive in hiring decisions in the first periods. This is due to the assumption that workers with higher personality levels have higher initial productivity caused by high motivation and capacity. Also, some workers with low personality levels become more attractive in training in the first periods because there are many workers with low personality at the beginning of the planning horizon, and it is more economical to train the existing workforce rather than fire them since the training costs and salary are assumed to be less than hiring and firing costs. Moreover, firing occurs more in high skills and personality levels in the latest periods. This is due to the fact that most workers are trained and hired in the first periods and they are used till there is no demand and so it is more economical to fire them due to their high salary costs. However, this highly depends on the initial settings. If the parameter settings change, the results may be changed.

4.3.5 Insights on Human Factors Effects

During peak time, companies may choose between different scenarios such as overtime, training existing workers or hiring new workers. To illustrate the effects of overtime and training on the workforce planning decisions, four sets of experiments were conducted. It is assumed that there is no information about personality levels or productivity levels and they are neglected. Appendix B shows the mathematical modeling for this section. The first experiment incorporates both overtime and training options. The second experiment demonstrates the importance of incorporating training programs within a planning system from the organizational perspective. For this experiment, it is assumed that workers cannot be improved and trained to upper skills. The total cost for this experiment is $1,524,627, which is approximately 1.5% higher than the optimal MILP solution that considers both training and overtime options. In the third experiment, we assume that workers cannot work overtime. The total costs for this experiment is $1,695,360, which is approximately 12.8% higher than the optimal MIP solution that considers both training and overtime together, as shown in Table 4.5. This experiment shows that overtime helps in cutting costs because hiring new workers requires arranging for new infrastructures as the new staff works simultaneously and alongside existing staff. Overtime also helps reduce new employee hiring and training costs considerably.

Table 4.5: Costs Differences Between Different Options

Experiment #	Overtime included	Training included	Total costs
1	Yes	Yes	$1,502,868
2	Yes	No	$1,524,627
3	No	Yes	$1,695,360
4	No	No	$1,739,150

Finally, if both overtime and training are ignored in the model, the total costs are $1,739,150, which is approximately 15.7% higher than the optimal MIP solution that considers both training and overtime together.

These experiments illustrate that if the model considers overtime and training within workforce planning, we may be able to make better and effective decisions regarding human resource actions, such as, how many should be hired, fired or trained. We conclude that by offering more capacity options for the model, the total cost will be reduced.

4.4 Insights on Model Parameter effects

In the previous section, a simple numerical example is given to illustrate the performance of the model. In this section, the same example is used to study the effects of human factors and other important model parameters on workforce decisions. These factors are personality levels, worker capacity, motivation, initial number of workers, customers demand, and training and hiring cost.

4.4.1 Impact of Worker Differences on planning decisions

Most previous models published in the literature do not consider human differences in workforce planning. However, considering human differences that exist between workers results in more effective and accurate workforce decisions. In this experiment, two different scenarios are considered: the first one represents the case where there is no information about human differences and costs of hiring, firing, and training the workers are set to be the average costs used in the previous example, and the productivity of all workers is set to be 0.75. In the second scenario, we assume that workers differ from each other and the productivity is determined based on the learning rate model for all workers. The total cost when personality level differences are not considered at all is \$1,832,761 while in scenario 2, in which we consider workers' differences, the total cost is \$1,669,220. These differences in total costs between the two scenarios are due to the differences in labour, hiring, firing, and training costs and performance. The results show that by considering worker differences in the model and by comparing the scenario 1 with scenario 2, there is a cost reduction of 9.8%. However, if the manager decides to change the average productivity or costs the results will be changed. For example, if we assume that the average productivity for all workers is 0.6, the total costs are increased to $2,161,686, which means the costs are increased by 22.8% from the scenario 2. Moreover, if the initial number of workers is changed, the number of hired, fired or trained workers is changed which will change the total costs. Parameter analysis is discussed in more detail in the next sections.

On the other hand, Figure 4.1 shows the resulting workforce plan generated by scenario 1. It can be seen from the plan in scenario 1 most of the hired workers have low level of personality However, this plan is generated based on the input data that are estimated by the researcher without considering human differences which may give inaccurate results. Figure 4.2 shows the resulting workforce plan generated by scenario 2. In this scenario, there are more training options from lower skills to the upper skills, and most trained workers have low to intermediate personality and skill levels. Also, the majority of the fired workers have high levels of personality, due to the upgrading policy used in the model.

This experiment shows that if the workforce planning model considers human factors such as personality, we may be able to make better decisions regarding production and employees. For instance, by using a plan that considers the worker's skills and personality, the decision of assigning the right worker to a right machine level will be made without need to modify the scheduling process every period so that the total cost and time will be reduced. Thus, the workforce plan highly depends on several parameters such as initial number of workers, worker personality and salary and training costs, which affect decision-making. Figures 4.1 and 4.2 illustrate both scenarios 1 and 2.

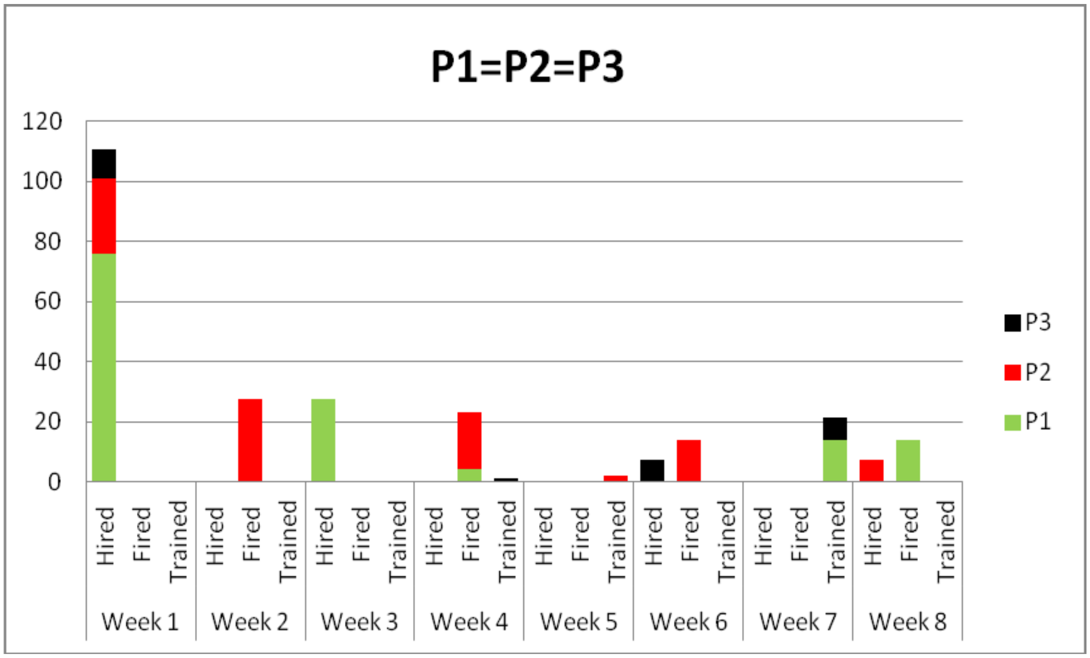

Figure 4.1: Number of Workers Hired, Fired, or Trained for Scenario 1

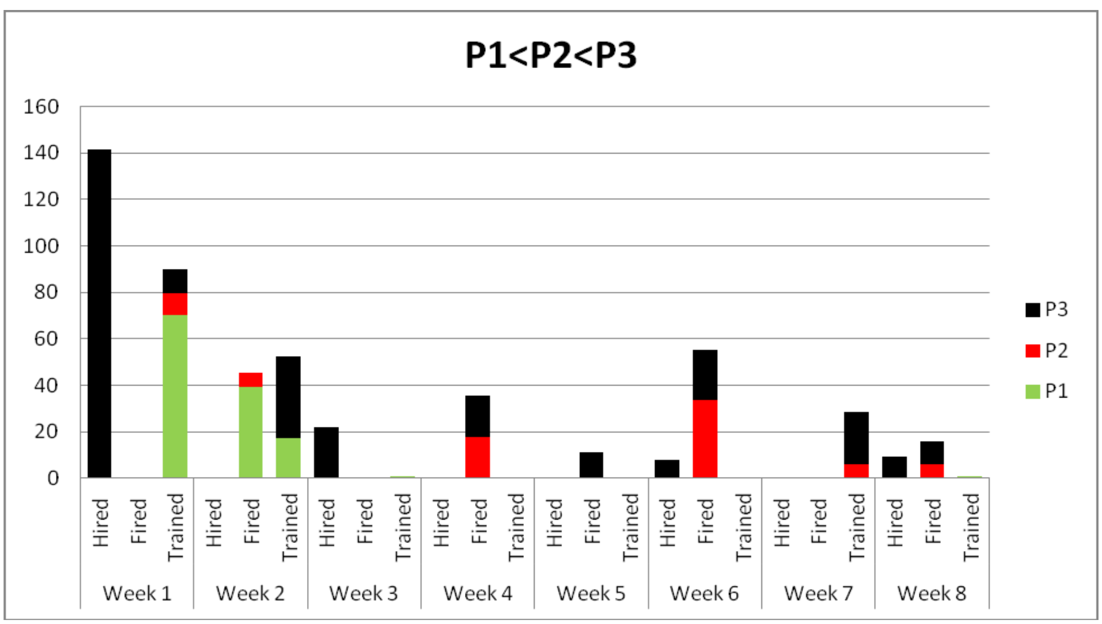

Figure 4.2: Number of Workers Hired, Fired, or Trained for Scenario 2

4.4.2 Impact of Productivity Levels and costs structure on the planning

We use small problem instances to demonstrate the effects workers differences on the model performance. We compare the solution obtained by a model that considers personality levels with different productivity levels to the one obtained by a model without the consideration of personality level differences. This experiment aims to determine if the consideration of workers differences results in more effective set of hiring and training decisions. Seven scenarios with different working productivity were studied, as shown in Table 4.6. Scenario A represents the ideal case for working environment where the costs for workers are different and depends on both skills and personality levels, and all workers have full productivity from the first period. Scenario B represents the case where the costs for workers in each personality level are different and the productivity of the workers are changing based on the learning curve model. Our model represents this practical scenario that incorporates differences among workers' skills and their task-learning rates. In scenario C, the productivity of the workers is based on the learning rates model but the costs are set to be the average of the cost used in the proposed model. This average cost is the costs for personality level of 2. In scenarios D, E and F, the working productivities are equal for all personality level workers, but we assume that all workers are identical in scenario D and their costs are different in scenario E with 0.75 productivity, and in scenario F the productivity is equal to 0.5. Finally, scenario G represents the case that all workers have constant initial productivities and their costs are different based on their skills and personality levels.

In scenario A, since the working productivity is 100% for all workers, the results show the best case for worker schedule in terms of costs and performance. Scenario B and C gives the same performance output for the workers but Scenario B is better than scenario C since it is not realistic to give the same salary for every worker typing without considering their skills or experience. However, the results showed that total costs are not

Table 4.6: Seven Scenarios with Different Productivity Factors

Scenario	Description	W11	W12[a]	W13	W21	W22	W23	W31	W32	W33	P[b]	Costs ($)
A	Ideal	1	1	1	1	1	1	1	1	1	144	1,402,082
B	Practical	0.36-0.62	0.5-0.83	0.73-1	0.5-0.89	0.63-1	0.75-1	0.62-1	0.78-1	0.89-1	124.2	1,669,220
C	Same Costs	0.36-0.62	0.5-0.83	0.73-1	0.5-0.89	0.63-1	0.75-1	0.62-1	0.78-1	0.89-1	124.2	1,744,898
D	Identical	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	101	2,056,058
E	Constant Productivity 1	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	101	1,869,312
F	Constant Productivity 2	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	72	2,369,203
G	Initial Productivity	0.3	0.42	0.56	0.42	0.53	0.64	0.52	0.64	0.76	82.8	2,147,378

[a] W12 represents worker with skill 1 and personality level 2

[b] P represents Output Performance

significantly different in their values because the model contains the productivity factor in both scenarios which has the major effect on the workforce decisions. The little difference in cost is due entirely to the differences in the costs of personality levels. These results are based on the initial costs assumed to be the average. Changes in the cost structure would alter the results. Scenario D shows the worst case when the scheduler treats workers as identical, and ignore their individual differences in either skills or personality, which results in high costs and low performance. Compared to Scenario B, there is a cost reduction of 18.8% (from $2,056,058 to $1,669,220). The main reason for this significant difference is that workers in scenario D are assumed to have constant low productivity compared to the dynamic one presented in scenario B. Scenarios E, F and G supports the fact that considering different productivity of workers can result in better schedule output in terms of performance and costs. We can see that our proposed model (scenario B) generates results nearly close to the ideal case (the second order). These comparisons shows that if more information about the workers is known and used in the planning process, we may able to make better decisions regarding various human resource actions. Figures 4.3 and 4.4 illustrate these seven scenarios.

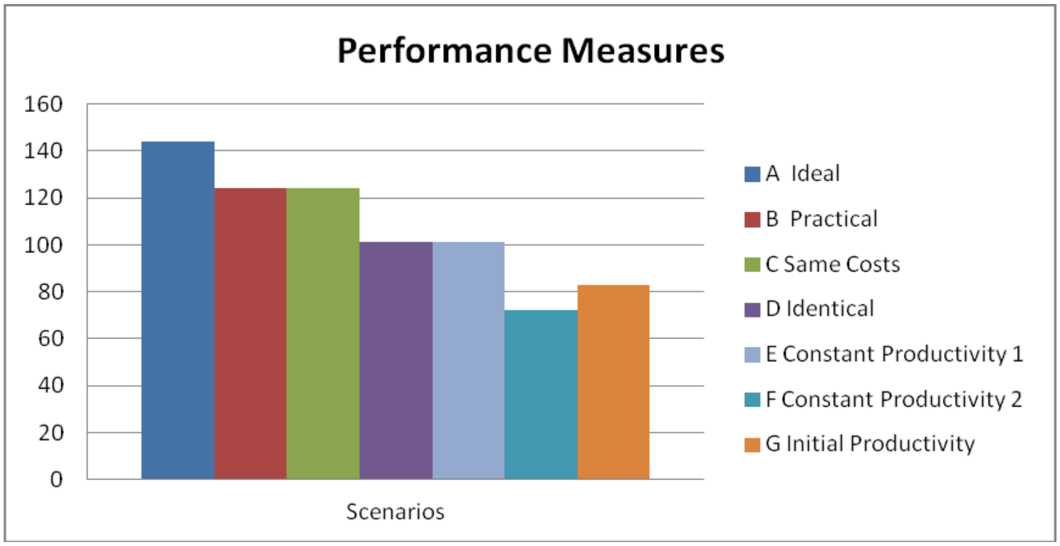

Figure 4.3: Total Performance for Different Scenarios

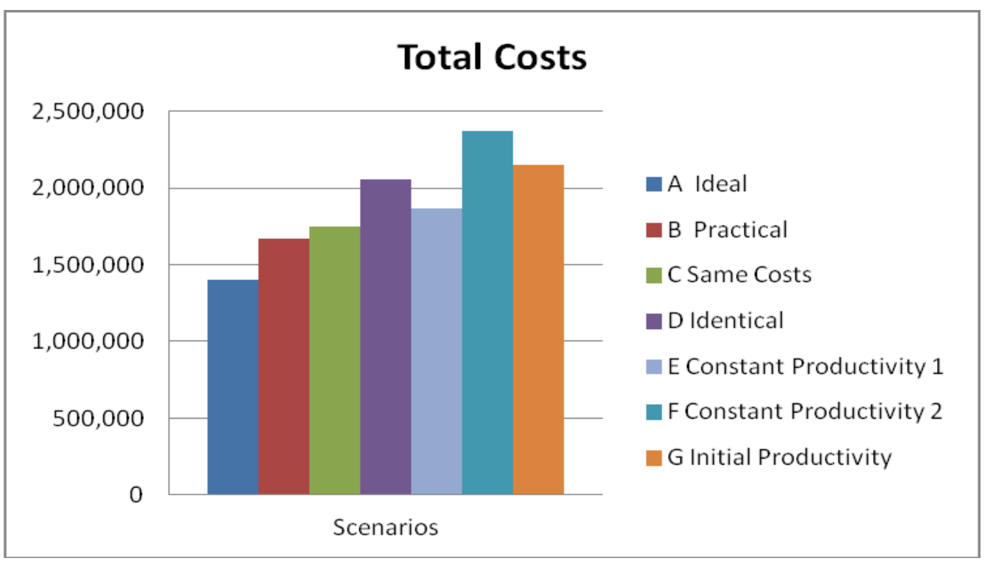

Figure 4.4: Total Costs for Different Scenarios

4.4.3 Impact of Initial Number of Workers

In this experiment, the effect of initial number of workers with different personality level is studied. First of all, we assume the demand is the same for all workers skills and is equal to 3200 hours a week. Four workforce profiles are considered. In the first one, we assume we don't have any initial workforce in the company for each personality level. In the second profile, we assume that workers with personality level 1 make up half of the total workforce; workers with personality level 2 make up 30% of the total workforce, while workers with personality level 3 make up 20% of the total workforce. The third profile has an equal number of workers for all personality levels. The last profile shows that workers with high personality level 3 make up half of the total workforce, workers with personality level 2 make up 30% of the total workforce, while workers with low personality levels make up 20% of the total workforce. Table 4.7 illustrates these four profiles.

