# Effects of Human Factors on Workforce Scheduling 

M. Othman, N. Bhuiyan, G. J. Gouw


#### Abstract

In today's competitive market, most companies develop manufacturing systems that can help in cost reduction and maximum quality. Human issues are an important part of manufacturing systems, yet most companies ignore their effects on production performance. This paper aims to developing an integrated workforce planning system that incorporates the human being. Therefore, a multi-objective mixed integer nonlinear programming model is developed to determine the amount of hiring, firing, training, overtime for each worker type. This paper considers a workforce planning model including human aspects such as skills, training, workers' personalities, capacity, motivation, and learning rates. This model helps to minimize the hiring, firing, training and overtime costs, and maximize the workers' performance. The results indicate that the workers' differences should be considered in workforce scheduling to generate realistic plans with minimum costs. This paper also investigates the effects of human learning rates on the performance of the production systems.


Keywords-Human Factors, Learning Curves, Workers' Differences, Workforce Scheduling

## I. InTRODUCTION

HUMAN capital is the sum of the knowledge, experience, expertise, capability, capacity and creativity possessed by the individuals of an organization. Workforce scheduling 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. It 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. 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 [1]-[3]. As one of the main elements in production planning, human issues cannot be ignored without considerably reducing benefits of the production system.
M. Othman is with the Mechanical and Industrial Engineering Department Concordia University, Montreal, Quebec, Canada H3G 1M8 (phone: +1514-836-3771; fax: +1514-848-3175; e-mail: mohothman2002@yahoo.com).
N. Bhuiyan is with the Mechanical and Industrial Engineering Department Concordia University, Montreal, Quebec, Canada H3G 1M8 (e-mail: bhuiyan@alcor.concordia.ca).
G. J. Gouw is with the Mechanical and Industrial Engineering Department Concordia University, Montreal, Quebec, Canada H3G 1M8 (e-mail: gerard.gouw@concordia.ca).

There are few reported research results related to human factors incorporated in production planning. The advantages derived from integrating human factors with production systems have been discussed [4]-[5]. 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.

In this paper, a new model for workforce scheduling to support production planning is developed to achieve better production performance. The model considers several human aspects skills, training, motivation, workers' personalities, workers' capacities and workers learning rates. This research aims to study how worker differences affect workforce planning and management decisions at tactical and operational levels. This research is organized as follows: section II presents a literature review of human factors and their relation to workforce planning. Section III introduces a formal definition of the problem along with a mathematical formulation that addresses the various aspects of the workforce planning process. Next, section IV addresses the importance of incorporating the human differences into workforce planning process by considering personality and productivity in the model. It provides some insights into the impact of some interrelated human factors on the workforce planning decisions under stable operating conditions. Finally, section V presents the conclusions and future research directions for this paper.

## II.Literature Review

Effective production planning processes are essential for success in manufacturing operations. Several research papers have highlighted the importance of interactions between some key human factors and the production system and the need to incorporate organizational behavior issues in operations management [6]-[7]. 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 [6]. A mathematical model was developed to deal with a simultaneous dynamic cell formation and worker assignment problem [7]. 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. A more recent comprehensive review of the literature on the human factors of production scheduling is provided [8].
Human Factors (HF), or ergonomics, has been defined as "the theoretical and fundamental understanding of human behavior and performance in purposeful interacting sociotechnical systems, and the application of that understanding to the design of interactions in the context of real settings"'[9]. Previous literature on workforce management has addressed various issues such as worker differences and how much performance improvement can be gained [10]-[14]. Human performance is the accomplishment of a task by a human operator. A model that highlights the four components of job performance a manager controls was presented [15].
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 [16]. 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. Motivation is generally the most accepted mediator of personality dimensions and job performance relationship [17].
A model that studies the interaction among three variables which affect the job design was proposed [18]. These variables are personal psychological state, jobs characteristics, and individual's attributes that determine his response for a challenging work. A model that can link between worker motivation and productive performance was developed [19]. 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 [11]. Many attributes, conditions, and reactions affect the person's performance [20].

Examples of these factors are task type, task quantity, task environment, person's capability and attitude. The impact of worker differences on the production system was studied since individual differences can result in substantial loss in throughput [21]. As far as the authors are aware, incorporating human factors such as personality, capacity, skill, training, learning, productivity and motivation together into workforce planning has not been previously considered in the existing literature. Recently, a new approach to workforce planning problem in order to incorporate human issues into production planning was presented [22].

