Ain Shams Engineering Journal 13 (2022) 101575

Contents lists available at ScienceDirect

Ain Shams Engineering Journal

journal homepage: www.sciencedirect.com

Mechanical Engineering

Aggregate production planning considering organizational learning with case based analysis

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ARTICLE INFO

Article history:
Received 6 June 2020
Revised 29 March 2021
Accepted 4 September 2021
Available online 20 October 2021

Keywords:
Aggregate production planning
Learning curves
Organizational learning
Mixed integer linear programming
Manufacturing of electric motors

ABSTRACT

Responding rapidly to customer needs is one of the main targets of industrial organizations that want to survive in the current market competition. This objective can be attained through robust planning. Workforce productivity is considered one of the important entities in production planning. However, it has a dynamic nature, i.e. the productivity growths thanks to on-job training or learning phenomenon. Considering this fact in manufacturing planning enhances the robustness of the developed plans. The present paper presents a mathematical model for medium-range production planning that is used to find the optimal aggregate production plan. The model aims to optimize the total production costs while respecting most of the operational constraints and considering the process of organizational learning. The presented model is constructed relying on the real industrial practices; the outcome is a mixed-integer linear program. The model was validated and checked using real data collected from an Egyptian factory that produces electric motors for home appliances. The proposed mathematical model was optimally solved using "ILOG-CPLEX 12.6". By comparing the results obtained versus that of the method adopted in the factory, a cost reduction of 6.3% is achieved for the presented data set. A set of managerial aspects are concluded after the model analysis. Moreover, the impact of using detailed learning rates on the production cost is discussed.

1. Introduction

Responding rapidly to customer needs is one of the main targets of industrial organizations that want to survive in the current market competition. One of the most crucial needs is to deliver the required products at minimum lead-time and price while respecting the pre-specified specifications. These strategic targets can be attained by developing a robust production plan. A plan that accurately considers the available capacities for successfully executing the production activities. Tactical planning level or medium-term planning is considered as one of the essential industrial planning. For this level, the different production capacities should be assessed for meeting the required demand. This planning level is known as Aggregate Production Planning (APP). APP is located between strategic planning and highly detailed operational planning. As known, there are three levels of production planning: strategic, tactical, and operational. These three levels are interrelated with a hierarchical nature. This nature should be consistent, in which the decisions of the superior level impose constraints on the decisions of the lower level. While the lower level provides the required feedback to regulate the decisions of the higher level, e.g. the top management strategies of using part-time workers or external subcontracts impose constraints on the APP models. Consequently, the master production schedule and material requirement planning depend on the results of the APP. Regarding the duration of the planning horizon of APP, the literature provides a

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Peer review under responsibility of Ain Shams University.

Production and hosting by Elsevier

https://doi.org/10.1016/j.asej.2021.09.002
2090-4479/

Nomenclature

Indices

m Represents the product family/model, $m = 1,2,\ldots,M$, where M equals the total number of products,

t Represents the planning period, $t = 1,2,\ldots,T$, where T is the total number of planning periods.

Parameters

$A_{av.}$ Real positive number, $A_{av} \in [0,1]$ represents the average machine availability

C_{HP} Integer number, represents the hiring cost of a part-time worker,

$CI_{m,t}$ Real positive number, represents the average inventorying cost of m, during t,

C_{LP} Constant represents the cost of firing a part-time worker.

$CM_{m,t}$ Real positive number, represents the estimated material cost for m, during t,

C_{OPWh} / C_{OPWn} Real positive number, represents respectively the average overtime hourly cost during a day-off, normal working day for a part-time worker,

C_{ORWh} / C_{ORWn} Real positive number, represents respectively the average overtime hourly cost during a day-off, normal working day for a permanent worker,

C_{RW} / C_{PW} Real positive number, represents respectively the average salary per period for a permanent worker and the average wages per period of a part-time worker,

$CR_{m,\ t}$ Real positive number, represents the estimated operation cost of m during t,

$Csub_{m,t}$ Real positive number, represents the subcontracting cost per unit from m, during t,

$D_{m,t}$ Integer positive number, represents the demand forecast from model m, during t,

h_t Integer positive number, represents the number of days-off during t,

$I_{m,0}$ Integer positive number, represents the initial inventory of m just before the first period of t = 1,

$K_{I\ \max}$ / $K_{I\ \min}$ Fraction, represents respectively the maximum and minimum allowable storing level as a ratio from demand, $K_{I\ \max}$ and $K_{I\ \min} \in [0,1]$.

$MD_{m,t}$ Real positive number, represents the amount of man-days required to complete a production of 1000 units from model m during t,

n_s Integer positive number, represents the number of working hours per shift,

n_t Integer positive number, represents the number of normal working days during t,

OT_h / $OTh_{max(t)}$ Real positive numbers, represent the amount of overtime hours worked during a day-off from period t, respectively the allowable and the maximum amounts,

OT_n / $OTn_{max(t)}$ Real positive numbers, represent the amount of overtime hours worked during a normal working day from period t, respectively the allowable and the maximum amounts,

$Pr_{av.}$ Real positive number, represents the machine average productivity,

PW_{max} Integer number, represents the maximum number of part-time workers during t,

RW_{max} Integer number, represents the maximum number of permanent workers during t,

RW_{min} Integer number, represents the minimum number of permanent workers during t,

V_{RW} Integer number, represents the maximum permissible difference of workforce size for two successive periods.

Auxiliary variables

$OTPh_t$ / $OTPn_t$ Real positive number, represents the total overtime hours for part-time workers during respectively the days-off and normal working days for t,

$OTRh_t$ / $OTRn_t$ Real positive number, represents the total overtime hours for permanent workers during respectively the days-off and normal working days for t,

Decision variables

H_t Integer variable, represents the number of part-time workers to be hired at t, $H_t \geq 0$,

$I_{m,t}$ Integer variable, represents the inventory level of product m, at the end of t, $I_{m,t} \geq 0$,

L_t Integer variable, represents the number of part-time workers to be fired at the end of t, $L_t \geq 0$,

$OTPh_{m,t}$ / $OTRh_{m,t}$ Real variables, represent the overtime hours required from respectively the part-time and permanent workers for product m during days-off of period t, $OTPh_{m,t} \geq 0$, $OTRh_{m,t} \geq 0$,

$OTPn_{m,t}$ / $OTRn_{m,t}$ Real variables, represent the overtime hours required from respectively the part-time workers and permanent workers for product m during normal working days of period t, $OTPn_{m,t} \geq 0$, $OTRn_{m,t} \geq 0$

$P_{m,t}$ Integer variable, represents the production quantity of m that will be produced during t, $P_{m,t} \geq 0$,

$PW_{m,t}$ Integer variable, represents the number of part-time workers assigned to m during t, $PW_{m,t} \geq 0$,

$O_{m,t}$ Integer variable, represents the outsourcing quantity from model m, in period t, $O_{m,t} \geq 0$,

$RW_{m,t}$ Integer variable, represents the number of permanent workers assigned to m during t, $RW_{m,t} \geq 0$,

$S_{m,t}$ Real variable, represents the number of production shifts required for m during t, $S_{m,t} \in [0,3]$.

variation for this planning attribute. It is a subjective nature i.e. it can vary from one firm to another - or more exactly from one production kind to another. According to the literature, it can vary from three months up to eighteen months: we can find periods of three months [1,2], six months [3], eight periods [4], from 2 to 8 planning periods [5], thirteen planning periods [6], eighteen months [7]. Others like [8] considered it in terms of weeks. However, the length of the planning horizon should be specified formerly to the execution of the production plan. During this planning horizon, the APP is used to evaluate the relation between the available capacities and the demand to fit the required production quantities. For each period, it provides the production levels from each product, size of the permanent workforce, number of part-time manpower, the existence of overtime working hours, the levels of outsourcing, and the size of inventory. The targets of the APP model are not restricted to maximizing the company outcomes, but they can also be used to achieve many other objectives e.g. maximizing resource utilization, minimizing production changes, minimizing the variation of permanent workforce size, and minimizing outsourcing. Therefore, it is important to exactly identify the objective function of the APP model. According to Chen and Liao [6], multiple objectives can be used to get a more realistic model. Minimizing the total production cost is the common objective of the APP models that include costs include regular production, inventory, backlogging, outsourcing, capacity holding, and so on. The objective of the APP can be formulated as a maximization of profit function (e.g. [9]), minimization of cost function (e.g. [10]) or combination of multi-objective (e.g. [2,5,11–14]).