Table 4.7: Four Different Profiles for Initial Workforce for each Skill Level

Profile	Description	P1	P2	P3	Performance	Costs ($)
1	No Workforce	0	0	0	124.2	1,758,175
2	Higher Low Personality	50	30	20	124.2	1,722,398
3	Same Ratios	33.3	33.3	33.3	124.2	1,700,200
4	Higher High Personality	20	30	50	124.2	1,675,000

From Figures 4.5, we can see different numbers of workers hired because the initial numbers of workers are different for each profile. It can be seen that the number of workers hired is high in profile 1 compared to other profiles because we assume that we do not have any initial workers at the beginning of the planning horizon. Also, we can notice that higher personality level workers are generally preferred for hiring and cross training.

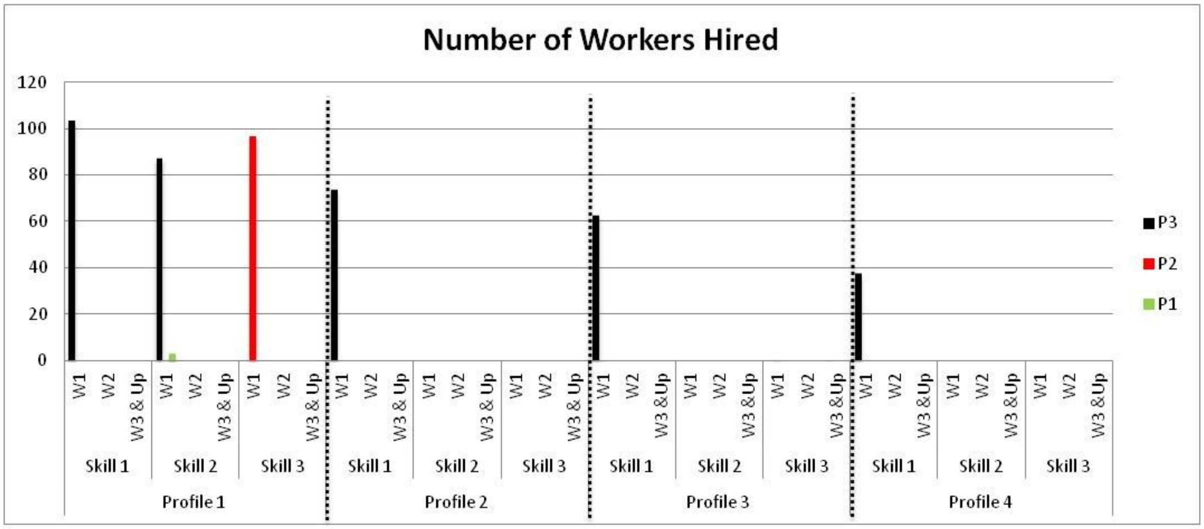

Figure 4.5: Number of Workers Hired for Four Different Profiles

However, the amount of hired is reduced when the personality levels have same ratios as in profile 3 and the number of workers trained are increased especially with medium personality levels in profiles 2 and 3. Even though the costs differences are minimal, the last profile is better than the other profiles in terms of costs and performance. The reason for small costs differences is that all scenarios are based on the learning curve model and they have same input data except for the number of initial workers. So the costs of hiring and firing are close to each others. Profiles 2 and 4 have different decisions since in profile 2 there are more hirings of workers with high personality, and more trainings with medium personality levels. But, there are less hirings of workers with high personality levels, and less workers trained with medium personality levels in profile 4. This is also due to the differences in the number of initial workers and the productivity to the costs ratios. These results confirm that initial profiles have a significant impact on the amount workers hired and cross training. Figure 4.6 illustrate the number of workers trained for four profiles..

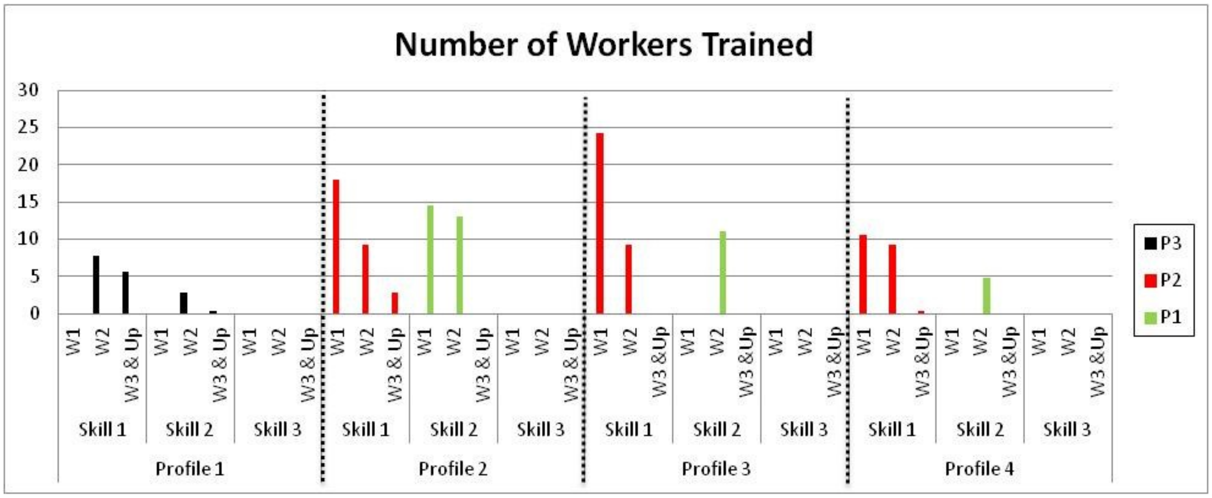

Figure 4.6: Number of Workers Cross-Trained for Four Different Profiles

4.4.4 Impact of Demand Variation

In this experiment, the demand per period for each skill level is changed. Five scenarios, each with different demand structure for each skill, were studied, as shown in Table 4.8. The initial number of workers is fixed and equal to the profile 3 in the previous subsection. Scenario 1 represents the case where demand is constant for each skill level. Scenario 2 shows increasing demand for each period. Scenario 3 shows decreasing demand for each period. Scenario 4 represents the case where demand for skill 2 remains constant and demand for skill 1 increases and demand for skill 3 decreases. Scenario 5 represents the case where demand for skill 2 remains constant, demand for skill 1 decreases and demand for skill 3 increases.

Table 4.8: Demand Scenarios of Worker Skills in each Week (worker-hours)

Scenario	Worker Skill	W1	W2	W3	W4	W5	W6	W7	W8
1	1	3200	3200	3200	3200	3200	3200	3200	3200
	2	3200	3200	3200	3200	3200	3200	3200	3200
	3	3200	3200	3200	3200	3200	3200	3200	3200
2	1	400	800	1200	1600	2000	2400	2800	3200
	2	400	800	1200	1600	2000	2400	2800	3200
	3	400	800	1200	1600	2000	2400	2800	3200
3	1	3200	2800	2400	2000	1600	1200	800	400

	2	3200	2800	2400	2000	1600	1200	800	400
	3	3200	2800	2400	2000	1600	1200	800	400
4	1	400	800	1200	1600	2000	2400	2800	3200
	2	3200	3200	3200	3200	3200	3200	3200	3200
	3	3200	2800	2400	2000	1600	1200	800	400
5	1	3200	2800	2400	2000	1600	1200	800	400
	2	3200	3200	3200	3200	3200	3200	3200	3200
	3	400	800	1200	1600	2000	2400	2800	3200

The amount of workers hired for each scenario from left to right are shown in Figure 4.7. In scenario 1, enough workers for all the periods are hired during the first week. All workers hired have high personality levels. Cross-training occurred in both low and high personality levels. Most workers who have low personality levels are trained during the first two weeks of the planning horizon. In scenario 2, demand for both skills

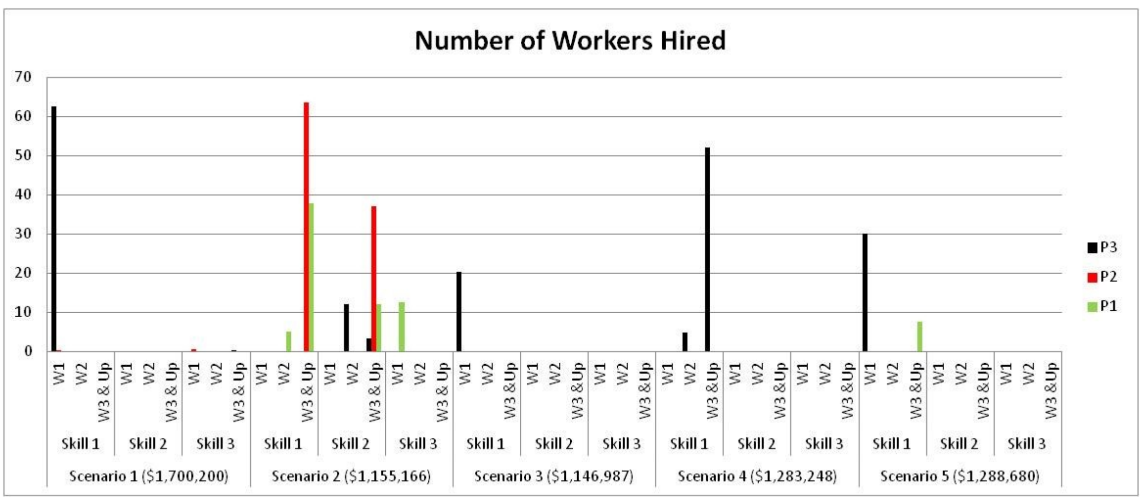

Figure 4.7: Number of Workers Hired for Different Demand Scenarios

increases. There are more workers hired in each period to satisfy the demand. We can notice that the workers hired always have high skills with low personalities or low skills with high personalities which mean that the model always prefers to hire the top performers. More workers with lower personality level are trained after the third week of the planning horizon. Scenario 3 shows demand decreasing over the planning horizon. Workers with high personality level are hired only in the first period and no cross-training is required because there are enough workers. Also, this scenario generates many firing decisions due to the decreased demand. In scenario 4, demand skill 1 increases but demand for skill 3 decreases. Workers with skill 1 are hired more after period 3. Also, cross-training occurs only in skill1 due to the increasing demand. In scenario 5, demand for skill 1 decreases while demand for skill 3 increases. Very few workers are hired from both skill 2 and skill 3 and most workers are trained from lower skills to upper skills. Mostly the highest personality workers with skill 1 or the lowest personality workers with skill 2 are selected for cross-training after period 3. The amount of workers trained for each scenario from left to right are shown in Figure 4.8.

From this experiment, it is shown that hiring occurs more when there is increasing demand over the planning horizon. Also, cross-training increases when the time required between the skills changes in the opposite directions as in scenario 5. Mostly, workers with the highest personality level are preferred for both hiring and cross-training.

Figure 4.8: Number of Workers Trained for Different Demand Scenarios

4.5 Discussion of Results

The previous experiment aimed to demonstrate how various factors affect decision making. Cross training and hiring decisions depend highly on several parameters such as productivity factors, salary, hiring, firing and training costs, demand structure, and initial number of workers. Costs have more effect on which personality level worker is selected for hiring or training than the other factors. For example, if there are big differences between costs, then lower personality levels become more attractive due to their low costs. Also, initial numbers of workers profiles and demand structure have a big impact on the amount of training. Generally, the highest personality level workers are shown to be more attractive for hiring and training decisions. These results are based in the assumption made in building this model that the workers with higher personality levels have higher productivity based on the learning curve. If the assumptions and parameters settings change, the results may be changed.

The results of this research are significant in a number of respects. Foremost among these was the use of theoretical frameworks proposed by Baines et al. (2005), Blumberg and Pringle (1982) and Jones (1993) to identify the most important human factors that affect the workforce planning process. In contrast to prior research that has relied exclusively on ignoring workers' differences, this approach allowed us to address incorporating the personality factor to decide what is the best scenario for hiring, firing and training workers to satisfy a company's goals and without changing their rules. Second, the results indicate that worker differences should be considered in workforce planning to generate realistic plans with minimum costs. Thus, we have shown that incorporating worker differences in the planning process reduces the total costs. Third, unlike most prior studies of workforce planning, the current study suggests ways to quantify the intangible human factors that are difficult to measure. Finally, this thesis investigates the effects of human performance, learning and motivation on the workforce scheduling process. Human learning and performance are critical factors in hiring, layoff and training decisions. This model helps to find ways for keeping the workers based on their motivation and performance.

Despite these strengths, a number of features of the current work also limit the conclusions that can be drawn from these results. First, although the model seems to provide reasonable results, the input data are assumed and generated based on the experience and opinions. A second limitation of the current study is that all the human factors parameters and total demand are assumed to be certain and known, which may generate unrealistic results. A third limitation is that this model does not consider the negative outcomes resulted from workers layoffs. Firing workers may have many different effects on the other workers. Although we have specified penalties for layoffs, these penalties may not accurately consider the long term negative effects of employees leaving a company on worker morale, talents, and productivity. We do not take into account potential decrease in productivity due to lower motivation (willingness) which may result when several people are fired at the same time. Following the firing of a number of workers, the existing workers' motivation and morale may be taken into account through the adjustment of the input data following the firing period. Also, a manager may add a constraint to the model that allows only hiring but not firing of workers. However, the model may produce an infeasible solution due to the original constraint of overtime. So, sensitivity analysis should be done to determine the allowable ranges for firing, hiring or training to generate a feasible set of solutions. On the other hand, other planning strategies to cope with demand fluctuation can be used such as varying the production rate by holding inventory and planning backorders. These ways can be combined to create a large alternative production planning options. A fourth limitation is that this model ignores many human factors that can affect the planning process. Some of these factors are fatigue, communication, experience, and forgetting process. Luckily, fatigue and recovery rates are discussed in the next chapter. Although we did not study the relationships between human factors, we provided them as an aggregate number representing a group of workers having similar characteristics. Until further research clarifies the direction of these relationships and effects, causal statements can only be made with caution.

CHAPTER 5 MODEL B: EFFECTS OF WORKERS' FATIGUE ON PLANNING DECISIONS

5.1 Introduction

This chapter presents some important extensions to the mathematical model presented in the previous chapter. Mathematical model B integrates other important human factors into model A. It investigates the effects of human fatigue and recovery on workforce planning performance. Workers have a certain capacity during work, which is the maximum endurance time, defined as the length of time that workers can continue to work without becoming fatigued. It is assumed that endurance time increases as the personality level is increased. When the productive time increases, the average workload on the worker increases, so that rest breaks have to be given for the physiological recovery of a worker. Relaxation allowance is used to assist recovery from fatigue. It is an addition to the basic time intended to provide the worker with the opportunity to recover from the physiological and psychological effects of carrying out specified work under specified conditions. The amount of allowance will depend on the nature of the job, personality attributes and environment.

In this chapter, Model B is solved through using the same methodology that is used to solve Model A. the computational results for model B are then discussed. Different scenarios are studied to show the effects of various model parameters on the model output.

5.2 Model B Description

The proposed mathematical programming model is based on Model A assumptions except assumption 3. By using Model B, the amount of worker's breaks can be determined based on the mean endurance time of the worker and his recovery rate. In addition to these assumptions, we assume that fatigue accumulation and recovery curves are linear over time. Also, the fraction of maximum load capability is applied continuously by the worker when performing a task for a period equivalent to the task's duration. Moreover, the length of the break between tasks is not long enough to result in full recovery. Finally, it is assumed that the length of the shift work of a worker is less than 12 hours including overtime.

The model developed is a multi-objective mixed-integer non-linear programming model that allows a number of different staffing decisions to be made (e.g. hire, train, fire and overtime) in order to minimize the sum of hiring, firing, training and overtime costs and, minimize idle (unproductive) time and minimize the average fatigue. However, the developed model B can be formulated by adding some terms in the objective functions and modifying certain constraints of model A, as well as by adding some new parameters and decision variables.