The results showed that costs have a significant effect on the selection of the workers with different skill ability. Using this approach, there is a significant research opportunity to incorporate human differences in the planning process. On the other hand, researchers utilized mathematical models, heuristics and simulation to study the impact of some human
aspects such as cross-training, motivation, and learning curves on system performance. Four optimization models for different cross-training scenarios was developed to assist managers in deciding optimum tactical plans for training and assigning a workforce according to the skills required by a forecasted production schedule [23]. The concept of a multilevel flexibility workforce using simulation was investigated [24]. 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. An aggregate production planning model that includes workers' training, legal restrictions on workload and workforce size was developed [25]. General cognitive ability metric was used to model individual difference in efficacy of cross-training and worker productivity [14]. A MIP model for assigning workers to manufacturing cells in order to maximize the profit was proposed [26]. 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. A fuzzy multi-objective nonlinear programming model for aggregate production planning problem in a fuzzy environment was developed [27]. Learning curve effects have been considered in formulating the model. Workers motivation, learning and forgetting factors and workers' skills was considered to measure employees' boredom and skill variations during a production horizon [28]. A model that incorporates learning curves and workers experience in modeling a scheduling problem was developed [29]. 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. An approach to measuring organizational learning, wherein individual worker heterogeneity is modeled, was introduces [30]. An important extension of this approach by incorporating both learning and forgetting into an individual-based model of productivity was introduced [31]. In this model, both the learning and the forgetting components were shown to be preferred models among numerous candidate models [32]-[33].

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 [34]-[40]. There have been many interesting developments on the technical side of planning and control, but all of these models ignored most, if not all, of the important human factors that can be critical for production planning performance. Moreover, little work has been precisely modeled workforce planning problem that incorporates workers learning, with motivation and individual personal traits. However, the research to be presented in the next section will contribute to the literature by extending existing models of workforce planning beyond current capabilities. This provides the motivation to work towards
developing a more comprehensive model that includes manufacturing and human parameters.

## III. Mathematical Modeling

In this paper, we assume that we have a manufacturing company that has different machines types, which are grouped into three machine levels depending on their complexity. Machine level one contains machines that are easy to operate by 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. 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. 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. Worker skills include communication skills, leadership skills, planning skills, problem-solving skills, teamwork skills, and technical work skills. However, personal attributes include the worker who is creative, dynamic, educated, efficient, energetic, focused, healthy, intelligent, integrity, knowledgeable, organized, previous success in work, relationship with others, responsible, seek improvement, and strong. However, due to difficulty in measuring some of the subjective personal attributes, we divided the skill levels and the personal levels into three levels: level 1 indicates the lowest level, level 2 indicates the middle level, and level 3 indicates the highest level. In this paper, personality levels are measured based on percentile scores. Level 1 indicates the range from 0 to 33.3th percentile, level 2 indicates the range from 33.4th to 66.6 th percentile, and level 3 indicates the range from 66.7 th to $100^{\text {th }}$ percentile. For example, people 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 more traditional interests. However, people with similar characteristics are grouped into personality levels, which reduce the variability of considering individual personality profiles. In order to quantify the personality domains, a researcher can develop special personal tests and provide it the workers to estimate their personal abilities. Each worker has at least one skill or personal level and can be assigned to certain machine levels. In each period, workers can be trained in order to improve only their skill level. It is assumed that all workers have initial productivity to start their work at the first period depending on their capacity and 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 products and services that organizations produce them. In this paper, two performance measures are used to evaluate the generated workforce plan. The first one is to minimize the total costs resulted from the
hiring, firing and training, and over time in dollars unit. The second one is used to maximize workers performance. 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 much performance of the workers to be achieved?

## A. 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.
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 increased exponentially over time horizon.

## B. Model Development

The model developed is a multi-objective mixed integer nonlinear programming model 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 and maximize workers performance over all periods. In presenting the model, the following notations are used.

## 1. Indices

$$
\begin{aligned}
t & =\text { Index of planning periods (weeks), } t=1,2, \ldots, T \\
j, k & =\text { Index of human skill levels, } j, k=1,2, \ldots, S \\
x, y & =\text { Index of machine levels, } x, y=1,2, \ldots, M L \\
p & =\text { Index of personality attributes, } p=1,2, \ldots, P
\end{aligned}
$$

## 2. Parameters

| $h_{j t}$ | $=$Cost of hiring a worker with skill set $j$ in period <br> $t(\$ /$ worker-week) |
| ---: | :--- |
| $f_{j t}$ | $=$Cost of lay-off of a worker with skill set $j$ in <br> period $t(\$ /$ worker-week $)$ |
| $t r_{k j t}$ | $=$Cost of training a worker from skill set $k$ to skill <br> set $j$ in period $t(\$ /$ worker-week) |
| $s r_{j p t}=$ | weekly salary of a $p$ - level worker with skill set <br> $j$ at regular time in period $t(\$ /$ worker-week) |
| $s O_{j t}=$Hourly rate of a worker with skill set <br> overtime in period $t$ at $t /$ worker-hour) |  |