As it is well known, the number of the required workers depends on their working productivity. Moreover, manufacturing productivity has a dynamic nature, i.e. the manufacturing productivity growths thanks to the workforce experience gained over time. Such experience is gained due to many reasons e.g. on-job training of the direct workforce, mastering of production methods and procedures, developing of jigs and fixtures, implementation of performance improvement tools like total quality management, lean production or six-sigma, etc. This evolution phenomenon is known as manufacturing evolution function or learning curves. Accordingly, the improvement of the manpower productivity can be modeled as a function of the on-job training or the work repetitions. As discovered by Wright [15], a percentage of 20 percent can be gained as improvement each time the production quantity is doubled. This learning curve phenomenon could have a significant impact on the scheduling of production jobs, manpower staffing, and minimization of overtime hours Badiru [16]. This concept is often considered using the average learning rate that can be found in the literature. Besides, some considered the learning rate as constant for all products in the production plan. However, the learning rate can be varied among products. This practice contaminates the obtained results. For example, Zhang et al. [10] considered a learning rate of 85% in their work. Attia et al. [17] considered a learning rate of 80% for all activities. Tirkolaee [18] considered the slope of the learning curve as (-0.3) corresponding to a learning rate of about 81%. For the mosquito expellant products, Chen et al [19] used three categories of learning rates one for each production line within the interval [0.985, 0.995]. However, the values of these learning rates are very high that indicate that the effect of learning is very small and can be neglected.

The current paper presents an APP model that was formulated based on real industrial practice. It considers multi-product and multi-period aggregate production planning. It minimizes the different manufacturing costs while respecting most of the operational constraints. It minimizes the costs of material, machine, workforce (permanent, part-time, overtime), inventory, and outsourcing. It respects many types of constraints, e.g. demand satisfaction, levels of permanent workforce, levels of part-time workers, overtime limits, labor capacity, levels of safety stock, and maximum levels of subcontracting, in addition to some of the social aspects e.g. working during holidays or days-off. Backorders are not allowed in this study for assuring high levels of customer satisfaction. Moreover, the dynamic progress of the workforce productivity was considered based on the concept of organizational learning. The organizational learning curve of each product was considered relying on real data. This practice is not well addressed in the literature. Researchers often assume an average learning rate according to the trade. Others use a learning rate of 80% regardless of the application. The current paper proposes to estimate the evolution of workforce productivity relying on the learning curve of Wright [15]. This proposition has been validated after investigating the most mono-variable learning curves presented in the literature (method and results can be found in one of the current authors' work that was presented in [20]). The proposed mathematical model was coded and solved using ILOG-CPLEX 12.6. The result has been validated relying on data from real case studies and detailed analysis by planning experts. In addition, the impact of different managerial aspects on the plan cost has been investigated and conclusions are provided.

The remainder of this paper is organized in the following manner. The next section presents the literature review of the related work. Section 3 presents the problem description. The mathematical model is discussed in Section 4, while the case study is introduced in Section 5. The solution methodology and results are discussed in Section 6. The managerial aspects are discussed and analyzed in Section 7. The conclusions and perspectives are presented at the end of the paper. In addition, there are two appendices; Appendix A contains the data set for a production plan and Appendix B contains the associated optimal results.

2. Literature review

The literature provides enormous work on the topic of APP models and solution methodologies. The problem was formulated as a goal programming model in [2,14,21]. Pradenas et al. [9] created the problem with binary variables and quadratic constraints, then solved it using a heuristic-based algorithm. Zhang et al. [10] introduced a mixed-integer linear programming model for an APP problem with capacity expansion. Ramezanian et al. [22] considered the setup time and the associated cost in the problem and solved it using genetic algorithms and tabu search algorithms. In tactical production planning, setup can be considered when the change between families of products incorporates high system penalties (in terms of time and/or cost), for more details about the consideration of setup in the APP model one can see the work of [8,22–24]. Wang and Yeh [25] solved a mixed-integer linear programming model using a modified particle swarm algorithm. Others considered the uncertainty in the problem parameters. For example, Wang and Liang [26] formulated the problem as a possibilistic linear programming model. Chakrabortty et al. [27] considered also imprecise demand, operating costs, and capacity parameters in their model and used a modified variant of a possibilistic environment-based particle swarm optimization approach to solve it. Baykasoglu and Gocken [11]; Wang and Liang [28] formulated the problem as a multi-objective fuzzy model. Zhu et al. [29] modeled the problem as interval-based programming considering uncertainty and solving it using Lingo software. Moreover, Jamalnia et al. [30] evaluated the performance of the different strategies of the APP. For more details about the mathematical formulation, the work of [31] presents a survey of the different manufacturing aspects considered in the mathematical formulation of the problem. Recently, Cheraghalikhani et al. [32] reviewed the different characteristics and structure of the App models while [33] studied the different considerations of the uncertainty of APP models.

The concept of experience evolution was considered in many applications including APP [5,34,35], implementation of ERP [36], workforce flexibility [17], workforce assignment [37], and order picking planning [38]. Recently, Tirkolaee [18] considered the learning effect for the allocation and scheduling of disaster rescue units. Besides, [39] considered the learning effect for casting operations. Wei et al. [40] studied the impact of learning on inventory management with a stochastic learning rate. The learning curves can be classified into three major types: individual learning, group of individuals, and organizational learning [41]. The individual learning curve reflects the performance development in the function of work replication of a specified worker. The main difference between group learning and individual learning is the existence of knowledge transfer between individuals who are working in a group [42]. Organizational learning curves are recommended when the productivity development of a specified product is a function of the whole workforce rather than a specified worker(s). In the tactical level of APP, the organizational learning curves are rational to be used than individual or group learning curves for reasons of the aggregation of the planning data. Regarding the incorporation of manufacturing progress function and aggregate production planning, the work of [35] investigates the impact of the learning effect on the aggregate planning of machine requirements. They showed the importance of integrating such human factors. The pioneer work in this topic is the work of [34], although the drawbacks of his model were reported in the work of [43]: they reported that "the model does not incorporate the effect of learning properly". They regret the use of the learning phenomenon on an average basis. They suggested representing the productivity development on a group-basis, relying on clusters of workers. Recently, Alguliyev et al. [44] developed an efficient clustering algorithm that can be adopted for clustering workers. According to our point of view, in the tactical level of planning all data are aggregated and it is more convenient to consider the productivity development on an organizational basis rather than on an individual or group basis. In addition, the consideration of the human learning effect in a detailed level complicates the mathematical model. This complexity was highlighted in the work of [35], wherever this incorporation transforms the APP problem into a mixed non-linear program that is hard to be solved optimally in an acceptable computing time, especially for industrial problems. To the best of the authors knowledge, there is a shortage in the literature for the consideration of the learning effect in APP models relying on shop floor data and real managerial considerations. The current research tries to cover this shortage with an application on the manufacturing of electric motors.

3. Problem description

One of the problems facing manufacturing firms is the irregular demand; this irregularity leads to increase levels of inventory in periods of low demand especially for even production capacity. Consequently, the cost of the production plan increases that causes lower profitability, and increases the required storage space. The problem is to meet the required irregular demand with the optimal mix of production resources at minimum cost. To solve this problem for medium-term planning, one can adopt the aggregated production planning. For each planning period, the different attributes of the production plan should be determined optimally at minimum cost while respecting different operational constraints. These attributes contain the permanent workforce, amount of part-time workers, overtime hours, outsourcing of parts, inventory levels, and production quantities. On the other side, the operational constraints contain the available capacities of the workforce, inventory, maximum levels of overtime, the maximum size of part-time workers, etc. In the current problem, the penalties of switching off between product families are very small. Therefore, setup cost can be neglected for simplicity for this tactical level. Moreover, this work relies on the fact that productivity is a progressive property, i.e. the firm's productivity is continuously developed over time. To implement this assumption, the organizational learning curve is considered instead of individual or group learning curves. In organizational learning the development is gained from many sources: relying on the work of [45], the determinates of organizational learning can be categorized into three classes: -the first is the increased proficiency of direct production workers, engineers, and managers; -the second group is the improvements in organization's technology; -the third is the improvements in firm's structure, routines of products and methods of coordination. For considering all of these determinates, the learning progress is considered as a function of the accumulated production period rather than the accumulated production quantity. Argote [45] stated that there is a debate between researchers for the consideration of the learning curve relying on the cumulative number of units produced or cumulative production time. And both of the two independents are significant in predicting productivity advancement. Some concerns may appear affecting the pattern of organizational learning e.g. part-time workers, subcontracting, and overtime. From our experience in the application case study, the part-time workers can not affect the pattern of organization learning, where part-time workers commonly work as assistant or utility workers. Moreover, the levels of subcontracting and overtime have a negligible effect in our case for a monthly average production of about 17,000 units. For individual learning curves, this number of work replications is very large, i.e. it is sufficient to place the productivity in the plateau stage of the learning curve of any direct worker. For this massive production, the development of organizational learning relies mainly on the other determinates not directly to the experience of the direct workforce. The literature provides evidence for a low effect of the direct workforce on organizational learning as was proven in continuous production e.g. refined petroleum [46], and chemicals [47]. Continuous development is essential for a firm's survival. As known, one of the techniques that are used in managing firms' performance is the balanced Scorecard (BSC). One of the four dimensions of BSC is the ability of the firm to continue improving and creating value. This measure relies on two aspects: the firm's ability to innovate, and the improvement of the existing processes. According to Kaplan & Norton [48], many companies set continuous improvement targets e.g. "*Milliken & Co.*" implements an improvement program that improves performance with a specified factor periodically. Recently, Seleem, et al. [49] presented an industrial application that succeeded to improve productivity with 6.22% after the implementation of some performance improvement tools e.g. workforce training, processes standardization, applying of 5S program, applying autonomous maintenance, balancing assembly line, applying Kaizen, etc. Relying on this discussion, continuous improvement is one of the success factors of organizations that can be achieved through all determinates of organizational learning. The problem was mathematically modeled in cooperation with the industrial experts. After that, it was coded and solved using ILOG-CPLEX 12.6 platform. Fig. 1 shows the main steps for modeling and solving the problem.