Additional Model Parameters:

wt_{jps} - =1 if a p - level worker with skill level j can do task s; or 0 otherwise

fra_{ps} - Fraction of maximum load capability of p - level workers doing task s

MET_{ps} - Maximum endurance time of p - level workers doing task s (hours/period), where

$$MET_{ps} = \alpha \times e^{-\beta \times fra_{ps}}$$

$F\,max_{ps}$ - The maximum fatigue load p - level workers can accumulate in any task s (%. hour), where $F_{max\,p} = MLC \times fra_{ps} \times MET_{ps}$

REC_{ps} - Recovery allowance required by p - level for task s

MLC - Maximum load capability (force unit)

m - Number of cycles during a whole period of work

w_z - Positive weights that reflect the decision maker's preferences regarding the relative importance of each goal, $z = 1, 2, 3$

$goal_C$ - Desired cost level

$goal_B$ - Minimum amount of break time

$goal_F$ - Minimum fatigue level can be achieved

<u>Additional Model Continuous Decision Variables:</u>

TI_{jptsx} = Time p - level workers with skill level j spend on task s on machine level x during period t (worker-hours/period)

B_{jptsx} = Break time of p - level workers with skill level j following task s on machine level x during period t (worker-hours/period)

5.2.1 Objective Function and Constraints

Minimize: $OBJ = w_1 \times d_C^+ + w_2 \times d_B^+ + w_3 \times d_F^+$

1. Goal constraints:

$$\sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{j=1}^{S}\sum_{x=1}^{ML}\left(h_{jpt} \times H_{jptx} + f_{jpt} \times L_{jptx} + so_{jpt} \times OT_{jptx}\right) + \sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{j=1}^{S}\sum_{k=1}^{S}\sum_{x=1}^{ML}\sum_{y=1}^{ML}\left(tr_{kjpt} \times Y_{kjptyx}\right) + d_C^- - d_C^+ = Goal_C \qquad (25)(22)$$

$$\sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{j=1}^{S}\sum_{s=1}^{TS}\sum_{x=1}^{ML}\left(B_{jptsx}\right) + d_B^- - d_B^+ = goal_B \qquad (23)$$

$$\frac{m \times \sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{j=1}^{S}\sum_{s=1}^{TS}\sum_{x=1}^{ML}\left(fra_{ps} \times TI_{jptsx}\right) - m \times \sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{j=1}^{S}\sum_{s=1}^{8}\sum_{x=1}^{ML}\left(\frac{fra_{ps}}{REC_{ps}} \times B_{jptsx}\right) - (m-1) \times \sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{j=1}^{S}\sum_{s=9}^{9}\sum_{x=1}^{ML}\left(\frac{fra_{ps}}{REC_{ps}} \times B_{jptsx}\right)}{2 \times F\,max_{ps}} + d_F^- - d_F^+ = goal_F \qquad (24)$$

2. Subject to: constraints (2)–(12), (15), and (16-21)mentioned previously

3. Other constraints:

$$D_{jt} = \sum_{p=1}^{P}\sum_{x=1}^{ML}\left(A_{jt} \times \Pr_{jptx} \times W_{jptx} + OT_{jptx}\right) - N \times \sum_{p=1}^{P}\sum_{s=1}^{TS}\sum_{x=1}^{ML} B_{jptsx} \qquad \forall j,t \qquad (25)$$

$$N \times \sum_{s=1}^{TS}\left(TI_{jptsx} + B_{jptsx}\right) - N \times B_{jpt9x} = A_{jt} \times Pr_{jptx} \times W_{jptx} \qquad \forall j,p,t,x \qquad (26)$$

$$m \times \sum_{s=1}^{TS}\left(fra_{ps} \times TI_{jptsx}\right) - m \times \sum_{s=1}^{8}\left(\frac{fra_{ps}}{REC_{ps}} \times B_{jptsx}\right) - (m-1) \times \frac{fra_{p9}}{REC_{p9}} \times B_{jpt9x} \le F\,max_{ps} \qquad \forall j,p,t,x \qquad (27)$$

$$TI_{jptsx} \le MET_{ps} \times W_{jptx} \qquad \forall j,p,t,s,x \qquad (28)$$

$$TI_{jptsx} \le M \times WT_{jps} \qquad \forall j,p,t,s,x \qquad (29)$$

$$B_{jptsx} \le REC_{ps} \times TI_{jptsx} \qquad \forall j,p,t,s,x \qquad (30)$$

$$TI_{jptsx}, B_{jptsx}, d_B^-, d_B^+, d_F^-, d_F^+ \ge 0 \qquad \forall j,k,p,t,x,y \qquad (31)$$

The objective function aims to minimize: all costs incurred including worker hiring and firing, training costs and overtime costs, idle (unproductive) time, and the weighted average fatigue rate. The purpose of optimization is to minimize the deviations from specific goals based on the importance of each one. Constraints (22), (23), and (24) represent the cost goal, unproductive time goal and fatigue level goal constraints, respectively. Constraint (25) shows that the total regular time a worker spends on a task plus the total overtime hours are equal to the number of hours required for each skill in each period. Constraint (26) shows that the total regular time a worker spends on a task 1 to 9 plus the total breaks and interruptions during working day should not be greater than the available labour capacity. Constraint (27) ensures that the fatigue rate at the end of a period has to be less than the maximum fatigue load a worker can accumulate in any task. This equation is based on the assumption of having continuous static loading conditions.

Constraint (28) ensures that the processing time for any task cannot exceed the maximum endurance time for any individual performing that task. Constraint (29) states that the worker can perform any task if and only if the worker assignment to that task is possible. Constraint (30) ensures that the break time following any task is less than or equal to the recommended recovery duration for that task. It is assumed that the length of the break between tasks is not enough to result in full recovery. Finally, constraints (31) are the non-negativity constraints.

Goal programming can be used to solve the multi-objective functions. It provides a way of striving towards conflicting objectives simultaneously. The basic approach of goal programming is to establish a specific target for each of the objectives, formulate an objective function for each objective, and then seek a solution that minimizes the (weighted) sum of deviations of these objective functions from their targets. There are two methods for solving goal programs: the non-preemptive method (weights method) and the preemptive method. The weights methods form a single objective function consisting of the weighted sum of the goals, where all goals are roughly comparable of importance. On the other hand, the preemptive method organizes the goals one at a time starting with the highest priority goal and terminating with the lowest one without degrading the quality of a higher-priority goal (Hillier & Lieberman, 2010). In this research, the non-preemptive method can be used to solve the problem. The decision maker must determine penalty weights that reflect his preferences regarding the relative importance of each goal. For example, penalty weights equal to 1 signifies that all goal carry equal weights. The determination of the specific values of these weights is subjective. Different methods are developed to estimate the weights values (Tamiz et al., 1998; Cohon, 1978). The solution procedure considers one goal at a time, starting with the performance maximization goal, and terminating with the cost minimization goal. The process is carried out such that the solution obtained from a first goal never degrades the second solutions. However, weighted goal programming considers all goals simultaneously within a composite objective function comprising the sum of all deviational variables of the goals from their targets. One of the drawbacks of this method is the use of different units of deviational variables in an objective function where the sums of unwanted deviational variables are minimized. This different measurement unit may damage the relative importance of the objective to the decision maker or cause an unintentional bias towards the objectives with a larger magnitude (Tamiz et al., 1998). This problem can be solved by the use of a normalization procedure or simply using same unit for all deviational variables in the objective function. Different normalization techniques are suggested (De Kluyver, 1979; Jones, 1995; Masud & Hwang, 1981; Wildhelm, 1981). Therefore, the following steps can used to handle multi-objective functions:

1. Defining the LP1 as being the first linear programming model with an objective function: minimizing goal $_{c}$, LP2 is the second linear programming model with an objective function: minimizing goal $_{B}$, LP3 is the third linear programming model with an objective function: minimizing goal $_{F}$.
2. Identifying the goal values of each model in step 1 by solving the models LP1, LP2 and LP3, and adding these values to the right hand side of each objective function, as shown in constraints (22), (23), and (24), respectively.

3. Adding penalty weights in order to reflect the decision maker's preferences regarding the relative importance of each goal, such as to minimize total costs (goal C), its penalty weight is required to be multiplied by the amount over the costs target, which had been determined in step 2. Also, to minimize total breaks (goal B), its penalty costs needs to be multiplied by the amount over the breaks target, and so on.
4. Solving the combined objective function that minimizes the deviational variables. The latter represents all goals.

A normalization scheme technique is presented to scale all unwanted deviations on a 0-1 range. The value zero represents a deviation of zero and the value one represents the worst (highest) possible value of the deviation within the feasible set. The one value can be found by a single-objective maximization or minimization depending on the objective function. However, it is not possible to find this value when the objective function is unbounded. Table 5.1 illustrates the worst possible values of unwanted deviational variables.

Table 5.1: the Worst Possible of Deviational Variables

Unwanted Deviation	Maximum Value
d_C^+	703,236.4
d_B^+	5,728
d_F^+	18.5

This leads to the following objective function with the same set of constraints given previously.

$$OBJ = w_1 \times \left(\frac{d_C^+}{7032364} \right) + w_2 \times \left(\frac{d_B^+}{5728} \right) + w_3 \times \left(\frac{d_F^+}{18.5} \right)$$

Next section presented the resulting solution for the given problem.

5.3 Computational Results

In this section, the feasibility of applying the proposed method is demonstrated to assess the effect of workers' differences on the workforce schedule. Insights on the effect of various human factors on workforce scheduling decisions are presented. The sensitivity of decision parameters to the variations of relevant conditions based on the numerical example is tested to show the effects of fatigue level and personality levels on workforce decisions and performance.

5.3.1 Numerical Example

Model validation ensures that the model addresses the right problem, provides accurate information about the real system being modelled, and makes the model actually usable. In this section, a numerical example is given in order to demonstrate that the model generate reasonable results; we assume a company produces its products to fulfil known demand along an 8-days planning horizon. Also, it is assumed that the worker is available for 8 hours a day (160 hours per month) at regular time and for 2 hours a day (40 hours per month) at overtime. However, it is assumed that a worker is not productive during daily breaks and interruptions. Also, the maximum fatigue load a worker can accumulate in any task depends on the personality level. Many jobs require human effort, and some recovery allowance must be made from fatigue for relaxation. We assume that a worker with a high personality level and in top physical condition requires a smaller allowance to recover from fatigue than a low personality level worker. However, other factors such as the factors related to the nature of the work itself and the environment might affect the amount of relaxation allowances needed. Input data are shown in Tables D.1 to D.6 in Appendix D. Table D.6 shows the values of the maximum endurance time, fatigue fractions and the recovery rates for different workers. These values are estimated based on formulas which are adapted from Jaber and Neumann (2010). Using the input data presented, the model consists of 7846 variables and 13576 constraints and the optimal solution for the problem can be easily obtained using LINGO 13.0 software within one minute of program running.

Results from the model are shown in Table 5.2 and 5.3. In this research, many human factors such as workers' training, skills, overtime, workers' availabilities, workers' breaks, workers' personalities and workers' fatigue are considered to show their importance at the early planning stages. The results from the model offer staffing decisions on what, how and when to hire, fire and train. Also, the number of worker-hours during regular time and overtime and the number of hours during breaks workers can take are determined. The optimal plan is obtained based on the present input data; if the prioritization of the goals and initial settings are modified, the results are likely to be different. Figure 5.1 illustrates the learning curves for workers based on their skills and personalities. We can notice that workers with low skills and personalities need more time to reach their steady state since they are slow learners. But workers with high skills and high personality levels start with a relatively high initial productivity and reach their full productivity faster within the planning horizon.

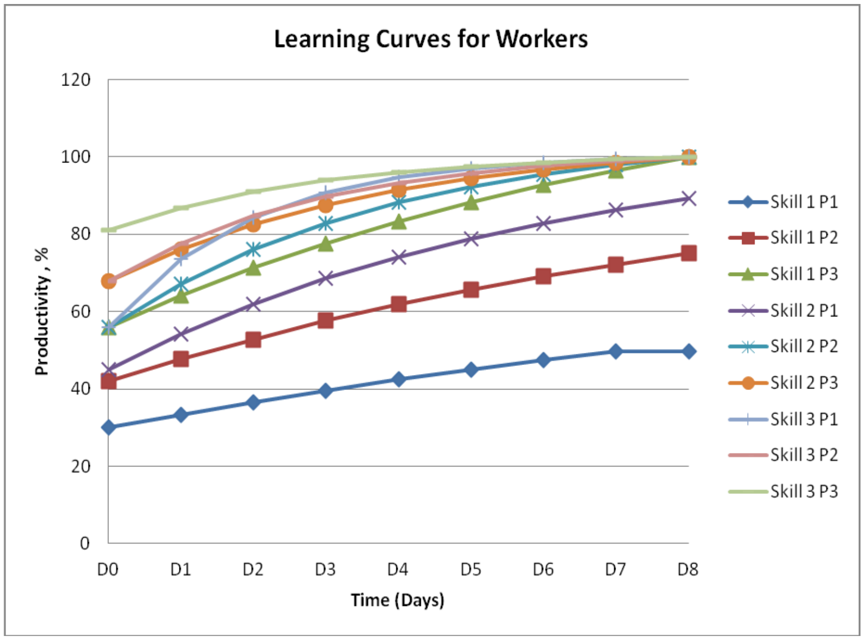

Figure 5.1: Learning Curves for each Worker Type

This research shows that workers' differences can be used to predict hiring, firing and training workers and total break time. Table 5.2 shows the number of workers hired, fired and trained in each period for different personality levels. Also, Table 5.3 shows the time workers spend on all the tasks to satisfy the demand and the amount of break they take due to the fatigue level for each worker. From Tables 5.2 and 5.3, it can be seen that the workers who are not working during regular time have no breaks. Also, we can notice from running the model with different objectives that a worker at higher personality level required less amount of break to recover than a worker with low personality level.

Most of the workers hired and trained have high personality level, which represents the normal scenario in practice. However, these results will be different when the company goals are changed, as shown in the next section.

Table 5.2: Resulting Daily Workforce Plan in Number of Workers

			D1	D2	D3	D4	D5	D6	D7	D8
		Demand (workers)	**40.0**	**20.0**	**40.0**	**40.0**	**40.0**	**40.0**	**40.0**	**40.0**
Worker Skill 1	P1	Workers used on level 1	12.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Workers hired on level 1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Workers fired from level 1	27.9	12.1	0.0	0.0	0.0	0.0	0.0	0.0
		Workers trained to level 2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Productivity, %	33.4	36.6	39.6	42.4	45	47.4	49.7	51.7
	P2	Workers used on level 1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Workers hired on level 1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Workers fired from level 1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Workers trained to level 2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Productivity, %	47.7	52.8	57.6	61.8	65.6	69.1	72.2	75
	P3	Workers used on level 1	43.6	33.6	44.5	44.5	40.6	40.6	38.0	37.1
		Workers hired on level 1	43.6	0.0	10.9	0.0	3.4	0.0	22.9	17.2
		Workers fired from level 1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Workers trained to Level 2	10.0	10.0	0.0	0.0	7.4	0.0	25.4	18.2
		Productivity, %	64.2	71.4	77.7	83.3	88.3	92.7	96.6	99.9
		Demand (workers)	**50.0**	**40.0**	**40.0**	**40.0**	**50.0**	**20.0**	**40.0**	**60.0**
Worker Skill 2	P1	Workers used on level 1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Workers used on level 2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Workers hired on level 1&2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Workers fired from level 1&2	30.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Workers trained to level 3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Productivity, %	54.2	62.0	68.6	74.2	78.9	82.9	86.3	89.2
	P2	Workers used on level 1	0.0	0.0	0.0	0.0	0.0	0.0	20.8	20.8
		Workers used on level 2	20.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Workers hired on level 1&2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Workers fired from level 1&2	20.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Workers trained to level 3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Productivity, %	67.2	76.0	82.8	88.2	92.3	95.5	98.0	99.9
	P3	Workers used on level 1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Workers used on level 2	40.4	42.6	40.8	40.8	48.3	24.9	37.4	55.6
		Workers hired on level 1&2	30.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Workers fired from level 1&2	0.0	0.0	1.8	0.0	0.0	23.4	0.0	0.0
		Workers trained to level 3	10.0	7.7	0.0	0.0	0.0	0.0	12.8	0.0
		Productivity, %	76.2	82.6	87.5	91.4	94.4	96.7	98.6	99.9
		Demand (workers)	**50.0**	**60.0**	**60.0**	**60.0**	**40.0**	**20.0**	**40.0**	**40.0**
Worker Skill 3	P1	Workers used on level 1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Workers used on level 2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Workers used on level 3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Workers hired on level 1,2&3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Workers fired from level 1&2&3	30.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Productivity, %	73.6	84.3	90.8	94.7	97.1	98.6	99.4	99.9
	P2	Workers used on level 1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Workers used on level 2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Workers used on level 3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Workers hired on level 1,2&3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Workers fired from level 1&2&3	30.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Productivity, %	77.7	84.7	89.7	93.3	95.8	97.7	98.9	99.9
	P3	Workers used on level 1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Workers used on level 2	31.6	31.6	31.6	31.6	31.6	24.2	24.2	24.1
		Workers used on level 3	20.0	27.7	26.2	25.2	5.8	0.0	12.8	12.8
		Workers hired on level 1,2&3	31.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Workers fired from level 1&2&3	0.0	0.0	1.5	0.9	19.4	13.2	0.0	0.1
		Productivity, %	86.8	90.9	93.9	96.0	97.5	98.6	99.4	99.9

Table 5.3: Resulting Daily Workforce Plan in Worker-hours

			D1	D2	D3	D4	D5	D6	D7	D8
		Demand (hours)	**320.0**	**160.0**	**320.0**	**320.0**	**320.0**	**320.0**	**320.0**	**320.0**
Worker Skill 1	P1	Regular time on level 1	21.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Breaks 1	10.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Overtime hours	24.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	P2	Regular time on level 1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Breaks 1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Overtime hours	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	P3	Regular time on level 1	186.8	160.0	230.9	247.6	238.9	250.7	244.0	245.8
		Breaks 1	37.4	32.0	46.2	49.5	47.8	50.1	49.5	50.6
		Overtime hours	87.3	0.0	89.1	72.4	81.1	69.2	76.0	74.1
		Demand (hours)	**400.0**	**320.0**	**320.0**	**320.0**	**400.0**	**160.0**	**320.0**	**480.0**
Worker Skill 2	P1	Regular time on level 1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Regular time on level 2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Breaks 1&2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Overtime hours	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	P2	Regular time on level 1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Regular time on level 2	28.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Breaks 1&2	33.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Overtime hours	40.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	P3	Regular time on level 1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Regular time on level 2	205.0	234.7	238.3	248.8	303.5	160.0	245.1	368.8
		Breaks 1&2	41.0	46.9	47.7	49.8	61.0	32.5	50.2	75.75
		Overtime hours	80.7	85.3	81.7	71.2	96.5	0.0	74.9	111.2
		Demand (hours)	**400.0**	**480.0**	**480.0**	**480.0**	**320.0**	**160.0**	**320.0**	**320.0**
Worker Skill 3	P1	Regular time on level 1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Regular time on level 2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Regular time on level 3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Breaks 1&2&3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Overtime hours	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	P2	Regular time on level 1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Regular time on level 2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Regular time on level 3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Breaks 1&2&3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Overtime hours	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	P3	Regular time on level 1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Regular time on level 2	181.0	193.1	200.3	204.8	207.5	160.0	160.7	160.4
		Regular time on level 3	115.7	168.2	163.9	161.5	37.6	0.0	85.2	85.7
		Breaks 1&2&3	59.3	72.2	72.8	73.2	49.0	49.1	49.1	49.2
		Overtime hours	103.2	118.7	115.6	113.6	74.8	0.0	74.1	73.8

5.4 Model Implementation and Results Analysis

All workers have the right to take breaks. The actual amount of break a worker receives is usually set out in his contract of employment. Although there are some kinds of jobs that do not allow workers to take breaks such as air or sea transport and working part time during busy peak periods, not taking a break can result in overloaded, stressed, and unproductive workers. Rest breaks are one of break types that workers can take under special rules written in the employment contact. This model can help to estimate the amount of break a worker can take during a working day in order to minimize the risk caused by worker fatigue. In the previous section, a simple numerical example is given to illustrate the performance of the model. In this section, we will study the effects of fatigue level and worker differences on workforce decisions.