$A_{j t}=$ Available regular working hours of a worker with skill set $j$ for each person in each period $t$ (worker-hours/worker-week)
$A O T_{j t}=$ Available overtime working hours of a worker with skill set $j$ for each person in each period $t$ (worker-hours/worker-month)
$C_{j p} \quad=\quad$ Capacity of a $p$-level worker with skill set $j$ for each person in each period
$O_{X}=$ Opportunity to work on machine level $x$ in each period
$R_{j p x}=$ Readiness (willingness) of $p$-level workers with skill set $j$ to work on machine level $x$
$D_{j t}=$ Demand for skill $j$ in period t (worker-hours)
$S s_{k j}= \begin{cases}1 & \text { If training } \\ \text { possible; }\end{cases}$
If working on machine level $x$ with skill level
$w s_{j x}= \begin{cases}1 & \text { If working on } \\ j & j \text { is possible; }\end{cases}$
$I N P_{j p x}=\quad$ Initial productivity level for worker $p-$ level workers with skill level $j$ working on machine level $x$
$E_{j p x}=\quad \begin{aligned} & \text { Difference in rate of output between the initial } \\ & \text { rate of } I N P_{j p x} \text { and the maximum rate of }\end{aligned}$ productivity (Pr)
$L E_{j p x}=$ Individual learning constant for worker $p$-level workers with skill level $j$ working on machine level $x$
${ }^{0.8}$ Initial number of workers with skill set $j$
required to be assigned to machine level $x$ (worker-weeks)
$M \quad=\quad \mathrm{A}$ big number
$w_{z} \quad=\quad$ Positive weights that reflect the decision maker's preferences regarding the relative importance of each goal, $Z=1,2$
$Z_{1}=$ Desired cost level
$Z_{2}=$ Desired performance can be achieved

## 3. Decision Variables

$W_{j t x}=\quad$ Number of workers with skill set $j$ required to be assigned to machine level $x$ in period $t$ (workerweeks)
$H_{j t x}=$ Number of workers with skill set $j$ hired and assigned to machine level $x$ in period $t$ (workerweeks)
$L_{j t x}=$ Number of existing workers with skill set $j$ who are assigned to machine level $x$ in period $t-1$ and they are laid-off in period $t$ (workerweeks)
$Y_{\text {kjtyx }}=$ Number of workers who were assigned to machine level $y$ and then are trained from skill set $k$ to skill set $j$ and assigned to a higher machine level $x$ in period $t$ (worker-weeks)
$O T_{j i x}=$ Overtime hours of a level workers with skill set $j$ in period $t$ (worker-hours)
$V_{j p t x}=\left\{\begin{array}{l}1 \begin{array}{l}\text { if a } p-\text { level worker with skill level } j \text { can work on } \\ \text { machine level } x \text { in period } t ;\end{array} \\ 0 \begin{array}{l}\text { otherwise }\end{array}\end{array}\right.$ Productivity if a $p$ - level worker with skill level $j$
$P r_{j p t x}=\quad$ does work on machine level $x$ during time $t$ (based on time-constant leaning model)
The output performance from a $p$ - level worker
$P O_{j p t x}=\quad$ with skill level $j$ working on machine level $x$ during time $t$

## 4. Objective Function

The objective is to minimize costs and maximize workers' performance over the time horizon:
Goal 1: minimize:

$$
\begin{aligned}
& Z_{1}=\sum_{t=1}^{T} \sum_{p=1}^{P} \sum_{j=1}^{S} \sum_{j=1}^{M L}\left(s_{j p t} \times W_{j p t x}+h_{j p t} \times H_{j p t x}+f_{j p t} \times L_{j p t x}\right) \\
& +\sum_{t=1}^{T} \sum_{p=1}^{P} \sum_{j=1}^{S} \sum_{j=1}^{M L}\left(s o_{j p t} \times O T_{j p t x}\right)+\sum_{t=1}^{T} \sum_{p=1}^{P} \sum_{j=1}^{S} \sum_{k=1}^{S} \sum_{x=1}^{M L} \sum_{y=1}^{M L}\left(t r_{j k p t} \times Y_{j k p t x y}\right)
\end{aligned}
$$