4. Mathematical model

Mathematical model
Minimize:

$$F = F_1 + F_2 + F_3 + F_4 + F_5 \tag{1}$$

$$F_1 = \sum_{t=1}^{T}\sum_{m=1}^{M} CM_{m,t} \times P_{m,t} \tag{2}$$

$$F_2 = \sum_{t=1}^{T}\sum_{m=1}^{M} CR_{m,t} \times P_{m,t} \tag{3}$$

$$F_3 = F_{RW} + F_{PT} \tag{4}$$

$$F_{RW} = \sum_{t=1}^{T}(C_{RW} \times RW_t + C_{ORWn} \times OTRn_t + C_{ORWh} \times OTRh_t)$$

$$F_{PT} = \sum_{t=1}^{T}(C_{PW} \times PW_t + C_{OPWn} \times OTPn_t + C_{OPWh} \times OTPh_t + C_{HP} \times H_t + C_{LP} \times L_t)$$

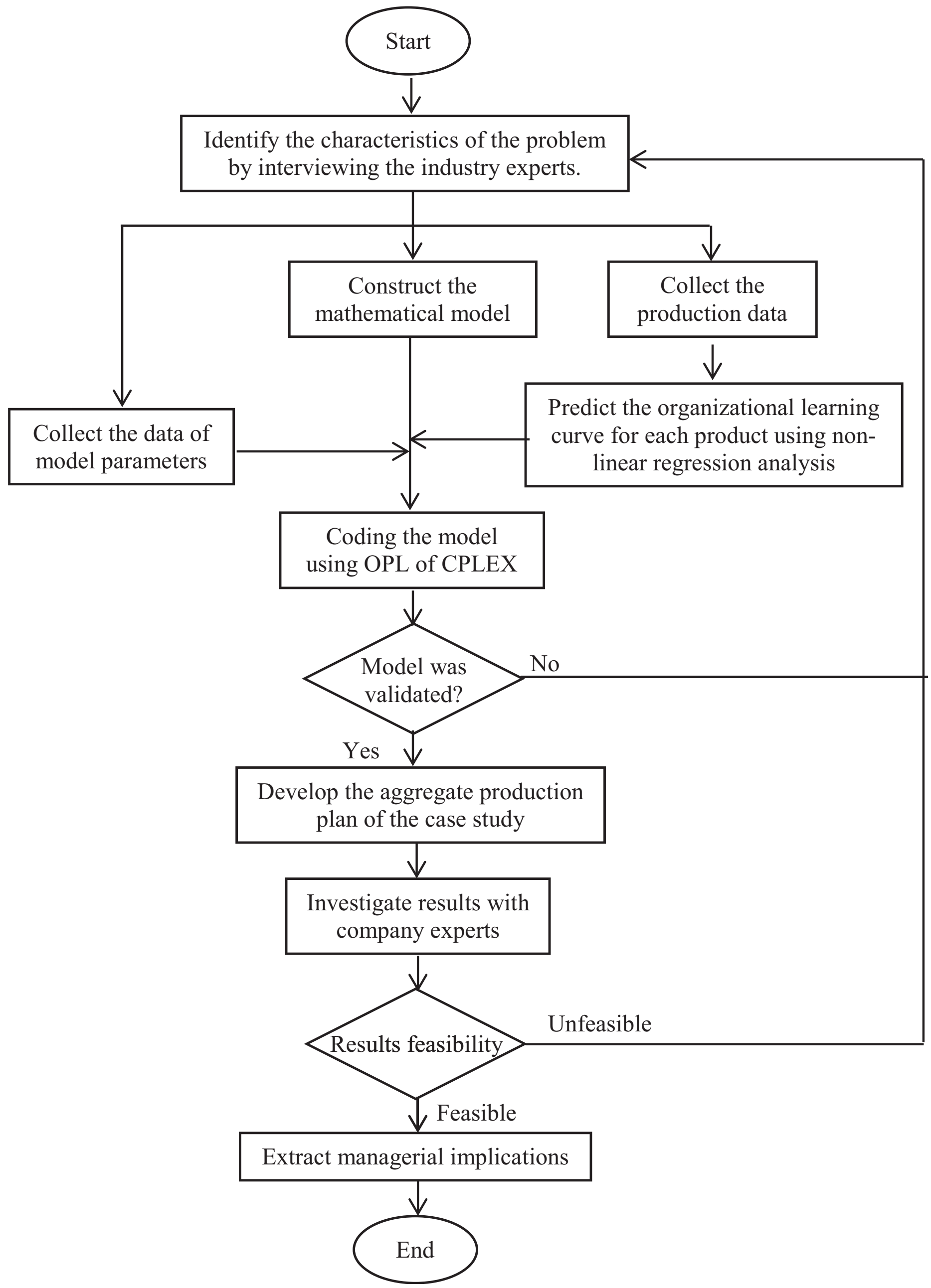

Fig. 1. An overall flowchart of the research methodology.

$$RW_t = \sum_{m=1}^{M} RW_{m,t} \forall t$$

$$OTRn_t = \sum_{m=1}^{M} OTRn_{m,t} \forall t$$

$$OTRh_t = \sum_{m=1}^{M} OTRh_{m,t} \forall t$$

$$PW_t = \sum_{m=1}^{M} PW_{m,t} \forall t$$

$$OTPn_t = \sum_{m=1}^{M} OTPn_{m,t} \forall t$$

$$OTPh_t = \sum_{m=1}^{M} OTPh_{m,t} \forall t$$

$$F_4 = \sum_{t=1}^{T} \sum_{m=1}^{M} \left(CI_{m,t} \times \frac{I_{m,t} + I_{m,t-1}}{2} \right) \tag{5}$$

$$F_5 = \sum_{t=1}^{T} \sum_{m=1}^{M} \left(Csub_{m,t} \times Q_{m,t} \right) \tag{6}$$

Subject to:

$$D_{m,t} + I_{m,t} = P_{m,t} + O_{m,t} + \ I_{m,t-1} \forall t, \forall m \tag{7}$$

$$RW_{min} \leqslant \ RW_t \leqslant \ RW_{max} \forall t \tag{8}$$

$$|RW_t - \ RW_{t-1}| \ \leqslant \ V_{RW} \forall t \tag{9}$$

$$0 \leqslant PW_t \leqslant PW_{max} \forall t \tag{10}$$

$$PW_t = PW_{t-1} - L_{t-1} + H_t \forall t \tag{11}$$

$$OTRn_t + OTPn_t \leqslant OTn_{max(t)} \forall t \tag{12}$$

$$OTRh_t + OTPh_t \leqslant OTh_{max(t)} \forall t \tag{13}$$

$$OTn_{max(t)} = OTn \times n_t \times (RW_t + PW_t) \forall t \tag{14}$$

$$OTh_{max(t)} = OTh \times h_t \times (RW_t + PW_t) \forall t \tag{15}$$

$$OTRn_t \leqslant K_{O.T} \times (RW_t + PW_t) \times (n_t) \forall t \tag{16}$$

$$OTRh_t \leqslant K_{O.H} \times (RW_t + PW_t) \times (n_h) \forall t \tag{17}$$

$$OTPh_t \leqslant OTRh_t \forall t \tag{18}$$

$$MDR_t \leqslant MDA_t \forall t \tag{19}$$

$$MDR_t = \sum_{m=1}^{M} \frac{P_{m,t} \times MD_{m,t}}{1000} \forall t \tag{20}$$

$$MD_{m,t} = MD_{ini}(APT + t)^b \forall t \tag{21}$$

$$MDA_t = (RW_t \times n_t + \frac{OTRn_t + OTRh_t}{n_s}) + (PW_t \times n_t + \frac{OTPn_t + OTPh_t}{n_s}) \forall t \tag{22}$$

$$P_{m,t} = MC_{m,t} \forall m\ , \forall t \tag{23}$$

$$MC_{m,t} = S_{m,t} \times (n_t + h_t) \times n_s \times Pr_{av.} \times A_{av.} \times q_{av.} \tag{24}$$

$$K_{I,min.} \times D_{m,t} \leqslant I_{m,t} \leqslant K_{I,max.} \times D_{m,t} \forall t, \forall m \tag{25}$$