Table 5.4 shows a comparison between the different cases with different goals. Also, it shows a comparison between two cases; the first one represents the case where fatigue level is different and the second one represents the case where the fatigue level is the same and very small. However, considering human differences that exist between workers results in more accurate workforce decisions. In the second case, it is assumed that human fatigue is ignored, and the fractions of maximum workers' capability are set to be close to 0. This fraction can be used to determine the values of maximum endurance time, recovery rate and maximum fatigue. Also, it is assumed that the decision maker is looking to achieve two goals; costs minimization and idle time minimization.

Table 5.4 illustrates the comparisons between two different cases regarding the importance of considering fatigue level differences between workers to generate a better solution. The total cost when the fatigue level is not considered in the model for all workers is \$271,957.3, but when we consider different fatigue levels between workers, the total cost is \$244,799.7. The results show that by considering fatigue levels in the model there is a cost reduction of 10.0%. Also, we can see when we consider fatigue level differences between workers, we can use fewer workers and still the total demand is satisfied within a good performance and fatigue level depending on the input data provided.

Table 5.4: Comparisons between the Different Goals

Total	Goal 1	Goal 2	Goal 3	Equal weights (Different fatigue)	Equal weights (No fatigue)
Objective Value	**234,570.6**	**1151.9**	**0.0**	**0.024**	**0.29**
Demand (W^c.days)	**8,080.0**	**8,080.0**	**8,080.0**	**8,080.0**	**8,080.0**
Regular Time (hrs)	6,379.7	6046.2	8,080.0	6,194.5	5,315.5
Overtime (hrs)	1,700.3	2033.7	0.0	1,885.5	2764.5
Breaks (W.hrs)	1973.8	1151.9	3210.6	1,206.9	2,657.7
Workers (W.days)	1203.9	1,016.9	1,758.9	1,042.7	1,382.2
Training (W.days)	72.2	2.4	137.6	102.0	129.7.9
Hiring (W.days)	73.9	287.8	1177	158.8	123.8
Firing (W.days)	120.4	338.8	1096.77	209.7	144.5
Fatigue (% .hr)	53.1	72.0	0.0	71.8	0.0
Costs (\$)	**234,570.6**	**279,235.8**	**515,202.8**	**244,799.7**	**271,957.3**

^{c} W represents Worker

Based on the cost comparisons, even though there is costs reduction from incorporating fatigue rate into workforce scheduling, the present study does not provide enough information about the effects of fatigue on scheduling day workers. Basically, the costs reductions come from the fact that constraint (28) defined the relationship between the maximum endurance time (MET) and workers hours required which restrict the number of workers that can used. For example, if we have very high MET values which represent the case of no fatigue, then there is more flexibility to use more workers in the model which increase the total costs. On the other hand, Constraint (30) can lead to an increased cost when we have high recovery rates, which allow the workers to take more breaks than it is needed. In conclusion, this result needs more investigations by conducting some experiments on the effects of changing the model parameters on the model output. The next section studies the effects of different fatigue parameters on the scheduling decisions. However, this model helps to determine the amount of the break workers can take depending on his personality and salaries profiles. Further research should be done on the effects of the fatigue on worker scheduling with different shifts. Moreover, if the initial number of workers is changed, the number of hired, fired or trained workers is changed which will change the total costs. Also, in Table 5.4, we can notice that the company can use this model in the planning process by selecting the specific goals based on its policy and budget. For example, we can assign a target value for each goal so that we can determine the number of workers needed in each period to satisfy the demand without exceeding the predefined goals.

5.5 Sensitivity Analysis

Realistic mixed integer non-linear programming models require large amounts of data. Accurate data are expensive to collect, so we will generally be forced to use data in which we have less than complete confidence. This section discusses the actual implementation of the proposed model by manipulating different alternatives and analyzing the sensitivity of decision parameters to the variation of relevant conditions, based on the preceding numerical example.

5.5.1 Implications Regarding Different Model Goals

A user of a model should be concerned with how the recommendations of the model are altered by changes in the input data. Table 5.5 illustrates the comparisons between different scenario problems and the effects of changing the weights of the company goals on the total costs and utilization of the work. In this table, we implement 10 scenarios to compare between the final results in terms of workers' utilization, workers' fatigue, and the total costs. The worker utilization is calculated by dividing the total productive time for all the workers by the total available hours. Worker break percentages represent the amount of break workers can take in average during a working day. Also, workers' fatigue represents the total physical load on the workforce during a working day. We change each scenario by changing the weights of the unwanted deviational variables in the objective function to show its effects on the final objective value. For example, in scenario 1, all goals have the same importance in the objective function.

Table 5.5: Weight Sensitivity Analysis

Goal #	W1	W2	W3	Obj. value	Utilization	Fatigue	Costs ($)
1	0.333	0.333	0.333	0.012	73.9%	0.0	246,401.9
2	0.994	0.003	0.003	0.002	65.8%	16.2	235,2448.7
3	0.003	0.994	0.003	0.0031	74.3%	72.0	263,763.0
4	0.003	0.003	0.994	0.0001	73.9%	0.0	246,401.9
5	0.495	0.495	0.01	0.017	74.2%	15.7	245,734.9
6	0.01	0.495	0.495	0.0057	74.2%	0.0	258,746.2
7	0.495	0.01	0.495	0.002	66.3%	0.0	235,923.5

In the weighted goal programming method, we can use a set of preference weights assigned to the penalisation of unwanted deviations to provide solutions that are of practical use to the problem owner. In this weight space analysis, it is assumed that all weighting vectors have been normalized and hence sum to one. Note that in practice the weight of an unwanted deviational variable has to be greater than zero to avoid the possibility of generating Pareto-inefficient solutions. Tamiz and Jones (1996) defined Pareto inefficiency as an objective that can be improved without worsening the value of any other objective. Therefore, a small weight (e.g. 0.005) is suggested to replace a zero weight. Heuristic method and sensitivity analysis are developed to find the weight values in the weighting space (Jones & Tamiz, 2010).

By comparing scenario 1 through 10, we can see that if we add more weight to the cost goal, the total costs are decreased. Also, the total fatigue of the workers will be increased if more weight is added to the breaks minimization goal. However, increasing the physical load of the workers may not be desirable due to desired quality levels or occupational health and safety issues. Therefore, the determination of the weight values is a process of interaction with the decision maker(s). By doing this sensitivity analysis we can find the solution that fit with any company requirements. For example, scenarios 3, 5 and 6 give a relatively high value of utilization compared to the other scenarios (e.g. scenario 2). This means that putting more weight on idle time minimization and performance maximization (e.g. by motivating employees) simultaneously can increases workforce efficiency. So the company can choose which scenario is best based on its policies and rules. However, sensitivity analysis can reveal which pieces of information should be estimated most carefully.

5.5.2 Impact of Different Loading Levels on the planning Decisions

One assumption of linear and non-linear programming is that all the parameters of the model are known constants. Actually, the parameter values used in the model are just estimates based on a prediction of future conditions. Sensitivity analysis investigates the changes to the optimal solution of a model as the result of changes in input data.

In this section, some input parameters are studied; recovery allowance, maximum fatigue and maximum endurance time. However, all of these parameters depend on the fractions of the maximum load capabilities of the workers. Table E.1 in Appendix E shows the scenarios with different load levels, recovery rates and maximum fatigue levels. So, the three scenarios will be studied based on different load levels. In this experiment, there are two stages in solving the model. The first stage is to solve the model by maximizing the workers' performance. The second stage is solving the model by minimizing the total costs based on the first stage output. For simplicity, we use the output productivities for every worker type in the first stage. By using this methodology, we change the model from a nonlinear model to a linear one so that the execution time will be significantly reduced. Three scenarios are discussed. In the first scenario, the lower personality workers recover faster than higher personality level workers. Scenario 2 is the same as the previous scenarios except all workers have the same fraction levels equal to 0.5. Scenario 3 assumes that the load levels are increasing as the personality levels are increasing. Table 5.6 illustrates these different scenarios showing the costs, utilization and total fatigue for each scenario.

Table 5.6: Three Scenarios with Different Loading Levels

Scenario	Fraction	Fatigue	Utilization (%)	Costs ($)
1	Decreasing	74.6	55.7	252,342.9
2	Constant	71.2	54.1	253,140.4
3	Increasing	76.5	55.7	251,828.7

In this experiment, we assume that the company is concerned solely on the minimization of the total costs incurred. So the effects of other goals are eliminated from the model to compare the results from one perspective. Figures 5.2 and 5.3 show the number of workers hired, and trained respectively. The results show the differences in fatigue fractions between the three scenarios do not greatly affect the total costs. However, scenario 3 performs better in terms of costs and fatigue levels. Also, we can notice that the high costs in scenario 2 come from ignoring the differences between in workers in their fatigue levels. The main reason for not having a big a difference in the results is that the suggested fatigue input parameters are close and the differences are minimal.

This experiment clarifies that fatigue is not significantly important for scheduling day workers from the economics perspective, but it helps to determine the amount of break that workers can take depending on their personal and salaries profiles. Figures 5.2 and 5.3 illustrate the number of workers hired and trained for different workload scenarios, respectively. We can see that the workforce decisions are almost the same even though fatigue information is different.

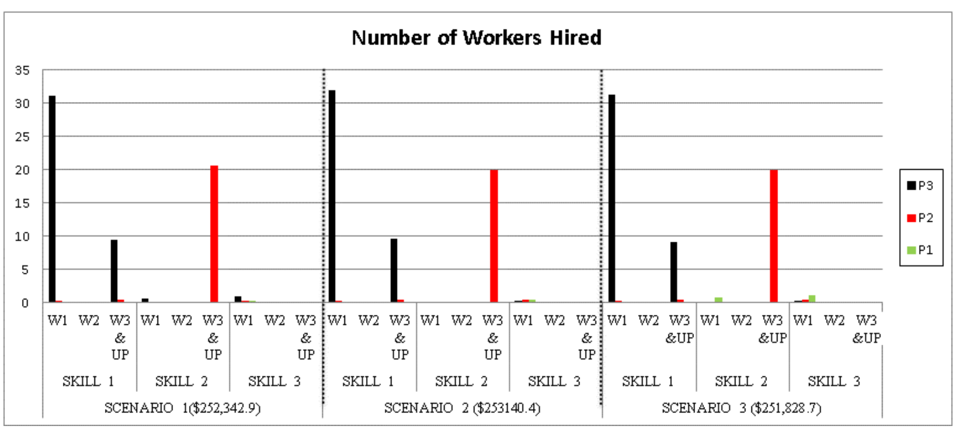

Figure 5.2: Number of Workers Hired for Different Workload Scenarios

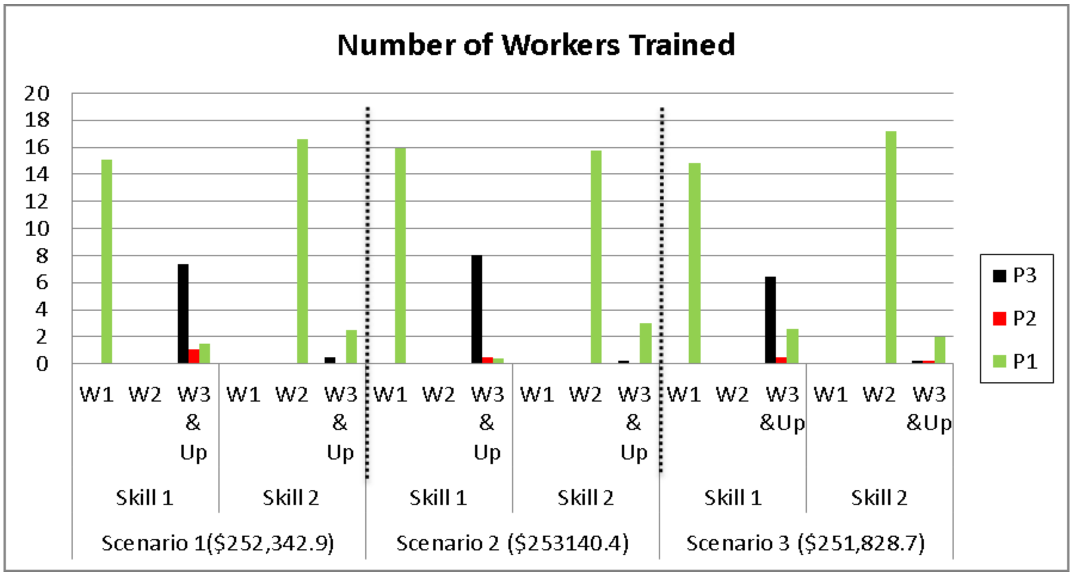

Figure 5.3: Number of Workers Trained for Different Workload Scenarios

5.6 Chapter Summary

In chapter 5, some extensions are brought to model A with a view to incorporate more human factors in the planning process. Model B is thus formulated to integrate fatigue and recovery rates in workforce planning framework. Several problems have been solved through the mixed integer non-linear program B using global solver supported by LINGO 13.0 software. The solutions obtained demonstrate that fatigue rate and recovery rates can be integrated in the model to reduce the costs and increase utilization. The results show that if the workforce scheduling model considers human factors such as personality, worker recovery rate, and worker fatigue rate, we may be able to make better decisions regarding production and employees. For instance, by using a plan that considers the worker's skills and personality, the decision of assigning the right worker to a right machine level will be made without the need to modify the scheduling process every period so that the total cost and time will be reduced. However, sensitivity analysis shows that there are some important parameters that a company should pay more attention to since any changes in these parameters can greatly affect the generated schedule. These parameters are demand values, cost coefficients, and initial number of workers. On the other hand, other fatigue parameters such as maximum endurance time, maximum fatigue, and recovery rates, which depend on the fraction of the maximum worker capability, have little effect on the fatigue index. But, this study shows that we can have better workforce schedule when we have different fatigue information. More precisely, it is recommended to assign workers with different load levels in order to attain better system performance. By using this model, managers can choose among different scenarios that fit within their plans and budget. Also, they can use scenarios' analysis to predict the behaviour of the model when the input data are changed. Finally, further research is also needed using more realistic fatigue-recovery models in generating the workforce schedule since we assumed that these models are linear in this preliminary model. Also, real-world applications need to be applied to validate and support the generated results.

CHAPTER 6 DECISION SUPPORT SYSTEM FOR ROBUST WORKFORCE PLANNING

This chapter describes the development of a decision support system (DSS) to assist the workforce planning for job-shop production planning. The prototype system determines the optimum worker-hours required to satisfy the demand requirements by considering human aspects such as skills, learning, personality, capacity, motivation, and training. A unifying model, based on goal programming, was employed to solve the workforce planning issues involved in reaching the optimal workforce schedule. The developed prototype decision support system interfaces with LINGO 13.0 via Excel software in a Microsoft Windows environment. This DSS provides a valuable decision maker tool for production planning under different circumstances.