## Goal 2: maximize

$Z_{2}=\sum_{t=1}^{T} \sum_{p=1}^{P} \sum_{j=1 x=1}^{S L} P O_{j p t x}$

## Subject to:

$\times A_{j t} \times\left(\sum_{p=1}^{P} \sum_{x=1}^{M L} P r_{j p x} \times W_{j p x}\right)+\sum_{p=1}^{P} \sum_{x=1}^{M L} O T_{j p x}=D_{j t} \quad \forall j, t$

$$
\begin{align*}
& W_{j p t x}=W_{j p t-1 x}+H_{j p t x}-L_{j p t x}+  \tag{1}\\
& \sum_{k=j-1}^{j} \sum_{y=x-1}^{x}\left(Y_{k j p t y x}\right)-\sum_{k=j+1}^{k} \sum_{y=x+1}^{y}\left(Y_{j k p t x y}\right) \quad \forall j, p, t, x
\end{align*}
$$

$$
\begin{equation*}
\sum_{\substack{k=1 \\ k>j}}^{S} \sum_{y=1}^{S L} Y_{j k p x y}+L_{j p t x} \leq W_{j p, t-1, x} \quad \forall j, p, t, x \tag{3}
\end{equation*}
$$

$$
\begin{equation*}
L_{j p t x} \leq M \times w s_{j p x} \quad \forall j, p, t, x \tag{4}
\end{equation*}
$$

$$
\begin{equation*}
H_{j p t x} \leq M \times w s_{j p x} \quad \forall j, p, t, x \tag{5}
\end{equation*}
$$

$$
\begin{equation*}
Y_{k j p t y x} \leq M \times w s_{k p y} \quad \forall j, k, p, t, x, y \tag{6}
\end{equation*}
$$

$$
\begin{equation*}
Y_{k j p t y x} \leq M \times w s_{j p x} \quad \forall j, k, p, t, x, y \tag{7}
\end{equation*}
$$

$$
\begin{equation*}
Y_{k j p y x} \leq M \times s s_{k j} \quad \forall j, k, p, t, x, y \tag{8}
\end{equation*}
$$

$$
\begin{equation*}
\sum_{k=1}^{s} Y_{k j p y x} \leq M \times Z_{j p x} \quad \forall j, p, t, x, y \tag{9}
\end{equation*}
$$

$$
\begin{equation*}
L_{j p x} \leq M\left(1-Q_{j p x x}\right) \quad \forall j, p, t, x \tag{10}
\end{equation*}
$$

$$
\begin{equation*}
H_{j p x} \leq M \times Q_{j p x} \quad \forall j, p, t, x \tag{11}
\end{equation*}
$$

$$
\begin{equation*}
L_{j p t x} \leq M\left(1-U_{j p t x}\right) \quad \forall j, p, t, x \tag{12}
\end{equation*}
$$

$$
\begin{equation*}
P O_{j p t x} \leq V_{j p t x} \times P r_{j p t x} \quad \forall j, p, t, x \tag{13}
\end{equation*}
$$

$$
\begin{equation*}
P r_{j p x} \leq 1 \quad \forall j, p, t, x \tag{14}
\end{equation*}
$$

$$
\begin{equation*}
V_{j p t x} \leq M \times w s_{j p x} \quad \forall j, p, t, x \tag{15}
\end{equation*}
$$

$$
\begin{equation*}
W_{j p t x} \leq M \times V_{j p t x} \quad \forall j, p, t, x \tag{16}
\end{equation*}
$$

$$
\begin{array}{rr}
I N P_{j p x}=C_{j p} \times O p_{x} \times R_{j p x} & \forall j, p, x  \tag{18}\\
P r_{j p t x}=I N P_{j p x}+E_{j p x}\left[1-\exp \left(-\frac{\sum_{i=1}^{t} V_{j p i x}}{L E_{j p x}}\right)\right] & \forall j, p, t, x \\
W_{j p t x}, H_{j p t x}, L_{j p t x}, Y_{k j p t y x} \geq 0 \text { and } & \\
U_{j p t x}, Q_{j p t x}, V_{j p t x} \in\{0,1\} & \forall j, k, p, t, x, y
\end{array}
$$

Constraint (1) shows 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) ensures that the overtime workforce available should be less than the maximum overtime workforce available in each period. Constraint (4) ensures that the total number of workers who are assigned to machine level x in period $\mathrm{t}-1$ and now fired or trained for upper skill levels should not be greater than the number of workers required in previous period. Constraint (5) ensures that workers can be fired if and only if the assignment is possible. Constraint (6) denotes that workers can be hired if and only if the assignment is possible. Constraint (7) Training for better skills is possible if and only if the previous assignment is possible. Constraint (8) ensures that training for better skills is possible if and only if the latter assignment is possible. Constraint (9) ensures that training for better skills is possible if and only if training to that skill is possible. Constraints (10) and (11) guarantee the workers who are trained for skill level $j$ should not be fired in the same period. Constraints (12) and (13) ensure that either hiring or firing workers occurs but not both. Constraint (14) ensures that the total output, $P O$, is always less than the productivity of the workers. The approximation is reasonable for relatively short periods. Constraint (15) ensures that the productivity of each worker is less than or equal to one during each time interval. Constraint (16) ensures that each worker is assigned at specific machine level during each time interval. Constraint (17) 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 (18) states that the initial productivity level for worker ( $j, p$ ) on machine level x depends on the working opportunity, workers capacity and their willingness. Constraint (19) 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. Finally, constraint (20) shows the non-negativity constraint and the binary variables.