$$O_{m,t} \leqslant Max\_Sub_{m,t} \forall m, \forall t \tag{26}$$

The objective function of the current APP model expresses the sum of the different costs; therefore, it will have to be minimized. Here, there is a difference between overtime costs of working during weekly working days or days-off. Besides, the back-orders are not allowed to satisfy the customer needs. The objective function is a summation of five sub-functions as represented by equations (1 to 6). In which F_1 is the material cost, F_2 is the operating cost, F_3 is the labour cost, F_4 is the inventorying cost, and F_5 is the outsourcing cost. Equation (2) signifies the material cost that is required throughout the production horizon for manufacturing the required product mix. For any given product, the material cost can be calculated based on its Bill Of Materials. This cost can differ from one period to another depending on the inflation rate or money exchange rate between currencies. The total amount of material costs is computed by simply aggregating all material costs of all products produced during the planning horizon, considering that $CM_{m,t}$ is constant along period t, but it can be varied from period t to $t + 1$. Equation (3) represents the operation costs that contain all costs resulting from the use of the different production facilities: it includes machine and utility costs, etc. This set of expenses was supposed to be known in advance. For a given product, it can be estimated from the manufacturing route and the standard time for each operation. The planner can consider these factors as constant during all periods $t = 1, 2,\ldots, T$, or varying them from one period to another. Regarding the labour costs (equation set 4), two types of labour are considered here: the first is the direct manpower or permanent workers (F_{RW}), the second results from part-time workers (F_{PT}). The permanent workforce represents the regular or the salaried workers. The costs associated with permanent manpower are computed relying on the working hours and overtime during the normal weekly working days and days-off. The hiring and laid-off costs are not considered for the permanent workforce. It was assumed that the number of permanent workers can be varied within a specified amount. This variation is resulting from absenteeism, social considerations, or transfer between factories. Besides, the hiring plan is a strategic plan that depends on the vision and goals of the company. For part-time workers, three main sources of cost were considered: - the cost of normal working hours during weekly working days and days-off, - the cost of overtime worked during weekly working days and days-off, - the costs of hiring and laid-off a part-time labour. These types of labour costs can be formulated as in equations (4-a) and (4-b). These equations contain many parameters that cannot be considered specifically for each worker, but they can be considered via average values. Since APP provides capacity planning in an aggregated manner during a planning horizon of medium-range (e.g. one year in this study) and does not provide work scheduling and resources allocation in a detailed manner. Contrary, the detailed values of such parameters for each worker should be considered in the short-range planning horizon. Regarding the rewards of the overtime, it is often considered as one plus a fraction of the standard rates. The cost of hiring can be considered as the costs induced by administration work and training of part-time workers. The cost of dismissal of the worker depends on the firm's strategy; it can be set to a specified value or zero. Equation (5) represents the inventory cost that results from storing parts, semi-finished or finished products. The inventorying costs are aggregated from many attributes include space utilization, material spoilage, insurance, capital immobilization, etc. Based on the lean philosophy, inventory is one of the principal sources of wastes. Consequently, the levels of inventory should be minimized. Practically, the inventory cost can be estimated as a periodic percentage of the part/product value. It is assumed here that; the firm has the inventory cost per product. Outsourcing of parts is essential for almost all manufacturing enterprises. Equation (6) represents the outsourcing costs. Firms use outsourcing to solve the problem of high production demand that inducing a shortage in machine or labour capacity. It is frequent to outsource or subcontract the non-critical or standard parts. Without loss of generality, subcontracting here is assumed to be considered at the level of products. In order to transform this level of subcontracting from product level to that of parts, the percentage of the subcontracted work $O_{m,t}$ to the total production quantity can be computed. This percentage can be used to compute the amount of work-content that could be outsourced and consequently, the amount of work-content can be outsourced at parts level.

A set of operational constraints should be respected. Here, these constraints can be clustered into five major categories. Which are demand satisfaction, labour capacity, production facilities, inventory capacities, and decisions that govern inventory levels or outsourcing quantities. Equation (7) represents the demand satisfaction constraints. For each time period t, the demand can be fulfilled by both the production ($P_{m,t}$) and the stored products ($I_{m,(t-1)}$). The constraint ensures that at the end of each planning period t, the end period safety stock ($I_{m,t}$) plus the required demand should be equal to the production level plus the start period safety stock ($I_{m(t-1)}$), in addition to subcontracting, if any. Normally, industrial organizations rely on permanent workers to satisfy their production demand. It may be a point of interest for organizations to know their optimal number of permanent workers while minimizing the total plan cost. Actually, the size of the permanent direct employees can fluctuate on a daily basis in reasons of holidays, absenteeism, social factors, sick leaves, etc. However, in some ways, it should remain between maximum and minimum limits. Consequently, the planner should develop a production plan that is capable to accommodate this variation. Here, these maximum and minimum thresholds are respectively (RW_{max}, RW_{min}), as expressed by equation (8). This proposal is different from the past research works that permit the repeatedly hiring and dismissal of permanent workers. There are three reasons for adopting the idea of using minimum and maximum limits for the permanent workforce instead of hiring and firing workers continuously. The first reason is the variability nature of the permeant workers in reasons of absence due to social factors, sick leaves, entertainment vacations, etc. The second reason is the enterprises' capability to transfer employees between their production sectors according to the production plans. The third reason is the strategic nature of the hiring and firing decision, it could not be applied on monthly basis. It is assumed that, the values of RW_{max} and RW_{min} can be estimated based on the real shop floor data. The fluctuation of the permanent workforce from one period to another should be held as smooth as possible. For that reason, the absolute difference between the numbers of permanent workers for two successive working periods should be kept at a given maximum level of variation (V_{RW}) that should be assessed by the management committee, as represented by constraints (9). On the other side, the maximum number of part-time should be specified. As it is well known, the main skills of the firm should be trusted to permanent workers, for preserving performance and developing a continuous improvement. As equation (10), the number of part-time workers for each period *t* should have a pre-defined bound. This bound can be specified according to the management strategies – usually, it can be considered as a fraction of the permanent workers. Over the production periods, the continuity of the amounts of part-time workforce constraints should be satisfied, as modelled by equation (11). The overtime is adopted here to overcome the shortage in production capacity to satisfy the demand. The overtime hours can be worked during normal weekly working days or days-off. Of course, compensations for working during days-off are greater than that of weekly days. The overtime is allowed for all workers with specified limits during weekly days (equation (12)) and days-off (equation (13)). These limits are computed as represented by equation (14) for weekly days and equation (15) for days-off. According to the industrial common practice, the total number of overtime hours worked per a given period (e.g. month) during normal working days should be fewer than a pre-specified fraction ($K_{O.T}$) of the standard hours that were worked in that period – to our experience, this percentage may be estimated around 15%. This industrial restriction was also considered in the model as equation (16). The same concept is also considered for working during days-off with a pre-specified proportion ($K_{O.H}$), as equation (17). Restrictions also exist on the number of part-time manpower during days-off, expressing that it is not comfortable to depend overly on part-time workers, for assuring safety or quality issues. Equation (18) expresses this restriction by ensuring that, the overtime hours of permanent workers are superior or equal to that of part-time.

For presenting the constraints associated with the workforce capacity, the term "man-day" should be clarified. A "man-day" represents the number of labours required to produce a set of 1,000 units from a given product or item during only one standard production shift. Equation (19) makes sure that for each period *t*, the number of man-days required to manufacture the production plan (MDR_t) is lower than or equal to the number of the available man-days (MDA_t). Equation (20) is used to compute the required number of man-days for all products. $MD_{m,t}$ can be predicted relying on the organizational learning curve. Consequently, the number of the required man-days for each product is developed over time. Relying on the investigation study of Attia et al. [20], the learning curve of Wright [15] can be used competently for representing organizational learning (equation (21)). In which, the variable *APT* represents the number of the actually worked production periods, *b* represents a constant that can be computed in the function of the average learning rate (*LR*) for product *m* as ($b = Ln(LR)/Ln(2)$). The learning rate = 1- Progress ratio. The Progress ratio is the ratio between the effort reduction due to work replication and the initial effort required at the first execution. The effort is often represented in terms of time, cost, man-hour, or man-day (in the current research). While MD_{ini} is the initial man-day found in the first production period. The two factors MD_{ini} and *b* can be predicted based on the real production data. In this model, the learning phenomenon is represented as a function of the cumulated production periods rather than the cumulated units produced. This concept is adopted to overcome the complexity raised from incorporating the learning effect: i.e. integrating the learning effect as a function of the cumulated production changes the mathematical model to a nonlinear one. This non-linearity complicates the possibility of getting an optimal solution to the problem, especially for problems of the real industrial size. On the other side, the presented formulation of equation (21) is proven to be relevant rather than most of the mono-variable learning curves [20]. Concerning the available number of man-days, it can be determined relying on all direct workforce and all working hours, as represented by equation (22).

Machines have limited capacities. Therefore, the available machines have to fulfil the capacity required by the production plan. By adopting the working on a shift basis, the machine capacity can be doubled or tripled depending on the production volume required. These types of constraints are modelled by Equation (23). Equation (24) is used for determining the capacity of machines per period t ($MC_{m,t}$) relying on the productivity per hour (Pr_{av}), the average availability (A_{av}), the average quality index (q_{av}), and the maximum allowable working hours (number of shifts ($S_{m,t}$) × number of permissible working days per period ($n_t + h_t$) × working hours per shift (n_s)). The multiplication of the three terms (productivity, availability, and quality index: ($Pr_{av.} \times A_{av.} \times q_{av}$) formulates the average overall equipment effectiveness (OEE) of the machines used in the production for product *m*. Finally, the inventory also imposes another set of constraints as demonstrated by equation (25). It limits the storage level to be within a pre-specified range that is located between Min. ($I_{m,t}$) and Max. ($I_{m,t}$). The safety stock is very important it works as a hedge against uncertainty. These limits are considered as a proportion (K_I) from $D_{m,t}$. As a result of common industrial practice, the proportion of the minimum level of safety stock can be regulated at 20%, and that for the maximum level can reach 40%. These fractions can vary from one firm to another according to many variables including management strategies, machines' reliability, resources' availability, unanticipated fluctuations in demand, etc. Firms should minimize the number of outsourced items and limit it to standard or auxiliary parts, yet subcontract offers solutions when there is a shortage in machine or labour capacity. As mentioned earlier, subcontracting at the product level is considered in this research. But, the subcontracted quantity is restricted by a maximum permissible limit, as equation (26). Besides, the model considers the non-negativity constraints for all decision variables.