6.1 Design of an Interactive DSS

A standard framework of a decision support system consists of many components. The important key components are a database, a model base and an interactive user interface. First, the database typically requires external and internal data input. One can get most of the benefits of using LINGO in conjunction with Excel spreadsheets. Excel has built it tools to help a user to keep track of data and to find specific information when he wants it. Various salaries, hiring, firing and training costs, objective weights, and personal profiles data are stored in excel worksheets. The outputs can be generated in well-designed reports or additional files. Second, the model base composed of the different LINGO models that can solve the required problem based on the input data given by the user. A small hidden Visual Basic for Applications (VBA) program is implemented in the spreadsheet to solve the required LINGO model. Finally, Excel contains many user form objects that make up part of an application's user interface. These forms can be used as a tool to enter the input data into the spreadsheet files and integrated with LINGO to find the optimal solution. Since the interaction with the LINGO module was a major aspect of the DSS, it is worthwhile to provide some details to explain this technical matter. Appendix F provides a sample LINGO command script that is used embedded in excel worksheets and another sample of Excel Visual Basic macro to solve the model.

This application tool is developed to help the decision maker to create a realistic workforce schedule based on some given input data. In a multi-criteria decision making context, the decision maker has to study every possible scenario based on different input options to generate measurable outputs. In practice, mathematical programming is considered a powerful tool to assist in the process of searching for decisions which best conflicting objectives. In chapter 4, model A that aims minimize the total costs is developed. Upon studying the properties of the presented mathematical model, it turned out that such model is not easily solvable within a reasonable amount of computational time, when it contains nonlinear terms. Although the current model is not considered as a big size problem, but typically, MINLPs are not readily solvable using off-the-shelf optimization packages. So to help the decision maker find a solution for a certain scenario within a reasonable amount of time, a solution methodology that can solve any given problem effectively is presented. Figure 6.1 shows the flow chart for the proposed methodology for solving Model A.

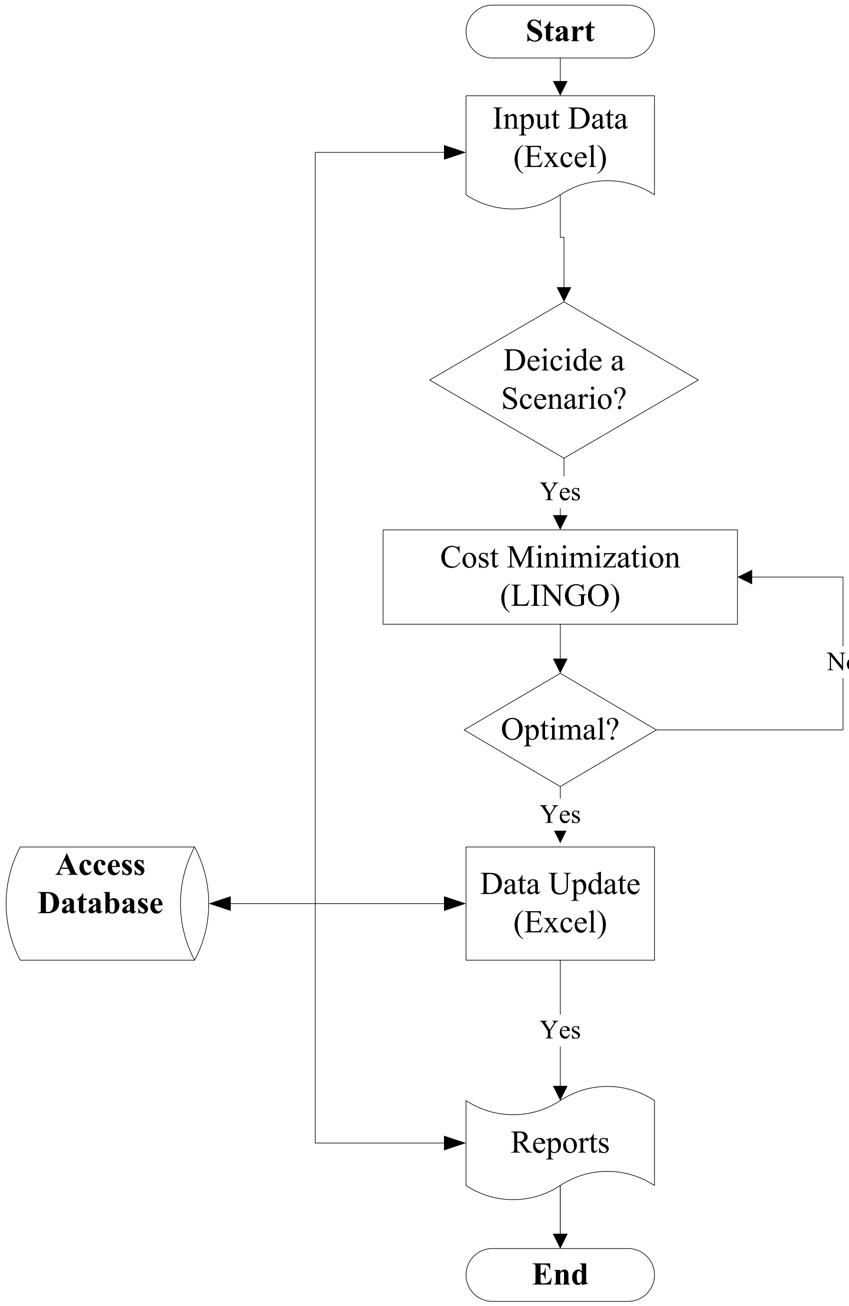

Figure 6.1: Flow Chart Showing Running the Model A

6.2 A Decision Support System Description

In this chapter, a decision support system to solve this problem based on the Linear Programming solver LINGO 13.0 is presented. First, a system user has to enter the historical demand in each period, e.g. 8 periods. Then, hiring, firing, training costs, regular and overtime salary must be input. Also, working opportunity and workers capacities and willingness are entered to the database. Figure 6.2 shows the presentation menu for the input data for an 8 weeks planning periods problem. The user will then have different scenarios to choose from. The program includes “switches” to turn features on or off, yes or no (1 is on/yes, 0 is off/no) to make selections among training, salary, objective function and overtime options as shown in Figure 6.3. The effect of these switches is that we change the constraints in the actual LINGO model. Also, it is important that the user starts to solve the problem with a first priority goal and then solve the other problem to identify the values of the objective functions that the company wants to achieve. Then, one can solve the combined problem by assigning weights to the coefficients of the deviations based on the company concern.

It can be cumbersome and impractical to try to maintain workforce data in a LINGO model file. For this reason, LINGO program is linked to Excel through real-time Object Linking and Embedding (OLE) feature. OLE automation links can be used to drive LINGO from Excel macros, and embedded OLE links that allow you to import the functionality of LINGO into Excel. The computerized DSS presented herein makes the model an extremely useful problem-solving tool for managers. The system has been designed to have an efficient interface with Excel, so the user can import input data directly from the organization’s database and export the output of the model to another database in the organization.

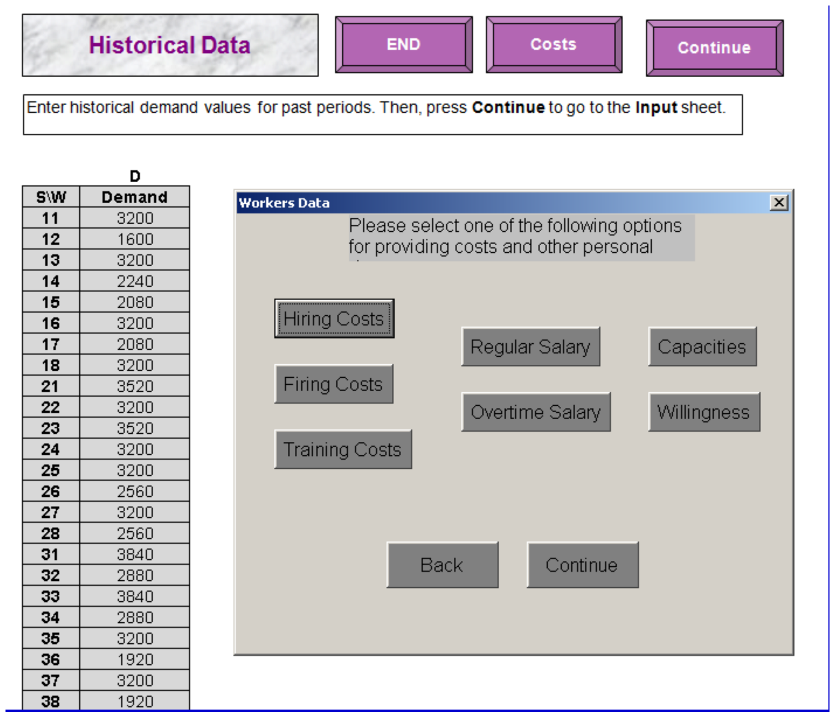

Figure 6.2: Presentation Menu

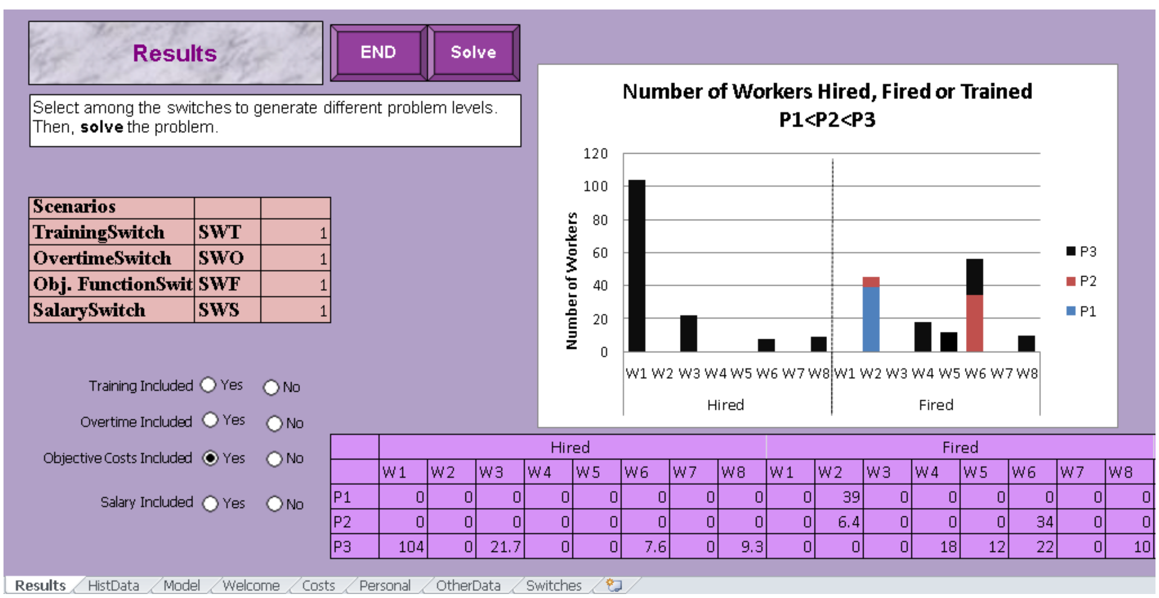

Figure 6.3: Generated Results Menu

In order to solve any given problem, the user has to go through three phases. During the first phase, the user enters the necessary input data for solving model, such as hiring, firing, training costs, regular and overtime salaries, and the estimated human attributes, as shown in Figure 6.2. This can be done through a user form designed for a user convenience. The entered data are stored directly in an Excel worksheet to be used as an input section for the LINGO program. In the second stage, the user can add or remove some options such as training and overtime from the original model by assigning 0 or 1 to each one, as shown in Figure 6.3. The switches options provide the manager the advantage of conducting "what-if type" analyses to determine if the solutions are sensitive to different parameter values of a given problem. In the third stage, the user needs to assign different weights to each goal based on the company policies and rules and then solve the model to generate the results that show how many workers hired, fired or trained for each personal level in each period. The results help the user to evaluate and compare various alternatives and decisions by considering different human aspects in a workforce planning problem. Finally, interfacing the LINGO model with Excel provides an efficient methodology to store a huge number of input data so that the proposed DSS can solve very large problems.

For practicing managers without the necessary mathematical knowledge on workforce planning models, finding an analytical solution to the proposed model can be quite challenging. However, the computerized DSS presented here makes the model a relatively easy to use problem-solving tool for such managers. The purpose of the DSS is to help managers, the intended users, obtain “the best solution” for a given problem without having to familiarize themselves with the mathematical complexities associated with the model. These findings provide motivation towards making the proposed model represent the current production systems in industrial companies.

CHAPTER 7 CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

7.1 Summary

In this thesis, a new approach for integrating human factors with production planning is proposed. A model was used to test configurations and evaluate their effects on the organizations' goals. This model can take into account human aspects to plan the production activities so that the customers' satisfaction will be achieved with minimum cost. Also, variations in human performance will be considered to ensure the applicability of the model. Some experimental designs can be conducted in order to test the influence of different human, technological and organizational aspects on the production planning process.

The research has demonstrated the importance of considering human factors within production planning models of manufacturing systems. It is one of the attempts to bridge the gap between the theory and practice of workforce production planning models. By considering the technical and human factors, the proposed model can be used as a tool to support real-world decision-making process in a manufacturing system.

7.2 Thesis Contributions and Major Findings

The importance of this research is its contribution to the production planning problem by incorporating the human as being an integral part of the production system to represent the actual situation inside organizations. Furthermore, this research will provide the company's management with a clear understanding of how to integrate the human factors into production planning for better performance of production systems. Also, this research is one of the first attempts to bridge the gap between the production planning and human factors literatures. The contributions of this research lie in developing:

- A workforce planning framework to show the diverse human factors inherent in production planning
- Two simplified mathematical models that, for the first time, consider a number of human aspects such as personality, capacity, motivation, fatigue rate, recovery rates and breaks together to order to plan the production activities and to reduce the costs.
- A decision support system to enhance the application of the workforce planning model into practice.

The research presented in this thesis has been classified into three parts where each part tackles a certain aspect of the production planning problem. The first part presents a new approach to the workforce planning problem and has made the following contributions:

- **A New Workforce Planning Approach:** The workforce planning problem has been discussed widely in the literature. Hence, before attempting to tackle the problem, the related literature concerning production planning has been classified based on their distinguishing characteristics. In particular, the contributions made by researchers to production planning from human factors perspectives have been highlighted. We also pointed out the importance of incorporating human elements in the planning process. The author's survey of literature did not identify any study that incorporated HF such as personality, capacity, skill, training, learning, fatigue, productivity and motivation together into workforce planning. The specific contribution of this research is the development of a theoretical workforce planning framework for incorporating the aforementioned human factors (personality, capacity, skill, training, learning, fatigue, productivity and motivation) in production planning. This will help production planners in research, education and practice to understand how to incorporate these different human factors in production planning.

- **Mathematical Modeling:** The optimized workforce schedule is obtained through the development of a mixed integer nonlinear program (MINLP) that addresses the problem under static demand conditions. However, our review showed that individual methods published recently addressed only limited subsets of HF. To this end, the novelty of this model is that it jointly accounts for the distinguishing features associated with the manufacturing process of many companies including personality, capacity, motivation, learning curve, fatigue rate, overtime, training, workers skill levels and machine levels. The objective of the model is to provide insights into the effect of human factors on the planning decisions. Numerical examples using small size problems, all solved by LINGO, were presented to demonstrate the model and its potential benefits. The relative importance of the HF can easily be modified by adjusting their corresponding weight factors. The model considers the effect of motivation on workers' productivity, effects of fatigue and recovery rates on availability and effects of workers differences on final output schedule. This model highlights the importance of incorporating human factors in the planning process since it reduces the total costs.
- **Hiring, Firing, Overtime and Training:** different experiments are conducted to study the effects of hiring, firing, training and overtime on planning decisions. This study shows that if we consider more options, such as overtime and training within

workforce planning, and incorporate different skill levels and machine levels we may have flexible workforce plans with minimum costs. Specifically, the model results show that:

- Training workers is more cost effective, and thus reduce total cost, if the cost of hiring and firing is comparatively high.
- Allowing workers to work overtime shifts will reduce the total costs especially when the cost of hiring and training new workers are high.
- The experiments illustrate that if the model considers overtime and training within workforce planning, we may be able to make better and effective decisions regarding human resource actions, such as, how many should be hired, fired or trained.

In the second part of this research, we introduce the individual differences into workforce planning. Personality, fatigue, recovery, motivation and learning rates are incorporated in the model in order to account for impact of worker differences in the planning decisions which results in the following contributions:

- **Personality and Motivation Factors:** Developing the workforce schedule on a rolling horizon basis, where workers are considered identical generates unrealistic results which can be hard to implement in practice. As a remedy to this issue, we proposed a workforce model that considers personality traits to measure the individual differences. The results from the optimization model provided answers to when, where, and whom to hire, train, or fire workers. The model was used to study the impact of various factors such as personality levels and initial number of workers on workforce decisions. In general terms, the experiments illustrate that if more information about workers is known, we may be able to make better decisions regarding workers schedule which result in substantial savings in cost. Specifically, the model results show that:

- The highest personality level workers are more attractive for hiring and training decisions
- Incorporating worker differences in terms of personality and motivation in the planning process reduces the total costs
- Firing workers effects the exiting workers motivation, which means it realistic to adjust the motivation factor for these workers right after the layoff period.