Goal programming can be used to solve the problem. The decision maker must determine the 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 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 the first goal never degrades the second goal solutions. However, the following steps can used to handle multi-objective functions:

1) Define the LP1 as the first linear programming model with objective function $Z_{1}$ and LP2 is the second linear programming model with objective function $\mathrm{Z}_{2}$.
2) Identify the goals of the model and rank them in order of importance: goal 1: minimize total costs $\left(Z_{1}\right)$, goal 2 : maximize the total workers performance $\left(\mathrm{Z}_{2}\right)$.
3) Solve LP2 that maximizes $Z_{2}$, and then solve LP1 that minimize $Z_{1}$ and add the previous objective functions $Z_{1}$ and $Z_{2}$ to the initial constraints to ensure the goals $Z_{1}$ and $\mathrm{Z}_{2}$ are not degraded.
4) Solve the combined objective function that minimizes the deviational variables which represents both goals.
First, additional terms are defined. Let

| $S_{1}^{+}$ | $=$The positive deviation from goal 1 |
| :--- | :--- |
| $S_{1}^{-}$ | $=$The negative deviation from goal 1 |
| $S_{2}^{+}$ | $=$The positive deviation from goal 2 |
| $S_{2}^{-} \quad=\quad$ The negative deviation from goal 2 |  |

All these deviations should be measured in terms of value. Then the formulation of the problem reduces to:
Minimize: $F=w_{1} \times S_{1}^{+}+w_{2} \times S_{2}^{-}$
Subject to:
$\sum_{t=1}^{T} \sum_{p=1}^{P} \sum_{j=1}^{S} \sum_{x=1}^{M L}\left(s_{j p t} \times W_{j p t x}+h_{j p t} \times H_{j p t x}+f_{j p t} \times L_{j p t x}\right)$
$+\sum_{t=1}^{T} \sum_{p=1}^{P} \sum_{j=1}^{S} \sum_{x=1}^{M L}\left(s o_{j p t} \times O T_{j p t x}\right)+$
$\sum_{t=1}^{T} \sum_{p=1}^{P} \sum_{j=1}^{S} \sum_{k=1}^{S} \sum_{x=1}^{M L} \sum_{y=1}^{M L}\left(t r_{j k p t} \times Y_{j k p t x y}\right)+S_{1}^{-}-S_{1}^{+}=Z_{1}$
$\sum_{t=1}^{T} \sum_{p=1}^{P} \sum_{j=1}^{S} \sum_{x=1}^{M L} P O_{j p t x}+S_{2}^{-}-S_{2}^{+}=Z_{2}$
Next section explains the previous procedure through a given numerical example.

## IV. Computational Results

To illustrate the model proposed in this paper and assess the effect of workers` differences on total costs and workforce plan, a simple example is 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.

| A. Numerical Example | Skill | regular time | 40 | 40 | 40 | 40 | 40 | 40 | 40 | 40 |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| A company produces its products to fulfil known demand | overtime | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 |  |

TABLE III training costs are assumed to be higher for higher skill and personal 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 tables I-VII. The known demand of worker skills in workerhours in each period is summarized in Table I. Table II shows workers' availabilities. Table III shows the available workforce at period zero. Table IV shows the cost of training from skill level to another skill level in each period. Willingness to perform $o$ each machine level for every personality level is illustrated in Table V. Learning parameters for each worker type are illustrated in Table VI. Hiring costs, lay-off costs, overtime costs and workers' capacities are shown in Table VII. Using the input data presented, the model consists of 4152 variables and 2903 constraints and the global optimal solution for the problem can be obtained using LINGO 13.0 software within 3 minutes of program running. The total performances of the workers are 124.2 and the total costs are $\$ 1,669,220$.