5. Case study

The real case study was conducted at an Egyptian manufacturing firm that specializes in the production of electric home appliances and named "El-Araby Group". This firm is a joint-stock family company established in 1964 and dedicated to producing high-quality products that integrate high technology in order to meet customer needs or expectations. It produces about 890 different products through 21 factories. Moreover, it relies on more than

20,000 employees. This study considers one factory only that produces electric motors. The production of electric motors has started to grow up in this firm since 1992. The factory under consideration manufactures 29 different products supplied to the other factories of the organization, plus some other references supplied to other external customers. The firm has a good market share and faces very high demand for some kinds of products: the production of ceiling fan motors is 1,800,000 units/year, table-fan motors 800,000 units/year and ventilation fan motors is 750,000 units/year. The manufacturing of these different families of products involve 110 production processes that must be performed to shape the required parts. These processes can be classified into six main groups. The first group of processes is the blanking and piercing operations of the steel strips that produce the steel laminations that shape the stator part of the electric motors. The second cluster is the die casting operations, producing some different parts such as the front and rear covers of the motors, and the cover of transmission gears for some other models. Following the die casting processes, there is a need for metal cutting processes e.g. turning, drilling, reaming, and tapping operations that structure the third category. The fourth group gathers the wiring operations that incorporate the stator with the required electric coils, and then insulation and treatment of coils should take place. There are some other processes such as pressing, grinding, knurling, shaft threading, etc. These processes, known in this company as "finishing", characterize the fifth category. Finally, the sixth category is the assembly process that gathers all parts together so as to form the final product. Following the production steps, we find the inspection and testing operations. Fig. 2 shows an illustration of two products: a table-fan motor and the stator of a ceiling fan motor.

6. Computational results

6.1. Basic data

After identifying the required parameters, the complete factory data sets were collected for three successive years, known here as yearly Plan-I, yearly Plan-II, and yearly Plan-III. These three plans were dedicated to producing a total of twenty-nine products. The complete data set for Plan-I is presented in appendix A. The learning curves expressing the evolution of the required effort in man-days are also provided. Regarding the prediction of these learning curves: For the same factory, the management committee was motivated to know the most appropriate learning curve that can be used to estimate the workforce productivity evolution over time. Responding to this incentive, an investigation study was performed. That uses a real production dataset of 42 months, with an average monthly production rate of about 17,000 units. The dataset used refers to 110 manufacturing processes and the different styles of final products. After conducting the non-linear regression analysis using ten formulas for mono-variable learning curves, the quality of each learning curve used to fit the data was evaluated. Five criteria were adopted for this quality evaluation: regression coefficient R^2, the stability of the learning model to fit the data, sum of squares of the errors (SSE), the variation of R^2, and variation of SSE. To prioritize these learning curves relying on the previous five criteria, the analytical hierarchy procedure (AHP) was adopted with the goal of finding the most appropriate learning curve for the current case study and the alternatives are the ten mono-variable learning curves. The analysis shows that the learning curve of Wright [15] is the most relevant curve to be used. The learning curve for each product is listed in table A-3 of appendix A, in the last column. For each product, the learning rate can be computed using the slope of the curve. As example, for Product-1, the slope of the learning curve (-0.05632). Knowing that: Slope = ln(learning rate)/ln(2), one can compute the learning rate = $e^{(-0.05632\times\ln(2)}$ = 0.9617. As a percentage, the learning rate = 96.17% for Product-1. The detailed description of this investigation study is presented in the current authors work of [20].

6.2. Solution methodology

The presented APP model was solved optimally using ILOG-CPLEX-12.6. First, the model was coded via the OPL language. The data sets of the production plans were entered into the model. After running the model, the following average statistics of the three plans were obtained: total variables = 1,545, integer variables = 1,124, real variables = 421, constraints = 3,017, and non-zero coefficients = 5,769. In order to validate the model, the authors organized some workshops with the planning experts of the factory to investigate the quality and the applicability of the obtained results. First, the same real practice of the factory was considered: the part-time workers were not considered for Plan-I. Moreover, the evolution of workforce productivity is updated biannually with the actual values. The model is run to get results for each plan with an average computing time of about 31 sec using a machine with a Core i3 processor. The results of each run are extremely investigated, all constraints are satisfied, and all variables got the expected values. In addition, the costs of the obtained plans are lower than those of the actual plans as listed in Table 1. Relying on the experts' examinations, the results of the model were validated and its applicability was guaranteed. After the adoption of the learning effect on a monthly basis relying

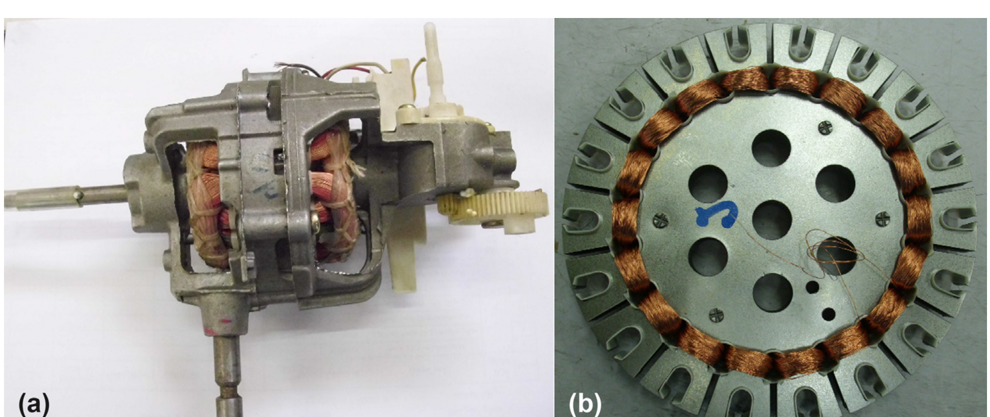

Fig. 2. Illustration of (a) table-fan motor (b) winded stator of ceiling fan motor under processing.

on the learning curve of Wright [15], the optimal results were obtained for the three plans. The objective function obtained for each plan is shown in Table 1.

By comparing the total costs of the optimal plans obtained and those already executed, the significance of applying the proposed model was concluded. Table 1 presents the comparison between optimal plans resulting from the model and the corresponding values of the firm. Relying on Table 1 the model gives hope to a cost reduction of about 7% for a computing time lower than one minute. Moreover, the impact of considering the effect of organizational learning on a monthly basis and that of a biannual basis is very small about 0.2% on average, but it can contribute to the total production cost saving.

The complete results of "Plan-1" are presented in Appendix B. By investigating table B-1, one can discover that the production of a specified product $P_{m,t}$ takes place to satisfy the customer forecasted demand $D_{m,t}$ presented in table A-1. Consequently, there is a discontinuity in the production of some products. As shown, the production quantity $P_{m,t} = 0$ for some specific periods e.g. for products 1, 16, 17, 18, and 24. The question that can be raised here: Does this discontinuance in the production have an effect on the learning rate for a specific product? For answering this question, we should consider two situations. The first situation is the production of all products requires the same processes with specific skills. In the current factory, the production of all products requires processes like blanking and piercing, die casting, turning, drilling, reaming, tapping, pressing, grinding, knurling, shaft threading, wiring, insulation, treatment of coils, and assembly. In such a working environment the effect of production discontinuance on the learning rate is very small and the justification of using the forgetting curve is very weak. The second case is found when the production of products requires different processes or different skills. In this case, the forgetting curve should be considered to represent the dynamic nature of the experience acquisition during working periods and losing it by forgetting during the non-production periods. The inventory levels are presented in table B-2. As obtained, the maximum quantities are given to products 3, 6, 8, 11, and 13. This trend is matched with the maximum quantities listed in table B-1. Besides, it is consistent with the forecasted demand presented in table A-1.

By reviewing table B-4, one can notice the high variation of $S_{m,t}$ over the interval [0, 3]. This variability is highly correlated to the production quantity $P_{m,t}$ of table B-1. As the production quantity $P_{m,t}$ increases the required machine capacity is increasing that can be doubled or tripled by working on shift bases. This high correlation between $S_{m,t}$, and $P_{m,t}$ can be discovered relying on equations (23) and (24). Besides, this correlation can be graphically noticed by comparing the plot of production plan $P_{m,t}$ with the graphical plot $S_{m,t}$. The variation in the number of shifts for each product does not effect on the learning process because for each workstation each worker is continually working on the same machines but only the initial machine setting can be changed for producing the second product. On the other side, the learning phenomenon has an indirect effect on the required machine capacity. This indirect effect comes from the reduction of machine idle time, preparation processes, using suitable working speeds, etc. In other words, the learning impact comes from the experience gained by the workers.