- **Fatigue and Recovery Rate:** Most previous applications of the workforce planning approach have assumed that workers can work same as machines. Fatigue affects workers' productivity and lead to increase the costs. In this thesis, the impact of some fatigue parameters such as maximum endurance time, recovery rates, and maximum fatigue on the scheduling process are studied. Specifically, the model results show that:

  - Fatigue rate and recovery rates can be integrated in production planning model to reduce the costs and increase utilization.
  - The amount of break that workers can take may be determined depending on their personal and salaries profiles
  - The assignment of workers with different load levels is recommended in order to attain better system performance.

- **Learning Rate:** Generally, most of the models developed to solve workforce planning problem assume constant productivity throughout the planning horizon. This research includes more realistic assumptions regarding productivity and learning rates. Two models that may aid in understanding of productivity and flexibility in workforce planning are presented. The models incorporate the effects of individual worker learning for workforce scheduling. The effects of some model parameters such as initial number of workers, demand values, and costs coefficients on the workforce scheduling decisions are studied. This research shows the importance of including the learning rates in the scheduling to reduce the costs and improve the performance. Specifically, the model results show that:

  - Considering workers with different Learning rates generates results close to the ideal case (100% productivity) of working environment.

  - Individuals with high rates in motivation and personality factors are selected for hiring because these factors have a significant effect on worker's productivity and total costs.

The last part of this research is directed towards developing a decision support system of workforce planning, resulting in the following contribution:

- **Robust Workforce Planning:** In practice, robust workforce plans need complete data and information. Not only have we combined the approaches of workforce planning and HF into the same mathematical model, but we also presented a Decision Support System that calls for the implementation of these approaches in order to handle changes that appear in the collected data. Specifically, the DSS allows the user to:

  - Easily input the data

- Study the effect of different weight to each goal based on company policies
- Study various possible scenarios to generate realistic schedules.
- Add or remove any constraints to incorporate human factors with other manufacturing parameters.

7.3 Future Work

This section identifies the direction that this research should take to support the progress of research in the production planning area. It is clear that human factors and production planning integration have much more research opportunities, and the path is still open to making the proposed model more comprehensive in a way that it considers other human factors such as worker experience, and worker communication, which can be a promising area of work for future research. For example, labour wages can be a function of time and experience, which reflects the current systems that management uses in different companies.

On the other hand, solving the proposed model for large-scale problems using a mathematical programming solver such as LINGO seems to be a difficult job and time consuming. Developing a fast and efficient solving methodology such as heuristics or simulation in order to get near-optimal results within a reasonable time can be a good subject for future research. However, typical simulation software does not consider worker differences and human behaviour in its algorithm, which means the simulation program should be developed based on the detailed theoretical production planning framework. Moreover, implementing heuristic search such as genetic algorithms, simulated annealing, and tabu search, have proven successful in obtaining "good quality" solutions to various combinatorial optimization problems within reasonable amount of computational time. Hence, the implementation of these heuristics methods is an area to be tested furthermore.

Additionally, other extensions to this research could include more specific cases regarding fatigue and worker productivity. The model could be extended to include nonlinearity in fatigue accumulations and recovery curves. Also, the level of fatigue such as physical fatigue at the level of the whole body, or at a specific body joint should be understood. However, this model could include forgetting effects that occur when workers move among different machine levels. These human factors and their relationships to learning process require deep investigations.

In this research all model objective functions, parameters, and decision variables are deterministic, which does not reflect the real situation in a manufacturing system. Thus, decision-making variables, coefficients, constraints and resources values should consider the uncertainties inherent in the production planning process. In practice, firms might face imprecision/fuzziness phenomena which need to be accounted for in the planning process. Also, further research should address uncertainties associated with the demand and the production capacity in the same model. Stochastic programming could be used to solve models considered uncertain demand. Therefore, developing a decision support system that will help managers to solve the model in the context of uncertainty of demand and cost parameters requires further investigation.

Finally, another way of extending the proposed model would be finding ways to incorporate new objective functions in the model so that many objectives can be achieved. Developing multi-objective production planning models where, in addition to cost minimization, performance maximization or idle time minimization, other performance measures such as and staff turnover rate minimization or error rate minimization are also optimized. This allows for the attainment of a compromise solution that satisfies all of the performance measures to the best possible extent. In practical production planning systems, multiple possibly conflicting objective functions should be considered taking into account interactions between human factors to make the plan work in real life.

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APPENDIX A: LINGO 13.0 PROGRAM

```
MODEL:
SETS:
!For our problem we choose these numbers to make a demonstration model;
    ! Eight planning periods (T);
    PERIOD / 1..8 /;
    ! Three human skill level (S);
    SKILLA / 1..3 /;
    SKILLB / 1..3 /;
    ! Three levels of worker personality(P);
    PES / 1..3 /:Fmax;
    ! Nine Tasks levels(S);
    TASK / 1..9 /;
    ! Three machine levels (L);
    MACHINE_L1 / 1..3 /:O;
    MACHINE_L2 / 1..3 /;
    ! Deviations (D);
    DEV / 1..6/;

DEVIATION(DEV):DE;
WORKER_NUM0 (SKILLA,PERIOD):D,AV,AOT;
HUMAN_SKILL(SKILLA,PES):WSP,C;
MACHINE_L(PES,MACHINE_L1);
PER_L(PES,TASK,MACHINE_L1);
HUMAN_TASK(SKILLA,PES,TASK):WT1;
WORKER_NUM1 (SKILLA,PES,PERIOD):H,F,S3,S4;
TRAINING_COST (SKILLB,SKILLA,PES,PERIOD):TR;
TRAINING (SKILLB,SKILLA):SS;
HUMAN_MACHINE (SKILLA,PES,MACHINE_L1):E,WS,INW,LE,WI,INP;
HUMAN_MACHINE2 (SKILLB,MACHINE_L2):;
HUMAN_MACHINE3 (SKILLB,PES,MACHINE_L2):WS3;
WORKER_NUM (SKILLA,PES,PERIOD,
MACHINE_L1):V,PR,OP,NW,NH,NL,OT,Z,U;
WORKER_NUM6 (SKILLB,PES,PERIOD, MACHINE_L2):NL2;
WORKER_TR (SKILLA,SKILLB,PES,PERIOD, MACHINE_L1,MACHINE_L2);
WORKER_TR1 (SKILLB,SKILLA,PES,PERIOD, MACHINE_L2,MACHINE_L1):Y;
RECOVER(PES,TASK):A,REC, FRA,MET;
FATIGUE_HUMAN(SKILLA,PES,PERIOD,TASK, MACHINE_L1):B,TI;

ENDSETS

! Objective functions minimize cost;

MIN=(1/703236.4 )*DE(2)+(1/5728)*DE(4)+(1/18.48000)*DE(6);
```

```
!1. Objective  function  constraints;
@SUM(WORKER_NUM(S1,P,T,L1)|  S1 #GE#
L1:S3(S1,P,T)*NW(S1,P,T,L1)+H(S1,P,T)*NH(S1,P,T,L1)+F(S1,P,T)*NL(S1,P,T,L1)+
S4(S1,P,T)*OT(S1,P,T,L1))+
@SUM(WORKER_TR1(S2,S1,P,T,L2,L1)|  S1 #EQ# S2+1#AND# L1 #GE# L2#AND#
S2 #EQ# L2#AND#S1#EQ#L1:TR(S2,S1,P,T)*Y(S2,S1,P,T,L2,L1))+DE(1)-DE(2)=
234570.6;
@SUM(FATIGUE_HUMAN(S1,P,T,S,L1)|S1  #GE#
L1:N*WT1(S1,P,S)*B(S1,P,T,S,L1))+DE(3)-DE(4)=  1151.910;
@SUM(FATIGUE_HUMAN(S1,P,T,S,L1)|S1#GE#L1:N*FRA(P,S)*TI(S1,P,T,S,L1)/2*
Fmax(P))-
@SUM(FATIGUE_HUMAN(S1,P,T,S,L1)|S#LE#8#AND#S1#GE#L1:N*A(P,S)*B(S1,
P,T,S,L1)/2*Fmax(P))-(N-
1)*@SUM(FATIGUE_HUMAN(S1,P,T,S,L1)|S#EQ#9#AND#S1#GE#L1:A(P,S)*B(S1,
P,T,S,L1)/2*Fmax(P))+DE(5)-DE(6)=0;

!2. Model constraints;
@FOR(WORKER_NUM0(S1,T):AV(S1,T)*@SUM(MACHINE_L(P,L1)|S1#GE#L1:P
R(S1,P,T,L1)*NW(S1,P,T,L1))-
@SUM(PER_L(P,S,L1)|S1#GE#L1:N*WT1(S1,P,S)*B(S1,P,T,S,L1))+@SUM(MACHI
NE_L(P,L1)|S1#GE#L1:OT(S1,P,T,L1))=D(S1,T));

@FOR(WORKER_NUM(S1,P,T,L1)|S1  #GE#
L1:PR(S1,P,T,L1)=INP(S1,P,L1)+E(S1,P,L1)*(1-@EXP(-
@SUM(PERIOD(I)|I#LE#T:V(S1,P,I,L1))/LE(S1,P,L1))));
@FOR(HUMAN_MACHINE(S1,P,L1)|S1  #GE#
L1:INP(S1,P,L1)=C(S1,P)*O(L1)*WI(S1,P,L1));
@FOR(HUMAN_MACHINE(S1,P,L1)|S1  #GE# L1:E(S1,P,L1)<=C(S1,P));
@FOR(WORKER_NUM(S1,P,T,L1)|S1  #GE# L1:PR(S1,P,T,L1)<=1);
@FOR(WORKER_NUM(S1,P,T,L1)|S1  #GE# L1:NW(S1,P,T,L1)<=M*V(S1,P,T,L1));
@FOR(WORKER_NUM(S1,P,T,L1)|S1  #GE#
L1:OP(S1,P,T,L1)<=V(S1,P,T,L1)*PR(S1,P,T,L1));
@FOR(WORKER_NUM(S1,P,T,L1)|S1  #GE# L1:V(S1,P,T,L1)<=M*WS(S1,P,L1));
@FOR(WORKER_NUM(S1,P,T,L1)|S1  #GE# L1:NW(S1,P,T,L1)<=M*WS(S1,P,L1));
@FOR(WORKER_NUM(S1,P,T,L1)|S1  #GE# L1:NH(S1,P,T,L1)<=M*WS(S1,P,L1));
@FOR(WORKER_NUM(S1,P,T,L1)|S1  #GE# L1:NL(S1,P,T,L1)<=M*WS(S1,P,L1));
@FOR(WORKER_NUM(S1,P,T,L1)|S1  #GE# L1#AND#T  #GE#
1:N*@SUM(TASK(S):TI(S1,P,T,S,L1)+B(S1,P,T,S,L1))-
N*B(S1,P,T,9,L1)=AV(S1,T)*PR(S1,P,T,L1)*NW(S1,P,T,L1));
@FOR(WORKER_NUM(S1,P,T,L1)|S1  #GE# L1#AND#T  #GE#
1:@SUM(TASK(S):B(S1,P,T,S,L1))<=@SUM(TASK(S):REC(P,S)*TI(S1,P,T,S,L1)));

@FOR(WORKER_NUM(S1,P,T,L1)|S1  #GE#
L1:@SUM(TASK(S):N*FRA(P,S)*TI(S1,P,T,S,L1))-
```

```
N*@SUM(TASK(S)|S#LE#8:A(P,S)*B(S1,P,T,S,L1))-(N-
1)*A(P,9)*B(S1,P,T,9,L1)<=Fmax(P));
@FOR(RECOVER(P,S):A(P,S)=FRA(P,S)/REC(P,S));
@FOR(FATIGUE_HUMAN(S1,P,T,S,L1)|  S1 #GE#
L1:TI(S1,P,T,S,L1)<=M*WS(S1,P,L1));
@FOR(FATIGUE_HUMAN(S1,P,T,S,L1)|  S1 #GE#
L1:TI(S1,P,T,S,L1)<=M*WT1(S1,P,S));
@FOR(FATIGUE_HUMAN(S1,P,T,S,L1)|  S1 #GE#
L1:TI(S1,P,T,S,L1)<=M*V(S1,P,T,L1));
@FOR(FATIGUE_HUMAN(S1,P,T,S,L1)|  S1 #GE#
L1:B(S1,P,T,S,L1)<=M*WT1(S1,P,S));
@FOR(FATIGUE_HUMAN(S1,P,T,S,L1)|  S1 #GE#
L1:TI(S1,P,T,S,L1)<=MET(P,S)*WT1(S1,P,S)*NW(S1,P,T,L1));
@FOR(RECOVER(P,S):MET(P,S)=P1*@EXP(-BET*FRA(P,S)));
@FOR(FATIGUE_HUMAN(S1,P,T,S,L1)|  S1 #GE#
L1:B(S1,P,T,S,L1)<=REC(P,S)*TI(S1,P,T,S,L1));
@FOR(FATIGUE_HUMAN(S1,P,T,S,L1)|  S1 #GE# L1:B(S1,P,T,S,L1)>=0);
@FOR(FATIGUE_HUMAN(S1,P,T,S,L1)|  S1 #GE# L1:TI(S1,P,T,S,L1)>=0);
@FOR(WORKER_NUM(S1,P,T,L1)  | T #GT# 1#AND # S1 #GE# L1:NW(S1,P,T-
1,L1)+NH(S1,P,T,L1)-NL(S1,P,T,L1)+@SUM(HUMAN_MACHINE2(S2,L2)|  S1 #EQ#
S2+1#AND# L1 #EQ# L2+1#AND# S2 #EQ# L2:Y(S2,S1,P,T,L2,L1))-
@SUM(HUMAN_MACHINE2(S2,L2)|  S2 #EQ# S1+1#AND# L2 #EQ# L1+1#AND#
S1 #EQ# L1:Y(S1,S2,P,T,L1,L2))=NW(S1,P,T,L1));
@FOR(WORKER_NUM(S1,P,T,L1)  | T #EQ# 1#AND # S1 #GE#
L1:INW(S1,P,L1)+NH(S1,P,T,L1)-
NL(S1,P,T,L1)+@SUM(HUMAN_MACHINE2(S2,L2)|  S1 #EQ# S2+1#AND# L1
#EQ# L2+1#AND#  S2 #EQ# L2:Y(S2,S1,P,T,L2,L1))-
@SUM(HUMAN_MACHINE2(S2,L2)|  S2 #EQ# S1+1#AND# L2 #EQ# L1+1#AND#
S1 #EQ# L1:Y(S1,S2,P,T,L1,L2))=NW(S1,P,T,L1));
@FOR(WORKER_NUM(S1,P,T,L1)|  T #GT# 1
:@SUM(HUMAN_MACHINE2(S2,L2)|  S2 #EQ# S1+1#AND# L2 #EQ# L1+1#AND#
S1 #EQ# L1:Y(S1,S2,P,T,L1,L2))+NL(S1,P,T,L1)<=NW(S1,P,T-1,L1));
@FOR(WORKER_NUM(S1,P,T,L1)|  T #EQ# 1:@SUM(HUMAN_MACHINE2(S2,L2)|
S2 #EQ# S1+1#AND# L2 #EQ# L1+1#AND#  S1 #EQ#
L1:Y(S1,S2,P,T,L1,L2))+NL(S1,P,T,L1)<=INW(S1,P,L1));
@FOR(WORKER_NUM(S1,P,T,L1)|  S1 #GE#
L1:OT(S1,P,T,L1)<=AOT(S1,T)*NW(S1,P,T,L1));
@FOR(WORKER_TR1(S2,S1,P,T,L2,L1)|  S2 #EQ# S1+1#AND# L1 #LE# L2#AND#
S1 #EQ# L1:Y(S1,S2,P,T,L1,L2)<=M*WS(S1,P,L1));
@FOR(WORKER_NUM(S1,P,T,L1)|  S1 #GE#
L1:@SUM(HUMAN_MACHINE2(S2,L2)|  S2 #EQ# S1+1#AND# L1 #LE# L2#AND#
S1 #EQ# L1:Y(S1,S2,P,T,L1,L2))<=M*Z(S1,P,T,L1));
@FOR(WORKER_NUM(S1,P,T,L1)|S1  #GE# L1:NL(S1,P,T,L1)<=M*(1-
Z(S1,P,T,L1)));
@FOR(WORKER_TR1(S2,S1,P,T,L2,L1)|  S1 #GE# L1 #AND#S2 #GE# L2#AND#S2
#EQ# S1#AND#L1  #EQ# L2:NL2(S2,P,T,L2)<=M*(1-Z(S1,P,T,L1)));
```

```
@FOR(WORKER_NUM(S1,P,T,L1)|  S1 #GE# L1:NH(S1,P,T,L1)<=M*U(S1,P,T,L1));
@FOR(WORKER_NUM(S1,P,T,L1)|  S1 #GE# L1:NL(S1,P,T,L1)<=M*(1-
U(S1,P,T,L1)));
@FOR(WORKER_TR1(S2,S1,P,T,L2,L1)  | S1 #EQ# S2+1#AND# L1 #GE# L2#AND#
S2 #EQ# L2:Y(S2,S1,P,T,L2,L1)<=M*WS3(S2,P,L2));
@FOR(WORKER_TR1(S2,S1,P,T,L2,L1)  | S1 #EQ# S2+1#AND# L1 #GE# L2#AND#
S2 #EQ# L2:Y(S2,S1,P,T,L2,L1)<=M*WS(S1,P,L1));
@FOR(WORKER_TR1(S2,S1,P,T,L2,L1)|  S1 #EQ# S2+1#AND# L1 #GE# L2 #AND#
S2#EQ# L2:Y(S2,S1,P,T,L2,L1)<=M*SS(S2,S1));
@FOR(WORKER_NUM(S1,P,T,L1)|S1  #GE# L1: @BIN( Z(S1,P,T,L1)));
@FOR(WORKER_NUM(S1,P,T,L1)|S1  #GE# L1: @BIN( U(S1,P,T,L1)));


DATA:

Tmax=   8;

Tmin=    0.2;

Fmax=   0.6,0.5,0.4;

BET=     0.21513;

P1=1.3;

REC=     0.5,0.5,0.5,1,1,1,1,1,1,
         0.45,0.45,0.45,0.45,0.45,0.45,1,1,1
         0.4,0.3,0.2,0.3,0.3,0.3,0.2,0.2,0.2;

FRA=     0.5,0.4,0.3, 1,1,1, 1,1,1,
         0.3,0.4,0.3, 0.4,0.4,0.5, 1,1,1
         0.3,0.2,0.2, 0.3,0.3,0.2, 0.3,0.3,0.1;

N=    5;

M=   1000000;

D=    320,160,320,320,320,320,320,320
      400,320,320,320,400,160,320,480
      400,480,480,480,320,160,320,320;

H=     80,80,80,80,80,80,80,80
       85,85,85,85,85, 85,85,85
       90,90,90,90,90,90,90,90
       95,95,95,95,95,95,95,95
       100,100,100,100,100,100,100,100
```

```
          115,115,115,115,115,115,115,115
          120,120,120, 120,120,120, 120,120
          125,125,125,125,125,125,125,125
          140,140,140,140,140,140,140,140;

C=    0.5,0.6,0.7
      0.6,0.7,0.8
      0.7,0.8,0.9;

O=    1,1,1;

WI=    0.6,0,0,0.7,0,0,0.8,0,0
       0.7,0.75,0,0.75,0.8,0,0.8,0.85,0
       0.7,0.75,0.8,0.75,0.8,0.85,0.8,0.85,0.9;

V=1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0, 1,0,0, 1,0,0
  1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0, 1,0,0, 1,0,0
  1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0, 1,0,0, 1,0,0
  1,1,0,1,1,0,1,1,0,1,1,0,1,1,0,1,1,0,1,1,0,1,1,0
  1,1,0,1,1,0,1,1,0,1,1,0,1,1,0,1,1,0,1,1,0,1,1,0
  1,1,0,1,1,0,1,1,0,1,1,0,1,1,0,1,1,0,1,1,0,1,1,0
  1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1
  1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1
  1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1;

F=     95,95,95,95,95,95,95,95
       100,100,100,100,100,100,100,100
       115,115,115,115,115,115,115,115
       120,120,120,120,120,120,120,120
       125,125,125,125,125,125,125,125
       140,140,140,140,140,140,140,140
       145,145,145,145,145,145,145,145
       140,140,140,140,140,140,140,140
       145,145,145,145,145,145,145,145;

!PR=
0.3344686,0,0,0.3665611,0,0,0.3964411,0,0,0.4242614,0,0,0.4501637,0,0,0.4742805,0,0,
0.4967347,0,0,0.51764,0,0

0.47770975,0,0,0.5287615,0,0,0.5755091,0,0,0.6178,0,0,0.6560816,0,0,0.690713,0,0,0.7
220488,0,0,0.7504026,0,0

0.64217904,0,0,0.7139701,0,0,0.7776685,0,0,0.8338821,0,0,0.8834905,0,0,0.9272697,0,
0,0.9659047,0,0,1,0,0

0.4905019,0.5421110,0,0.5527195,0.6200812,0,0.6076264,0.6860816,0,0.6560816,0.741
```