TABLE I

|  | $\mathrm{W}^{a}$ | 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 |

## ${ }^{a}$ W1 represents Week 1

Results from the proposed model are shown in Table VIII. In this paper, 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 II

| Workers' AVAILABILITIES (worker-hours) |  |  |  |  |  |  |  |  |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
|  |  | W1 | W2 | W3 | W4 | W5 | W6 | W7 | W8 |
| Skill | regular time | 40 | 40 | 40 | 40 | 40 | 40 | 40 | 40 |
| 1 | overtime | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 |
| Skill | regular time | 40 | 40 | 40 | 40 | 40 | 40 | 40 | 40 |
| 2 | overtime | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 |

TABLE V
WILLINGNESS TO WORK ON A MACHINE LEVEL IN EACH WEEK (\%)

|  |  | Level 1 | Level 2 | Level 3 |
| :--- | :--- | :--- | :--- | :--- |
| Worker | P1 | 60 | 0 | 0 |
| Skill 1 | P2 | 70 | 0 | 0 |
|  | P3 | 80 | 0 | 0 |


| Worker | P1 | 70 | 75 | 0 |
| :--- | :--- | :--- | :--- | :--- |
| Skill 2 | P2 | 75 | 80 | 0 |
|  | P3 | 80 | 85 | 0 |
| Worker | P1 | 70 | 75 | 80 |
| Skill 3 | P2 | 75 | 80 | 85 |
|  | P3 | 80 | 85 | 90 |

TABLE VI
LEARNING PARAMETER FOR A WORKER ON EACH MACHINE LEVEL (PERIODS)

|  |  | 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 |
|  | P 2 | 5 | 4 | M |
|  | P3 | 3 | 2 | M |
| Worker Skill 3 | P1 | 4 | 3 | 2 |
|  | P3 | 1 | 2 | 2 |
|  | 1 | 1 | 1 |  |

On the other hand, we see that hiring and cross-training highly depends on productivity factors, and salary and training costs. The highest personal 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, Low personality levels become more attractive in training because of the high differences between costs for different personality levels. 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 they become excess 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.

## B. Effects of Workers' Differences on Planning Decisions

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 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. Six scenarios with different working productivity were studied, as shown in Table IX. 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 tasklearning 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 and E, 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 Finally, Scenario E represents the case that all workers have constant initial productivities and their costs are different based on their skills and personality levels. Figs. 1 and 2 illustrate these six scenarios.

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 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. Scenario E, F and G supports the fact that considering different productivity of workers can results in better schedule output in terms of performance and costs. From figs. 1 and 2, we can see that our proposed model (scenario B) generates results nearly close to the ideal case. 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.

TABLE VII
HIRING, FIRING AND OvERTIME Costs (\$/worker-weeks)

|  |  |  | 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 VIII


TABLE IX
SIX Scenarios with Different Productivity Factors

| Scenario | Description | W11 | W12 ${ }^{\text {c }}$ | W13 | W21 | W22 | W23 | W31 | W32 | W33 | $\mathrm{P}^{\text {d }}$ | Costs (\$) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| A | Ideal | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 144 | 1,402,082 |
| B | Practical | $\begin{aligned} & 0.36- \\ & 0.62 \end{aligned}$ | $\begin{aligned} & 0.5- \\ & 0.83 \end{aligned}$ | $\begin{aligned} & 0.73- \\ & 1 \end{aligned}$ | $\begin{aligned} & 0.5- \\ & 0.89 \end{aligned}$ | $\begin{aligned} & 0.63- \\ & 1 \end{aligned}$ | $\begin{aligned} & 0.75- \\ & 1 \end{aligned}$ | $\begin{aligned} & 0.62- \\ & 1 \end{aligned}$ | $\begin{aligned} & 0.78- \\ & 1 \end{aligned}$ | $\begin{aligned} & 0.89- \\ & 1 \end{aligned}$ | 124.2 | 1,669,220 |
| C | Same Costs | $\begin{aligned} & 0.36- \\ & 0.62 \end{aligned}$ | $\begin{aligned} & 0.5- \\ & 0.83 \end{aligned}$ | $\begin{aligned} & 0.73- \\ & 1 \end{aligned}$ | $\begin{aligned} & 0.5- \\ & 0.89 \end{aligned}$ | $\begin{aligned} & 0.63- \\ & 1 \end{aligned}$ | $\begin{aligned} & 0.75- \\ & 1 \end{aligned}$ | $\begin{aligned} & 0.62- \\ & 1 \end{aligned}$ | $\begin{aligned} & 0.78- \\ & 1 \end{aligned}$ | $\begin{aligned} & 0.89- \\ & 1 \end{aligned}$ | 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 |

${ }^{\text {c }}$ W12 represents worker with skill 1 and personality level 2
${ }^{d}$ P represents Output Performance


Fig. 1 Total performance for different scenarios


Fig. 2 Total costs for different scenarios

## V.Conclusions

In this paper, an approach for integrating human factors with production planning is proposed. A model will be used to evaluate their effects on the organizations' goals. This model can take into account the human aspects and individual differences to plan the production activities. Also, variations in human performance are considered to ensure the validity of the model. The research has demonstrated the importance of considering human factors within production planning models of manufacturing systems.