Table B-5 shows the distribution of the number of part-time workers used by the model over the planning horizon. One can notice that the model always uses the maximum number of part-time workers when part-time is allowed and the minimum number of permanent workers are not sufficient to produce the production plan. For each production period t, the required labors (permanent or part-time) depends on the production quantity $P_{m,t}$. In the case of high demand, the model favors the options that are decreasing the total cost. By comparing the monthly wage of one part-time worker to the average monthly salary of one of the permanent workers, one can notice that the model should favor the part-time because it has the minimum cost. Consequently, as shown in table B-5, the model always uses the maximum permissible number of part-time workers to reduce costs. This trend can be noticed over the production horizon except the last quarter of the year (Sep., Oct., Nov., and Dec.). As a working strategy in the company, part-time workers are not allowed during the 4th quarter of the year. They adopted this strategy in reasons of the demand seasonality in the other factories of the enterprise thus they prefer to redistribute permanent workers instead of using part-time workers. As previously discussed, part-time workers are often working as utility workers or used for the easiest tasks that can be performed by anyone with minimum orientation and guidance.

7. Managerial aspects

In order to conclude some managerial aspects, a set of model parameters were investigated using the data-set of Plan-I. The results of Plan-I are kept as a reference (Table 1). First, the decision of having a smooth staff of permanent workers (V_{RW}) is examined. Adopting this factor instead of PW_{max} and PW_{min} forces the model to smooth the workforce relying on the available initial manpower at t_0. Fig. 3 shows the effect of the maximum limit of permanent workforce variation between two successive working periods on the total cost. It appears that the relation between the total cost and V_{RW} is a nonlinear reverse correlation. As this variation grows up, the total cost is reduced until it reaches a fixed value at V_{RW} = 328 workers. The cost of having a constant permanent workforce represents 1,260,930 MU, or 0.62% of the reference plan cost

Table 1
Comparison between the optimal cost and that obtained by firm methodology.

	Plan I	Plan II	Plan III
Optimal total cost (MU) with monthly evolution of workforce productivity.	202,129,291	218,142,308	230,584,606
Optimal total cost (MU) with biannually evolution of workforce productivity.	202,601,094	218,689,809	230,899,933
Actual cost (MU) obtained by the methodology of the factory.	215,630,247	236,522,013	250,716,198
Difference between actual and optimal cost (MU)	13,500,956	18,379,705	20,131,592
Reduction percentage (%)	6.261	7.771	8.030
Running time (sec)	31	44	47

Fig. 3. The effect of smoothing levels of permanent workforce on total plan cost.

(Table 1). To reduce this impact, organizations should find a compromise between having fixed permanent workers and allowing variation in total workforce staff by using part-time workers, transfer workers between factories, or by adopting the strategies of flexible working hours in case of variable demand over periods.

The second decision is the overtime levels used during normal working days. By keeping $V_{RW} = 0$, discussed above, and by changing the percentage of the allowable overtime used (by varying $K_{O.T}$); the resulting cost can be reduced. As shown by Fig. 4, the total plan cost decreases with an increased allowance of overtime. The reduction in the total cost is also non-linear and inversely correlated to the overtime and shows little change after a given percentage of ($K_{O.T}$) that can be considered as $K_{O.T}$ = 45%. By adopting the overtime strategy at $K_{O.T}$ = 45%, the effect of using a constant permanent workforce can be reduced by 66.2%.

The third decision is about the opportunity of working during days-off. The strategies of having $V_{RW} = 0$ and $K_{O.T}$ = 15% are kept. The effect of working during days-off can be investigated by varying the allowable work during days-off (i.e. by varying $K_{O.H}$). This factor has a similar effect on the total plan cost as the previously discussed factors as shown by Fig. 5. It was observed that no significant betterment is noticeable for $K_{O.T}$ greater than 30%. Adopting this strategy leads to reduce the cost of having constant permanent workforce by about 30%. It is obvious that, allowing overtime during normal working days brings better results than working during days-off, since the hourly rate is smaller. Working during days-off can be appreciated in case of unavailability of working with overtime during normal working days, e.g. as in case of 3 shifts work in a given facility.

The fourth decision is about the number of part-time workers. Here also, the strategies of using $V_{RW} = 0$, $K_{O.T}$ = 15%, and $K_{O.H}$ = 15% are kept during the study of this decision. In that view, the constraint of having zero part-time workers during the 4th quarter is relaxed. Fig. 6 displays this effect of part-time workers on the total cost: this cost is reduced with the increasing number of part-time until it reaches a given value above which this effect seems insignificant (≈ 140 workers) or null (≈160 workers). This strategy of increasing part-time workers up to 140 workers leads to saving the cost of having a completely constant permanent workforce. Moreover, it reduces the total cost by about 0.26% from the reference cost. The influence of hiring part-time workers comes from two aspects: the first is the hourly wages compared to overtime or working during days-off. The second is the effect of the part-time workers that palliates the variations in the total workforce needed to match demand fluctuations.

Regarding the minimum permissible levels of inventory ($K_{I\ \min}$), it is obvious that zero inventory is suicidal. It may appear optimal but not practical. On the other side, maximizing inventory ($K_{I\ \max}$) is preferred for operational reasons but it increases the associated cost. To investigate this factor, the strategies of using $V_{RW} = 0$, $K_{O.T}$ = 15%, $K_{O.H}$ = 15% and number of part-time workers PW = 80 are kept during the investigation. As shown by Fig. 7 the reduction of cost is highly correlated with the maximum limit of inventory levels. As an optimal practice, this limitation could be relaxed. The relaxation of this practical constraint allows the model to make a trade-off between periods. However, most organizations have inventory limits.

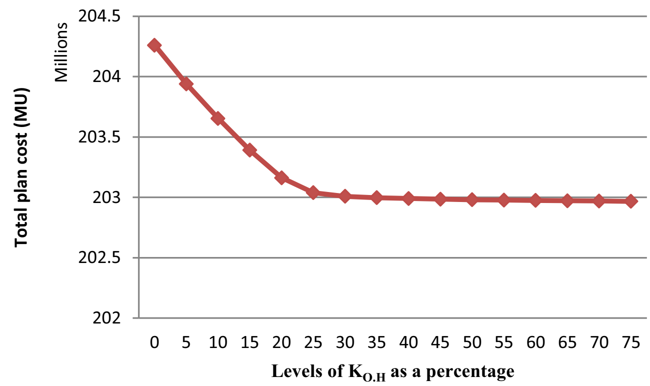

Fig. 5. The effect of $K_{O.H}$ on the plan total cost.

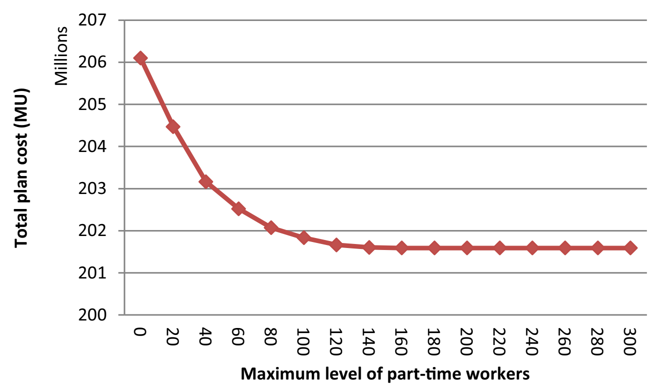

Fig. 6. The Effect of varying part-time workers on the plan total cost.

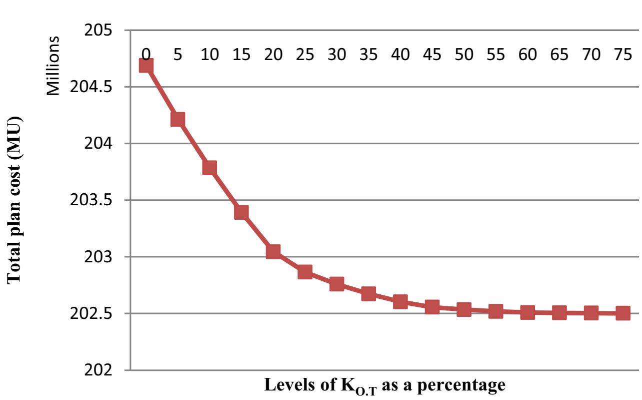

Fig. 4. The effect of $K_{O.T}$ on the total plan cost.

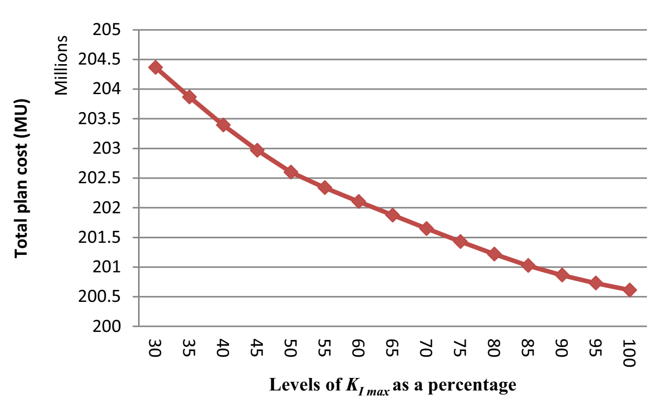

Fig. 7. The effect of $K_{I\ \max}$ on the plan total cost.