9497,0,0.6988431,0.7892411,0,0.7365801,0.8292723,0,0.7698828,0.8631581,0,0.799272
3,0.8918417,0

0.6328844,0.6725612,0,0.7212126,0.7602239,0,0.7935297,0.8284957,0,0.8527379,0.881
6658,0,0.901235,0.9230747,0,0.9409019,0.9553240,0,0.9733960,0.9804398,0,1,1,0

0.7496689,0.7618627,0,0.8282501,0.8256174,0,0.884556,0.8752696,0,0.9249009,0.9139
387,0,0.9538093,0.9440543,0,0.9745231,0.96757744,0,0.9893652,0.9857744,0,1,1,0

0.6944133,0.7153850,0.7363566,0.8183963,0.8308593,0.8433223,0.8935957,0.9008980,
0.9082002,0.9392065,0.9433786,0.9475507,0.9668708,0.9691444,0.9714180,0.9836501,
0.9847722,0.9858942,0.9938273,0.9942509,0.9946745,1,1,1

0.7603242,0.7842918,0.7774835,0.8575657,0.8718091,0.8473334,0.9165457,0.9248911,
0.8973831,0.9523188,0.9570869,0.9332453,0.9740163,0.9766147,0.9589416,0.9871766,
0.9884589,0.9773539,0.9951586,0.9956428,0.9905468,1,1,1

0.8052980,0.8591905,0.8678808,0.8664167,0.9163199,0.9093542,0.9102102,0.9509706,
0.9390712,0.9415896,0.9719873,0.9603644,0.9640739,0.9847346,0.9756216,0.9801846,
0.9924662,0.9865539,0.9917285,0.9971557,0.9943872,1,1,1;

TR= 0,0,0,0,0,0,0,0
0,0,0,0,0,0,0,0
0,0,0,0,0,0,0,0
4,4,4,4,4,4,4,4
5,5,5,5,5,5,5,5
6,6,6,6,6,6,6,6
0,0,0,0,0,0,0,0
0,0,0,0,0,0,0,0
0,0,0,0,0,0,0,0
0,0,0,0,0,0,0,0
0,0,0,0,0,0,0,0
0,0,0,0,0,0,0,0
0,0,0,0,0,0,0,0
0,0,0,0,0,0,0,0
0,0,0,0,0,0,0,0
4,4,4,4,4,4,4,4
5,5,5,5,5,5,5,5
6,6,6,6,6,6,6,6
0,0,0,0,0,0,0,0
0,0,0,0,0,0,0,0
0,0,0,0,0,0,0,0
0,0,0,0,0,0,0,0
0,0,0,0,0,0,0,0
0,0,0,0,0,0,0,0
0,0,0,0,0,0,0,0

```
              0,0,0,0,0,0,0,0
              0,0,0,0,0,0,0,0;

S3=    100,100,100,100,100,100,100,100
       110,110,110,110,110,110,110,110
       120,120,120,120,120,120,120,120
       130,130,130,130,130,130,130,130
       140,140,140,140,140,140,140,140
       150,150,150,150,150,150,150,150
       160,160,160,160,160,160,160,160
       170,170,170,170,170,170,170,170
       180,180,180,180,180,180,180,180;

S4=    18.5,18.5,18.5,18.5,18.5,18.5,18.5,18.5
       19.5,19.5,19.5,19.5,19.5,19.5,19.5,19.5
       20.5,20.5,20.5,20.5,20.5,20.5,20.5,20.5
       21.5,21.5,21.5,21.5,21.5,21.5,21.5,21.5
       22.5,22.5,22.5,22.5,22.5,22.5,22.5,22.5
       23.5,23.5,23.5,23.5,23.5,23.5,23.5,23.5
       24.5,24.5,24.5,24.5,24.5,24.5,24.5,24.5
       25.5, 25.5, 25.5, 25.5, 25.5, 25.5, 25.5, 25.5
       26.5,26.5,26.5,26.5,26.5,26.5,26.5,26.5;

AV=    8,8,8,8,8,8,8,8
       8,8,8,8,8,8,8,8
       8,8,8,8,8,8,8,8;

AOT=   2,2,2,2,2,2,2,2
       2,2,2,2,2,2,2,2
       2,2,2,2,2,2,2,2;

LE=    14,1000,1000,10,1000,1000,8,1000,1000
       8,6,1000,5,4,1000,3,4,1000
       2,2,2,2,2,3,3,2,3;

!E=    0.5,0,0,0.6,0,0,0.6960698,0,0
       0.6,0.6,0,0.5951609,0.5088678,0,0.3868819,0.3700856,0
0.5195153,0.4838622,0.4482092,0.4074629,0.3667166,0.343895,0.3009081,0.2393845,0
.2041877;

SS=    0,1,0
       0,0,1
       0,0,0;

WS=    1,0,0
       1,0,0
```

```
             1,0,0
             1,1,0
             1,1,0
             1,1,0
             1,1,1
             1,1,1
             1,1,1;
WS3=         1,0,0
             1,0,0
             1,0,0
             1,1,0
             1,1,0
             1,1,0
             1,1,1
             1,1,1
             1,1,1;
INW =        40,0,0,0,0,0,10,0,0
             0,30,0,0,20,0,0,10,0
             0,0,30,0,0,30,0,0,10;
WT1=         1  0  0 0 0  0  0  0  0
             1  1  0 0 0  0  0  0  0
             1  1  1 0 0  0  0  0  0
             1  1  1 1 0  0  0  0  0
             1  1  1 1 1  0  0  0  0
             1  1  1 1 1  1  0  0  0
             1  1  1 1 1  1  1  0  0
             1  1  1 1 1  1  1  1  0
             1  1  1 1 1  1  1  1  1;

ENDDATA
END
```

APPENDIX B: MATHEMATICAL PROGRAMMING FOR SECTION 4.4.2

Minimize:

$$Z = \sum_{t=1}^{T}\sum_{j=1}^{S}\sum_{x=1}^{ML}\left(h_{jt} \times H_{jtx} + f_{jt} \times L_{jtx} + so_{jt} \times OT_{jtx}\right) + \sum_{t=1}^{T}\sum_{j=1}^{S}\sum_{k=1}^{S}\sum_{x=1}^{ML}\sum_{y=1}^{ML}\left(tr_{jkt} \times Y_{jktxy}\right)$$

Subject to:

$$0.8 \times A_{jt} \times \left(\sum_{x=1}^{ML} W_{jtx}\right) + \sum_{x=1}^{ML} OT_{jtx} = D_{jt} \qquad \forall j,t \qquad (1)$$

$$W_{jtx} = W_{jt-1x} + H_{jtx} - L_{jtx} + \sum_{\substack{k=j-1\\ j\ge 2}}^{j} \sum_{\substack{y=x-1\\ x\ge 2}}^{x} \left(Y_{kjtyx}\right) - \sum_{\substack{k=j+1\\ k\ge 2}}^{k} \sum_{\substack{y=x+1\\ y\ge 2}}^{y} \left(Y_{jktxy}\right) \qquad \forall j,t,x \qquad (2)$$

$$OT_{jtx} \le AOT_{jt} \times W_{jtx} \qquad \forall j,t,x \qquad (3)$$

$$\sum_{\substack{k=1\\ k>j}}^{S} \sum_{y=1}^{ML} Y_{jktxy} + L_{jtx} \le W_{j,t-1,x} \qquad \forall j,t,x \qquad (4)$$

$$L_{jtx} \le M \times ws_{jx} \qquad \forall j,t,x \qquad (5)$$

$$H_{jtx} \le M \times ws_{jx} \qquad \forall j,t,x \qquad (6)$$

$$Y_{kjtyx} \le M \times ws_{ky} \qquad \forall j,k,t,x,y \qquad (7)$$

$$Y_{kjtyx} \le M \times ws_{jx} \qquad \forall j,k,t,x,y \qquad (8)$$

$$Y_{kjtyx} \le M \times ss_{kj} \qquad \forall j,k,t,x,y \qquad (9)$$

$$\sum_{y=1}^{ML}\sum_{k=1}^{S} Y_{kjtyx} \times L_{jtx} = 0 \qquad \forall j,t,x \qquad (10)$$

$$H_{jtx} \times L_{jtx} = 0 \qquad \forall j,t,x \qquad (11)$$

$$W_{jtx}, H_{jtx}, L_{jtx}, Y_{kjtyx} \ge 0 \qquad \forall j,k,t,x,y \qquad (12)$$

APPENDIX C: INPUT DATA FOR MODEL A

Table C.1: Demand of Worker Skills in each Week (worker-hours/week)

	W1[d]	W2	W3	W4	W5	W6	W7	W8
Worker Skill 1	3200	1600	3200	2240	2080	3200	2080	3200
Worker Skill 2	3520	3200	3520	3200	3200	2560	3200	2560
Worker Skill 3	3840	2880	3840	2880	3200	1920	3200	1920

[d] W1 represents Week 1

Table C.2: Workers' Availabilities (hours/week)

		W1	W2	W3	W4	W5	W6	W7	W8
Worker Skill 1	Availability (regular time)	40	40	40	40	40	40	40	40
	Availability (overtime)	10	10	10	10	10	10	10	10
Worker Skill 2	Availability (regular time)	40	40	40	40	40	40	40	40
	Availability (overtime)	10	10	10	10	10	10	10	10
Worker Skill 3	Availability (regular time)	40	40	40	40	40	40	40	40
	Availability (overtime)	10	10	10	10	10	10	10	10

Table C.3: Initial Workforce Available in each Machine Level (workers)

		Level 1	Level 2	Level 3
Worker Skill 1	P1[e]	40	0	0
	P2	0	0	0
	P3	10	0	0
Worker Skill 2	P1	0	30	0
	P2	0	20	0
	P3	0	10	0
Worker Skill 3	P1	0	0	30
	P2	0	0	30
	P3	0	0	10

[e] P1 represents Personality level 1

Table C.4: Training Costs in each Period ($/worker)

From		To	W1	W2	W3	W4	W5	W6	W7	W8
Worker Skill 1	P1	Skill 2	10	10	10	10	10	10	10	10
	P2	Skill 2	12	12	12	12	12	12	12	12
	P3	Skill 2	15	15	15	15	15	15	15	15
Worker Skill 2	P1	Skill 3	10	10	10	10	10	10	10	10
	P2	Skill 3	12	12	12	12	12	12	12	12
	P3	Skill 3	15	15	15	15	15	15	15	15

Table C.5: Willingness to Work on a Machine Level in each Week (%)

		Level	Level	Level 3
Worker Skill 1	P1	60	0	0
	P2	70	0	0
	P3	80	0	0
Worker Skill 2	P1	70	75	0
	P2	75	80	0
	P3	80	85	0
Worker Skill 3	P1	70	75	80
	P2	75	80	85
	P3	80	85	90

Table C.6: Salaries, Hiring, Firing, Overtime Costs and Workers' Capacities

			W1	W2	W3	W4	W5	W6	W7	W8
Worker Skill 1	P1	Salary, $	500	500	500	500	500	500	500	500
		Hiring Costs, $	400	400	400	400	400	400	400	400
		Firing Costs, $	500	500	500	500	500	500	500	500
		Overtime, $	18.5	18.5	18.5	18.5	18.5	18.5	18.5	18.5
		Capacity, %	50	50	50	50	50	50	50	50
	P2	Salary, $	525	525	525	525	525	525	525	525
		Hiring Costs, $	425	425	425	425	425	425	425	425
		Firing Costs, $	525	525	525	525	525	525	525	525
		Overtime, $	19.5	19.5	19.5	19.5	19.5	19.5	19.5	19.5
		Capacity, %	60	60	60	60	60	60	60	60
	P3	Salary, $	550	550	550	550	550	550	550	550
		Hiring Costs, $	450	450	450	450	450	450	450	450
		Firing Costs, $	550	550	550	550	550	550	550	550
		Overtime, $	20.5	20.5	20.5	20.5	20.5	20.5	20.5	20.5
		Capacity, %	70	70	70	70	70	70	70	70
Worker Skill 2	P1	Salary, $	575	575	575	575	575	575	575	575
		Hiring Costs, $	475	475	475	475	475	475	475	475
		Firing Costs, $	575	575	575	575	575	575	575	575
		Overtime, $	21.5	21.5	21.5	21.5	21.5	21.5	21.5	21.5
		Capacity, %	60	60	60	60	60	60	60	60
	P2	Salary, $	600	600	600	600	600	600	600	600
		Hiring Costs, $	500	500	500	500	500	500	500	500
		Firing Costs, $	600	600	600	600	600	600	600	600
		Overtime, $	22.5	22.5	22.5	22.5	22.5	22.5	22.5	22.5
		Capacity, %	70	70	70	70	70	70	70	70
	P3	Salary, $	625	625	625	625	625	625	625	625