The novelty to this model is that it jointly accounts for the distinguishing features associated with the manufacturing process of many companies including overtime, training, workers skill levels and machine levels. This model incorporates important human aspects such workers' personalities, capacity, motivation, and learning rates. The objective of the model is to provide insights into the effect of these human factors on the planning decisions. The experiments illustrate that if the model considers individual differences 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. This model highlights the importance of incorporating human factors in the planning process since it reduces the total costs and increase the total performance.
It is clear that human factors and production planning integration have much more research opportunities, and the path is still open to make 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. 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 optimal results within a reasonable time can be a good subject for future research. Moreover, 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.

## References

[1] R.J. Castley, "Policy-focused approach to manpower planning," International Journal of Manpower, vol. 17, no. 3, pp. 15-24, 1996.
[2] P.L. Jensen, "Human factors and ergonomics in the planning of production," International Journal of Industrial Ergonomics, vol. 29, no. 3, pp. 121-131, 2002.
[3] S. Birch, L. O’Brien-Pallas, C. Alksnis, G. Tomblin Murphy, and D. Thomson, "Beyond demographic change in human resources planning: an extended framework and application to nursing," Journal of Health Services Research and Policy, vol. 8, no. 4, pp. 225-229, 2003.
[4] G.G. Udo, and A.A. Ebiefung, "Human factors affecting the success of advanced manufacturing systems," Computers \& Industrial Engineering, vol. 37, no. 1-2, pp. 297-300, 1999.
[5] P. Oborski, "Man-machine interactions in advanced manufacturing systems," International Journal of Advanced Manufacturing Technology, vol. 23, no. 3-4, pp. 227-232, 2004.
[6] B. Bidanda, P. Ariyawongrat, K. LaScola Needy, B.A. Norman, and W. Tharmmaphornphilas, "Human related issues in manufacturing cell design, implementation, and operation: a review and survey," Computers \& Industrial Engineering, vol. 48, no. 3, pp. 507-523, 2005.
[7] M.B. Aryanezhad, V. Deljoo, and S.M.J. Mirzapour Al-e-hashem, "Dynamic cell formation and the worker assignment problem: a new model," The International Journal of Advanced Manufacturing Technology, vol. 41, no. 3-4, pp. 329-342, 2009.
[8] S. Crawford, and V.C.S. Wiers, "From anecdotes to theory: A review of existing knowledge on the human factors of production scheduling, in Human Performance in Planning and Scheduling (Eds. B.L. MacCarthy, J.R. Wilson), London: Taylor and Francis, 2001, Ch. 3.
[9] J.R. Wilson, "Fundamentals of ergonomics in theory and practice," Applied Ergonomics, vol. 31, no. 6, pp. 557-567, 2000.
[10] M.R. Barrick, and M.K. Mount, "The Big Five personality dimensions and job performance: A meta-analysis," Personnel Psychology, vol. 44, no. 1, pp. 1-26, 1991.
[11] J.E. Hunter, "Cognitive ability, cognitive aptitudes, job knowledge, and job performance," Journal of Vocational Behavior, vol. 29, no.3, pp.340-362, 1986.
[12] J.E. Hunter, F.L. Schmidt, and M.K. Judiesch, "Individual differences in output variability as a function of job complexity," Journal of Applied Psychology, vol. 75. no. 1, pp. 28-42, 1990.
[13] M.J. Ragotte, "The effect of human operator variability on the throughput of an AGV system. A case study: General Motors car assembly plant - door AGV system," M.A.Sc Thesis, Department of Management Sciences, University of Waterloo, Canada, 1990.
[14] P. Wirojanagud, E.S Gel, J.W. Fowler, and R. Cardy, "Modeling inherent worker differences for workforce planning," International Journal of Production Research, vol. 45, no. 3, pp.525-553, 2007.
[15] B. Jones, "The four domains affecting job performance," Internal Document, Delta Air Lines. Atlanta, GA. As found in, V. Mancuso, "Moving from Theory to Practice: Integrating Human Factors into an Organization," Seattle WA: Annual Flight Safety Foundation Conference. Retrieved Jan 17, 2011 from http://www.crmdevel.org/ftp/mancuso.pdf
[16] J.E. Bono, and T.A. Judge, "Core self-evaluations: A review of the trait and its role in job satisfaction and job performance," European Journal of Personality, vol.17, no. S1, pp. S5-S18, 2003.
[17] A. Erez, and T.A. Judge, "Relationship of core self-evaluations to goal setting, motivation, and performance," Journal of Applied Psychology, vol. 86, no. 6, pp. 1270-1279, 2001.