The last parameter to be investigated is the learning rate. It is interested in the area of operation management to measure the impact of learning-by-doing on the overall production cost (equation (21)). The following scenarios are used in this investigation, and keeping the model parameters as listed in Appendix A:

- Using the actual value of learning rate for each model as obtained from the application of regression analysis to real data (the result is the same as presented in Section 6.2 and known here as "Reference").

- Using an average learning rate for all models (learning rate = 95.45%).

- Using some other values around the average (No learning, 98, 96, 95, 94, 92...80%).

After solving the problem using all previous scenarios, Fig. 8 can be developed. It represents the relation between the learning rate and the total plan cost. As shown, the increase in the learning rate is accompanied by an increase in the plan's, total cost. This trend is normal, as the learning rate increases, the opportunity for reduction of the required working capacity vanishes. Relying on the relation of (learning rate = 1 – Progress ratio), a high learning rate means a small progress ratio. Therefore, for higher learning rate, the opportunity for enhancement in the workforce productivity will be very minuscule that tends to increase the plan cost. Besides, the plateau shape of the learning curve is reached faster than the case with a low learning rate. In other words, for a learning rate of 100% there is no improvement over time. The impact of considering the learning phenomenon in APP is significant – here, savings represent 7.26 Million (MU) or 3.59% of the total cost. The reduction of the plan cost comes from the development of the workforce productivity thanks to the experience gained from period to period. In the current model, the required man-day for producing a specified product is reduced from one period to the next thanks to the learning effect. In other words, the number of labors required to produce a number of 1,000 units of a given product is reduced over time. This reduction is remarkably noticed by comparing the reference cost with the case of no-learning shown by Fig. 8. According to this dataset, considering an average learning rate for the whole workshop rather than specific values for each product induces an underestimation of the cost: 0.3 Million (MU), or 0.15% of the total cost. We can retain from this investigation that the impact of the learning effect is significant on the cost of industrial operation. In that view, it makes sense to use an average value, easier to handle, instead of accurate measurements performed for every kind of operation or product family. Consequently, Firms should estimate the corresponding parameters of their products, and for simplicity of computation, they can use an average value instead of the detailed ones. On the other side, using values from literature for the learning rate is misleading especially if the applications are different.

8. Conclusion

The current paper presents a mathematical model for the problem of Aggregate Production Planning (APP). This model considers a wide range of cost sources: machines, manpower, inventory, subcontracting. Moreover, it considers the organizational learning concept to forecast the workforce productivity rates in terms of workload ("man-days", where a man-day is the number of labours required to produce a number of 1,000 units of a given product or part during one day"). Moreover, the different working constraints or restrictions were considered: demand, storing, manpower capacity, overtime hours of permanent or part-time workforce, etc. then the model was solved using ILOG-CPLEX software after it was coded with OPL language. A real case study was used to validate the model. The data were taken from a factory for electric motors. This factory is one of "El-Araby Group" for home appliance manufacturing. The results were analysed and validated by the excessive investigations of the company planning experts. By comparing the outcomes of the study against the adopted planning methodology of the firm, an average percentage of 6.3% of a cost reduction was achieved. This proportion can be transformed to about 17.3 million of Egyptian pounds. Moreover, the economic impact induced from the following managerial decisions are investigated: having a smooth permanent workforce, overtime levels, working during holidays/days-off, levels of part-time workers, and learning rates. The main limitations of the proposed model are the assumption of the deterministic nature of the model parameters. These parameters include forecasted demand, material costs, operating costs, etc. Moreover, it does not consider the changeover cost between models. As the perspectives of this work, the uncertainty of the different parameters can be considered to reflect the real aspects of the problem. Uncertainty can be considered using stochastic or fuzzy models.

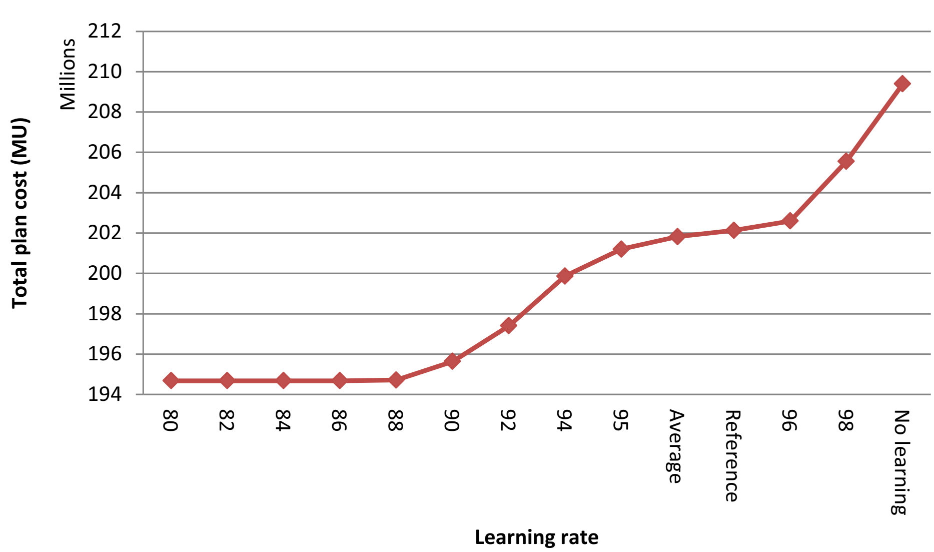

Fig. 8. The effect of learning rate on the total production cost of APP plan.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

This research was supported by the Deanship of Scientific Research at Prince Sattam Bin Abdulaziz University under the research project with grant number 2020/01/17181.

The authors also like to thank the industrial experts of "El-Araby Group" for the high cooperation provided.

Appendix A:. Data set of Plan-I

The data relating to Plan-I is presented in tables A1-A4. Table A1 represents the demand for a total of 22 products (numbered from product-1 to 24, with zero demand for products 19 and 23) over a yearly production horizon of 12 months. In addition, it presents the number of working days per period. Table A2 represents the material cost per product for each period. Table A3 shows the different costs per product: machine, inventory, and subcontracting. Column 4 provides the initial inventory at the beginning of the plan. Column 5 presents the machine productivity for each product. The learning curves expressing the evolution of the required effort in man-days are provided in the last column.

Table A1
Demand forecast for production Plan-I.

#	Product	Jan.	Feb.	Mar.	Apr.	May.	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.	TOTAL
1	Product 1	2200	0	0	0	2200	0	0	0	0	0	0	0	4400
2	Product 2	4400	11,000	9900	6600	6600	9900	9900	6600	6600	5500	7700	4400	89,100
3	Product 3	55,000	53,000	64,000	64,000	62,000	64,000	64,000	62,000	60,000	55,000	55,000	45,000	703,000
4	Product 4	2200	2200	2200	2200	2200	2200	2200	2200	2200	2200	2200	2200	26,400
5	Product 5	4400	3300	4400	4400	4400	4400	4400	4400	4400	4400	4400	4400	51,700
6	Product 6	37,000	31,000	37,000	40,000	40,000	40,000	40,000	47,000	47,000	47,000	47,000	31,000	484,000
7	Product 7	13,000	13,000	13,000	11,500	11,500	11,500	11,500	13,000	13,000	13,000	13,000	9500	146,500
8	Product 8	100,500	100,500	105,500	105,500	105,500	100,500	100,500	105,500	105,500	105,500	105,500	105,500	1,246,000
9	Product 9	5100	5100	5100	10,200	10,200	10,200	10,200	10,200	10,200	10,200	5100	5100	96,900
10	Product 10	5100	5100	10,200	10,200	10,200	10,200	10,200	5100	5100	5100	5100	5100	86,700
11	Product 11	100,500	100,500	105,500	105,500	105,500	100,500	100,500	105,500	105,500	105,500	105,500	105,500	1,246,000
12	Product 12	10,200	10,200	15,300	20,400	20,400	20,400	20,400	15,300	15,300	15,300	10,200	10,200	183,600
13	Product 13	65,000	65,000	75,000	70,000	70,000	75,000	75,000	70,000	70,000	65,000	65,000	50,000	815,000
14	Product 14	17,000	16,000	19,000	19,000	19,000	19,000	19,000	18,000	18,000	18,000	16,000	13,000	211,000
15	Product 15	2200	2200	4400	4400	2200	4400	4400	3300	4400	4400	4400	1100	41,800
16	Product 16	0	2200	0	0	2200	0	0	2200	0	0	1100	0	7700
17	Product 17	0	8500	0	0	8500	0	0	8500	0	0	4200	0	29,700
18	Product 18	0	2000	0	0	2000	0	0	2000	0	0	1000	0	7000
19	Product 20	2200	2200	2200	2200	2200	2200	2200	2200	2200	2200	2200	2200	26,400
20	Product 21	2200	2200	2200	2200	2200	2200	2200	2200	2200	2200	2200	2200	26,400
21	Product 22	11,000	14,000	13,000	11,000	12,000	13,000	13,000	11,000	11,000	10,000	11,000	8000	138,000
22	Product 24	0	0	0	0	0	0	50,000	60,000	70,000	70,000	80,000	80,000	410,000
Normal workdays		25	24	26	24	25	26	26	24	26	22	24	27	299
Days-off		6	4	5	6	6	4	5	7	4	9	6	4	66

Table A2
Material cost (in monetary units) per unit for the products of production Plan-I.