		Hiring Costs, $	510	510	510	510	510	510	510	510
		Firing Costs, $	625	625	625	625	625	625	625	625
		Overtime, $	23.5	23.5	23.5	23.5	23.5	23.5	23.5	23.5
		Capacity, %	80	80	80	80	80	80	80	80
Worker Skill 3	P1	Salary, $	650	650	650	650	650	650	650	650
		Hiring Costs, $	520	520	520	520	520	520	520	520
		Firing Costs, $	650	650	650	650	650	650	650	650
		Overtime, $	24.5	24.5	24.5	24.5	24.5	24.5	24.5	24.5
		Capacity, %	70	70	70	70	70	70	70	70
	P2	Salary, $	675	675	675	675	675	675	675	675
		Hiring Costs, $	550	550	550	550	550	550	550	550
		Firing Costs, $	675	675	675	675	675	675	675	675
		Overtime, $	25.5	25.5	25.5	25.5	25.5	25.5	25.5	25.5
		Capacity, %	80	80	80	80	80	80	80	80
	P3	Salary, $	700	700	700	700	700	700	700	700
		Hiring Costs, $	560	560	560	560	560	560	560	560
		Firing Costs, $	700	700	700	700	700	700	700	700
		Overtime, $	26.5	26.5	26.5	26.5	26.5	26.5	26.5	26.5
		Capacity, %	90	90	90	90	90	90	90	90

Table C.7: Learning Parameters for Workers on Each Machine Level (weeks)

		Level 1	Level 2	Level 3
Worker Skill 1	P1	8	M	M
	P2	7	M	M
	P3	6	M	M
Worker Skill 2	P1	7	6	M
	P2	5	4	M
	P3	3	2	M
Worker Skill 3	P1	4	3	2
	P2	1	2	2
	P3	1	1	1

APPENDIX D: INPUT DATA FOR MODEL B

Table D.1: Demand of Worker Skills in each Week (worker-hours/day)

	D1 [f]	D2	D3	D4	D5	D6	D7	D8
Worker Skill 1	320.0	160.0	320.0	320.0	320.0	320.0	320.0	320.0
Worker Skill 2	400.0	320.0	320.0	320.0	400.0	160.0	320.0	480.0
Worker Skill 3	400.0	480.0	480.0	480.0	320.0	160.0	320.0	320.0

[f] D1 represents Day 1

Table D.2: Workers' Availabilities (hours/day)

		D1	D2	D3	D4	D5	D6	D7	D8
Worker Skill 1	Availability (regular time)	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0
	Availability (overtime)	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0
Worker Skill 2	Availability (regular time)	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0
	Availability (overtime)	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0
Worker Skill 3	Availability (regular time)	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0
	Availability (overtime)	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0

Table D.3: Initial Workforce Available in each Machine Level (workers)

		Level 1	Level 2	Level 3
Worker Skill 1	P1 [d]	40.0	0.0	0.0
	P2	0.0	0.0	0.0
	P3	10.0	0.0	0.0
Worker Skill 2	P1	0.0	30.0	0.0
	P2	0.0	20.0	0.0
	P3	0.0	10.0	0.0
Worker Skill 3	P1	0.0	0.0	30.0
	P2	0.0	0.0	30.0
	P3	0.0	0.0	10.0

Table D.4: Training Costs in each Period ($/worker)

From		To	D1	D2	D3	D4	D5	D6	D7	D8
Worker Skill 1	P1	Skill 2	4.0	4.0	4.0	4.0	4.0	4.0	4.0	4.0
	P2	Skill 2	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
	P3	Skill 2	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0
Worker Skill 2	P1	Skill 3	4.0	4.0	4.0	4.0	4.0	4.0	4.0	4.0
	P2	Skill 3	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
	P3	Skill 3	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0

Table D.5: Salaries, Hiring, Firing, and Hourly Overtime Costs

			D1	D2	D3	D4	D5	D6	D7	D8
Worker Skill 1	P1	Salary, $	100	100	100	100	100	100	100	100
		Hiring Costs, $	80.0	80.0	80.0	80.0	80.0	80.0	80.0	80.0
		Firing Costs, $	95.0	95.0	95.0	95.0	95.0	95.0	95.0	95.0
		Overtime, $	18.5	18.5	18.5	18.5	18.5	18.5	18.5	18.5
	P2	Salary, $	110	110	110	110	110	110	110	110
		Hiring Costs, $	85.0	85.0	85.0	85.0	85.0	85.0	85.0	85.0
		Firing Costs, $	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
		Overtime, $	19.5	19.5	19.5	19.5	19.5	19.5	19.5	19.5
	P3	Salary, $	120	120	120	120	120	120	120	120
		Hiring Costs, $	90.0	90.0	90.0	90.0	90.0	90.0	90.0	90.0
		Firing Costs, $	115.0	115.0	115.0	115.0	115.0	115.0	115.0	115.0
		Overtime, $	20.5	20.5	20.5	20.5	20.5	20.5	20.5	20.5
Worker Skill 2	P1	Salary, $	130	130	130	130	130	130	130	130
		Hiring Costs, $	95.0	95.0	95.0	95.0	95.0	95.0	95.0	95.0
		Firing Costs, $	120.0	120.0	120.0	120.0	120.0	120.0	120.0	120.0
		Overtime, $	21.5	21.5	21.5	21.5	21.5	21.5	21.5	21.5
	P2	Salary, $	140	140	140	140	140	140	140	140
		Hiring Costs, $	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
		Firing Costs, $	125.0	125.0	125.0	125.0	125.0	125.0	125.0	125.0
		Overtime, $	22.5	22.5	22.5	22.5	22.5	22.5	22.5	22.5
	P3	Salary, $	150	150	150	150	150	150	150	150
		Hiring Costs, $	115.0	115.0	115.0	115.0	115.0	115.0	115.0	115.0
		Firing Costs, $	140.0	140.0	140.0	140.0	140.0	140.0	140.0	140.0
		Overtime, $	23.5	23.5	23.5	23.5	23.5	23.5	23.5	23.5
Worker Skill 3	P1	Salary, $	160	160	160	160	160	160	160	160
		Hiring Costs, $	120.0	120.0	120.0	120.0	120.0	120.0	120.0	120.0
		Firing Costs, $	145.0	145.0	145.0	145.0	145.0	145.0	145.0	145.0
		Overtime, $	24.5	24.5	24.5	24.5	24.5	24.5	24.5	24.5
	P2	Salary, $	170	170	170	170	170	170	170	170

	Hiring Costs, $	125.0	125.0	125.0	125.0	125.0	125.0	125.0	125.0
	Firing Costs, $	140.0	140.0	140.0	140.0	140.0	140.0	140.0	140.0
	Overtime, $	25.5	25.5	25.5	25.5	25.5	25.5	25.5	25.5
P3	Salary, $	180	180	180	180	180	180	180	180
	Hiring Costs, $	140.0	140.0	140.0	140.0	140.0	140.0	140.0	140.0
	Firing Costs, $	145.0	145.0	145.0	145.0	145.0	145.0	145.0	145.0
	Overtime, $	26.5	26.5	26.5	26.5	26.5	26.5	26.5	26.5

Table D.6: Fatigue Levels and Recovery Rates ($\alpha = 1.3, \beta = 0.215$)

		F_{max}	T1 [g]	T2	T3	T4	T5	T6	T7	T8	T9
Fatigue fraction	P1	0.6	0.5	0.4	0.3	-	-	-	-	-	-
	P2	0.5	0.3	0.4	0.3	0.4	0.4	0.5	-	-	-
	P3	0.4	0.3	0.2	0.2	0.3	0.3	0.2	0.3	0.3	0.1
Recovery rate	P1	0.6	0.5	0.5	0.5	-	-	-	-	-	-
	P2	0.5	0.45	0.45	0.45	0.45	0.45	0.45	-	-	-
	P3	0.4	0.4	0.3	0.2	0.3	0.3	0.2	0.2	0.5	0.2
Endurance Time	P1	0.6	1.17	1.19	1.22	-	-	-	-	-	-
	P2	0.5	1.22	1.19	1.22	1.19	1.19	1.17	-	-	-
	P3	0.4	1.22	1.25	1.25	1.22	1.22	1.25	1.22	1.22	1.27

[g] T1 represents Task 1

APPENDIX E: DIFFERENT LOADING LEVELS

Table E.1: Different Scenarios with Different Load Levels ($\alpha = 1.3, \beta = 0.215$)

Scenario		F_{max}	T1	T2	T3	T4	T5	T6	T7	T8	T9
1	P1	0.88	0.8	0.8	0.8	-	-	-	-	-	-
	P2	0.58	0.5	0.5	0.3	0.5	0.5	0.5	-	-	-
	P3	0.12	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
2	P1	0.58	0.5	0.5	0.5	-	-	-	-	-	-
	P2	0.58	0.5	0.5	0.5	0.5	0.5	0.5	-	-	-
	P3	0.58	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
3	P1	0.12	0.1	0.1	0.1	-	-	-	-	-	-
	P2	0.58	0.5	0.5	0.5	0.5	0.5	0.5	-	-	-
	P3	0.88	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8

APPENDIX F: SAMPLES CODING FOR THE DSS

F.1 LINGO Code for Excel Software:

```
SET ECHOIN 1
MODEL:
SETS:
!For our problem we choose these numbers to make a demonstration model;
      ! Eight planning periods (T);
       PERIOD  / 1..8 /;
      ! Three human skill level (S);
       SKILLA  / 1..3 /;
       SKILLB  / 1..3 /;
       ! Three machine level (L);
       MACHINE_L1  / 1..3 /;
       MACHINE_L2   / 1..3 /;
       ! Three levels of worker personality  (P);
       PES  / 1..3 /;

WORKER_NUM0 (SKILLA,PERIOD):D,A,AOT;
MACHINE_L(PES,MACHINE_L1):;
HUMAN_L(SKILLA,PES):;
MACHINE_OP(PERIOD,MACHINE_L1):O,NWL;
WORKER_NUM1 (SKILLA,PES,PERIOD):H,F,S3,S4,C;
TRAINING_COST (SKILLB,SKILLA,PES,PERIOD):TR;
TRAINING (SKILLB,SKILLA):SS;
!WORKER_NUM2 (PERIOD,MACHINE_L1):;
HUMAN_MACHINE (SKILLA,PES,MACHINE_L1):WS,INW;
HUMAN_MACHINE2 (SKILLB,MACHINE_L2):WS2;
WORKER_NUM (SKILLA,PES,PERIOD, MACHINE_L1):NW,NH,NL,OT,Z,U,W;
WORKER_NUM6 (SKILLB,PES,PERIOD, MACHINE_L2):NL2;
WORKER_TR (SKILLA,SKILLB,PES,PERIOD, MACHINE_L1,MACHINE_L2);
```

```
WORKER_TR1 (SKILLB,SKILLA,PES,PERIOD, MACHINE_L2,MACHINE_L1):Y;


ENDSETS

DATA:

!the following parameter values are estimation;

D, H, F, TR, SR, SO, A, AOT, INW, SS, WS1, WS2, AV,V, SWT, SWO, SWF,
SWS, M=@OLE ('C:\Users\Mohammed\Desktop\PhD papers\DSS.XLS','Demand',
'HiringCost',

'FiringCost', 'Training', 'RegularSalary', 'OvertimeSalary',

'RegularAvailability', 'OvertimeAvailability', 'IntialWorkers',

 'TrainingPossibility',
'SkilltoLevelA', 'SkilltoLevelB', 'Availability','CapabilitytoWork',
'TrainingSwitch',

 'OvertimeSwitch', 'ObjFunctionSwitch', 'SalarySwitch', 'BigNum');
 @OLE('C:\Users\Mohammed\Desktop\PhD
papers\DSS.XLS','WorkersUsed','WorkersHired', 'WorkersFired', 'WorkersTrained',

 'OvertimeHours')=NW,NH,NL,Y,OT;

ENDDATA

MIN =


SWF*(@SUM(WORKER_NUM(S1,L1,T)| S1 #GE# L1:H(S1,T)*NH(S1,L1,T)+

SWS*SR(S1,T)*NW(S1,L1,T)+F(S1,T)*NL(S1,L1,T)+SWO*SO(S1,T)*OT(S1,L1,T))+

@SUM(WORKER_TR1(S2,S1,L2,L1,T)| S1 #EQ# S2+1#AND# L1 #EQ# L2+1

#AND# S2 #EQ# L2:SWT*TR(S2,S1,T)*Y(S2,S1,L2,L1,T)))+

(1-SWF)*(@SUM(WORKER_NUM(S1,L1,T)| S1 #GE# L1:NH(S1,L1,T)+SWS*NW(S1,L1,T)+

NL(S1,L1,T)+SWO*(1/32)*OT(S1,L1,T))+

@SUM(WORKER_TR1(S2,S1,L2,L1,T)| S1 #EQ# S2+1#AND# L1 #EQ# L2+1

#AND# S2 #EQ# L2:SWT*Y(S2,S1,L2,L1,T)));



@FOR(WORKER_NUM1(S1,T) :AV*A(S1,T)*@SUM(MACHINE_L1(L1)| S1 #GE# L1
:NW(S1,L1,T))

+@SUM(MACHINE_L1(L1)| S1 #GE# L1:SWO*OT(S1,L1,T))=D(S1,T));

@FOR(WORKER_NUM(S1,L1,T) | T #GT# 1#AND # S1 #GE# L1:NW(S1,L1,T-1)

+NH(S1,L1,T)-NL(S1,L1,T)+@SUM(HUMAN_MACHINE2(S2,L2)| S1 #EQ# S2+1#AND#

L1 #EQ# L2+1#AND# S2 #EQ# L2:SWT*Y(S2,S1,L2,L1,T))
```

```
-@SUM(HUMAN_MACHINE2(S2,L2)| S2 #EQ# S1+1#AND# L2 #EQ# L1+1#AND#
S1 #EQ# L1:SWT*Y(S1,S2,L1,L2,T))=NW(S1,L1,T));
@FOR(WORKER_NUM(S1,L1,T) | T #EQ# 1#AND # S1 #GE# L1:INW(S1,L1)+
NH(S1,L1,T)-NL(S1,L1,T)+@SUM(HUMAN_MACHINE2(S2,L2)| S1 #EQ# S2+1
#AND# L1 #EQ# L2+1#AND# S2 #EQ# L2:SWT*Y(S2,S1,L2,L1,T))
-@SUM(HUMAN_MACHINE2(S2,L2)| S2 #EQ# S1+1#AND# L2 #EQ# L1+1#AND#
S1 #EQ# L1:SWT*Y(S1,S2,L1,L2,T))=NW(S1,L1,T));
@FOR(WORKER_NUM(S1,L1,T)| T #GT# 1 :@SUM(HUMAN_MACHINE2(S2,L2)|
S2 #EQ# S1+1#AND# L2 #EQ# L1+1#AND# S1 #EQ# L1:SWT*Y(S1,S2,L1,L2,T)
+NL(S1,L1,T))<=NW(S1,L1,T-1));
@FOR(WORKER_NUM(S1,L1,T)| T #EQ# 1:@SUM(HUMAN_MACHINE2(S2,L2)|
 S2 #EQ# S1+1#AND# L2 #EQ# L1+1
#AND# S1 #EQ# L1:SWT*Y(S1,S2,L1,L2,T)+NL(S1,L1,T))<=INW(S1,L1));
@FOR(WORKER_NUM(S1,L1,T)| S1 #GE# L1:SWO*OT(S1,L1,T)<=AOT(S1,T)*NW(S1,L1,T));
@FOR(WORKER_NUM(S1,L1,T)| S1 #GE# L1:NL(S1,L1,T)<=M*WS1(S1,L1));
@FOR(WORKER_NUM(S1,L1,T)| S1 #GE# L1:NH(S1,L1,T)<=M*WS1(S1,L1));
@FOR(WORKER_TR1(S2,S1,L2,L1,T) | S1 #EQ# S2+1#AND# L1 #EQ# L2+1#AND#
S2 #EQ# L2:SWT*Y(S2,S1,L2,L1,T)<=M*WS2(S2,L2));
!@FOR(WORKER_TR1(S2,S1,L2,L1,T) | S1 #EQ# S2+1#AND# L1 #EQ# L2+1
#AND# S2 #EQ# L2:SWT*Y(S2,S1,L2,L1,T)<=M*WS1(S1,L1));
@FOR(WORKER_TR1(S2,S1,L2,L1,T)| S1 #EQ# S2+1#AND# L1 #EQ# L2+1
#AND# S2 #EQ# L2:SWT*Y(S2,S1,L2,L1,T)
<=M*SS(S2,S1));

END
TERSE
GO
Quit
```

F.1 VBA Code for Solving the File Named "MODEL_1":

```
Dim LINGO As Object


Sub Auto_Open()
   Set LINGO = CreateObject("LINGO.Document.4")
End Sub
Sub LINGOSolve()
  Dim iErr As Integer
  iErr = LINGO.RunScriptRange("MODEL")
  If (iErr > 0) Then
    MsgBox ("Unable to solve model")
  End If


End Sub
```