[18] J.R. Hackman, and G.R. Oldham, "Motivation through the design of work: test of a theory," Organizational Behavior and Human Performance, vol. 16, no. 2, pp. 250-279, 1976.
[19] M. Blumberg, and C.D. Pringle, "The missing opportunity in organizational research: some implications for a theory of work performance," Academy of Management Review, vo. 7, no. 4, pp. 560569, 1982.
[20] K. Kroemer, H. Kroemer, and K. Kroemer-Elbert, "Ergonomics: how to design for ease and efficiency," (2nd ed.). Upper Saddle River, NJ: Prentice-Hall, 2001.
[21] J.A. Buzacott, "The impact of worker differences on production system output," International Journal of Production Economics, vol. 78, no. 1, pp. 37-44, 2002.
[22] M. Othman, N. Bhuiyan, and G.J. Gouw, "A new approach to workforce planning," ICMAME 2011: International Conference on Mechanical, Aeronautical and Manufacturing Engineering, no. 52, pp. 804-810, Venice, Italy, April 27-29, 2011.
[23] B.D. Stewart, D.B. Webster, S. Ahmad, and J.O. Matson, "Mathematical models for developing a flexible workforce," International Journal of Production Economics, vol. 36, no. 3, pp. 243-254, 1994.
[24] J.T. Felan, and T.D. Fry, "Multi-level heterogeneous worker flexibility in a Dual Resource Constrained (DRC) job-shop," International Journal of Production Research, vol.39, no. 14, pp.3041-3059, 2001. Barman, An interactive decision support system for an aggregate
[25] C.G. Da Silva, J. Figueira, J. Lisboa, and S. "production planning model based on multiple criteria mixed integer linear programming," The International Journal of Management Science, vol. 34, no. 2, pp.167177, 2006.
[26] B.A. Norman, W. Tharmmaphornphilas, K.L. Needy, B. Bidanda, and R.C. Warner, "Worker assignment in cellular manufacturing considering technical and human skills," International Journal of Production Research, vol. 40, no. 6, pp.1479-1492, 2002.
[27] A. Jamalnia, and M.A. Soukhakian, "A hybrid fuzzy goal programming approach with different goal priorities to aggregate production planning," Computers \& Industrial Engineering, vol. 56, no. 4, pp.1474-1486, 2009.
[28] N. Azizi, S. Zolfaghari, and M. Liang, "Modeling job rotation in manufacturing systems: The study of employee's boredom and skill variations," International Journal of Production Economics, vol. 123, no. 1, pp. 69-85, 2010.
[29] A. Corominas, J. Olivella, and R. Pastor, "A model for assignment of a set of tasks when work performance depends on experience of all tasks involved," International Journal of Production Economic, vol. 126, no. 2, pp.335-340, 2010.
[30] S.M. Shafer, D.A. Nembhard, and M.V. Uzumeri, "Investigation of learning, forgetting, and worker heterogeneity on assembly line productivity," Management Science, vol. 47, no. 12, pp. 1639-1653, 2001.
[31] D.A. Nembhard, and M.V. Uzumeri, "Experiential learning and forgetting for manual and cognitive tasks," International Journal of Industrial Ergonomics, vol. 25, no. 1, pp. 315-326, 2000a.
[32] D.A. Nembhard, and M.V. Uzumeri, "An individual-based description of learning within an organization," IEEE Transactions on Engineering Management, vol. 47, no. 1, pp.370-378,2000b.
[33] D.A. Nembhard, and N. Osothsilp, "An empirical comparative study of models for measuring intermittent forgetting," IEEE Transactions on Engineering Management, vol. 48, no. 3, pp. 283-291, 2001.
[34] G.M. Campbell, and M. Diaby, "Development and evaluation of an assignment heuristic for allocating cross-trained workers," European Journal of Operational Research, vol. 138, no. 1, pp.9-20, 2002.
[35] S.C.K. Chu, "A mathematical programming approach towards optimized master production scheduling," International Journal of Production Economics, vol. 38, no. 2-3, pp. 269-279, 1995.
[36] Y.Y. Lee, "Fuzzy set theory approach to aggregate production planning and inventory control," Ph.D. Dissertation. Department of Industrial Engineering, Kansas State University, 1990.
[37] S.C.H. Leung, and S.S.W. Chan, "A goal programming model for aggregate production planning with resource utilization constraint," Computers \& Industrial Engineering, vol. 56, no. 3, pp. 1053-1064, 2009.
[38] S.J. Nam, and R. Logendran, "Aggregate production planning - A survey of models and methodologies," European Journal of Operational Research, vol. 61, no. 3, pp. 255-272, 1992.
[39] R.C. Wang, and T.F. Liang, "Application of fuzzy multi-objective linear programming to aggregate production planning," Computers \& Industrial Engineering, vol. 46, no. 1, pp. 17-41, 2004.
[40] R.C. Wang, and T.F. Liang, "Applying possibilistic linear programming to aggregate production planning," International Journal of Production Economics, vol. 98, no. 3, pp. 328-341, 2005.