#	Product	Jan.	Feb.	Mar.	Apr.	May.	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
1	Product 1	45.02	46.88	46.88	51.32	51.32	51.32	51.99	50.94	51.80	52.97	53.30	52.51
2	Product 2	44.66	46.47	46.47	50.91	50.91	50.91	51.58	50.53	51.39	52.56	52.89	52.10
3	Product 3	41.75	43.29	43.29	45.03	45.03	45.03	47.91	45.89	46.47	48.68	48.86	47.73
4	Product 4	96.95	67.15	67.15	74.86	74.86	74.86	74.77	55.75	56.76	57.82	57.82	56.83
5	Product 5	36.25	36.91	36.91	36.69	36.69	36.69	39.77	38.04	39.08	40.88	40.98	39.80
6	Product 6	31.60	33.00	33.00	32.78	32.78	32.78	35.32	32.16	33.38	34.58	34.81	36.62
7	Product 7	31.87	33.19	33.19	33.01	33.01	33.01	35.85	32.41	33.62	34.81	35.04	36.84
8	Product 8	60.81	58.25	58.25	64.43	64.43	64.43	54.26	51.23	51.82	61.36	57.93	60.84
9	Product 9	51.50	45.98	45.98	56.21	56.21	56.21	50.73	48.65	48.45	52.85	54.07	48.45
10	Product 10	53.25	44.21	44.21	58.94	58.94	58.94	51.45	49.61	48.98	53.39	52.42	48.98
11	Product 11	12.75	12.75	12.75	12.75	12.75	12.75	12.75	12.75	12.75	12.75	12.75	12.75
12	Product 12	10.90	10.90	10.90	10.90	10.90	10.90	10.90	10.90	10.90	10.90	10.90	10.90
13	Product 13	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15
14	Product 14	0.17	0.17	0.17	0.17	0.16	0.16	0.17	0.17	0.17	0.17	0.17	0.17
15	Product 15	0.16	0.16	0.17	0.16	0.15	0.15	0.16	0.16	0.16	0.16	0.16	0.16
16	Product 16	0.13	0.13	0.13	0.13	0.12	0.12	0.13	0.13	0.13	0.13	0.13	0.13
17	Product 17	0.08	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
18	Product 18	0.00	3.40	3.40	3.40	3.40	3.40	3.40	3.40	3.40	3.40	3.40	3.40
19	Product 20	8.20	8.10	8.10	7.90	8.00	8.05	7.90	7.90	7.90	8.00	8.10	8.10
20	Product 21	4.00	3.98	4.00	3.95	4.00	4.00	3.95	3.95	3.95	4.00	4.00	4.00
21	Product 22	0.59	0.59	0.59	0.59	0.54	0.54	0.59	0.59	0.59	0.59	0.59	0.59
22	Product 24	8.00	7.90	8.00	8.38	8.38	8.45	7.90	8.61	8.62	8.53	8.61	8.62

Table A3
Other data per unit of production Plan-I.

#	Product	Costs (monetary units: MU)			Initial Inventory	Machine productivity (Units /hr)	Regressed learning curve from historical data for each product
		Machine	Inventory	Subcontracting			
1	Product 1	7.80	2.60	138.56	2050	57	$MD_{1,t} = 198.279((12 + t)^{-0.05632})$
2	Product 2	7.90	2.60	138.56	8053	57	$MD_{2,t} = 198.276((12 + t)^{-0.05632})$
3	Product 3	2.50	1.98	105.82	30,539	114	$MD_{3,t} = 154.368((12 + t)^{-0.08659})$
4	Product 4	39.80	2.70	144.00	4258	29	$MD_{4,t} = 344.260((12 + t)^{-7.356E-02})$
5	Product 5	1.50	1.98	105.82	8104	114	$MD_{5,t} = 122.607((12 + t)^{-0.05243})$
6	Product 6	1.50	1.60	85.40	21,410	191	$MD_{6,t} = 111.873((12 + t)^{-5.906E-2})$
7	Product 7	1.50	1.60	85.59	18,313	191	$MD_{7,t} = 111.846((12 + t)^{-5.904E-2})$
8	Product 8	0.30	2.15	114.40	70,549	295	$MD_{8,t} = 55.513((12 + t)^{-9.283E-02})$
9	Product 9	1.30	1.47	78.40	9051	114	$MD_{9,t} = 57.253((12 + t)^{-8.082E-02})$
10	Product 10	1.30	1.40	74.80	10,213	114	$MD_{10,t} = 57.277((12 + t)^{-8.093E-02})$
11	Product 11	0.30	0.56	30.00	36,588	214	$MD_{11,t} = 11.561((12 + t)^{-6.866E02})$
12	Product 12	0.30	0.41	22.00	10,970	43	$MD_{12,t} = 12.323((12 + t)^{-9.790E-02})$
13	Product 13	0.10	0.01	0.66	32,550	95	$MD_{13,t} = 2.492((12 + t)^{-6.425E-02})$
14	Product 14	0.20	0.03	1.46	4500	38	$MD_{14,t} = 6.836((12 + t)^{-5.339E-02})$
15	Product 15	0.20	0.03	1.46	25,500	38	$MD_{15,t} = 6.836((12 + t)^{-5.339E-02})$
16	Product 16	0.20	0.01	0.24	7000	38	$MD_{16,t} = 6.836((12 + t)^{-5.339E-02})$
17	Product 17	0.30	0.04	2.00	355	38	$MD_{17,t} = 5.014((12 + t)^{-0.147})$
18	Product 18	0.50	0.20	4.00	0	24	$MD_{18,t} = 4.854((12 + t)^{-8.355E-03})$
19	Product 20	20.10	0.68	36.00	3020	19	$MD_{20,t} = 61.343((12 + t)^{-4.200E-02})$
20	Product 21	13.20	0.30	16.00	833	33	$MD_{21,t} = 31.876((12 + t)^{-5.991E-02})$
21	Product 22	4.10	0.02	6.00	23,763	95	$MD_{22,t} = 9.013((12 + t)^{-5.887E-02})$
22	Product 24	0.30	0.39	20.77	1659	191	$MD_{24,t} = 28.636((12 + t)^{-7.302E-02})$

Table A4
Data of permanent and part-time workers.

	Salary/Wages per month (MU)	Overtime rates (MU) per hour		Hiring cost (MU)	laying off cost (MU)	Initial number of workers	Minimum level of workforce	Maximum level of workforce
		Normal working days	Days-off/ holydays					
Permanent workers	**3283**	**21.1**	**31.6**	**–**	**–**	**800**	**600**	**977**
Part-time workers	**1600**	**10.3**	**15.23**	**500**	**0**	**0**	**0**	**80**

Table B1
The optimal production Plan-I.

#	Product	Jan.	Feb.	Mar.	Apr.	May.	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.	TOTAL
1	Product 1	1030	0	0	0	1760	0	0	0	0	0	0	0	2790
2	Product 2	0	13,640	9460	3960	6600	10,560	11,880	5280	6600	5060	7040	3740	83,820
3	Product 3	46,461	52,200	59,103	60,497	61,600	65,892	72,737	60,740	62,231	42,000	55,000	43,000	681,461
4	Product 4	0	2200	2200	1386	1826	1826	1826	2640	2200	1826	1386	2200	21,516
5	Product 5	0	2200	4620	4400	4400	5280	4400	4400	4400	3520	4400	4400	46,420
6	Product 6	30,390	28,600	32,000	40,600	40,000	45,819	34,181	57,800	47,000	47,000	37,600	27,800	468,790
7	Product 7	0	13,000	10,400	11,200	11,500	13,800	9200	15,900	13,000	12,393	11,007	8800	130,200
8	Product 8	62,316	88,235	127,600	84,400	105,500	99,500	100,500	106,500	126,600	84,400	105,500	105,500	1,196,551
9	Product 9	0	4080	6120	10,200	10,200	10,200	10,200	10,200	12,240	10,200	2040	5100	90,780
10	Product 10	0	4080	13,260	8160	10,200	10,200	10,200	4080	6120	4080	5100	5100	80,580
11	Product 11	104,112	80,400	106,500	105,500	105,500	99,500	100,500	106,500	105,500	105,500	105,500	105,500	1,230,512
12	Product 12	3310	8160	16,320	21,420	20,400	20,400	20,400	14,280	15,300	15,300	9180	10,200	174,670
13	Product 13	58,450	54,748	60,614	58,658	60,614	58,658	60,614	60,614	58,658	60,614	58,658	47,000	697,900
14	Product 14	19,300	15,600	16,400	22,800	15,200	19,000	22,800	17,600	18,000	18,000	9280	12,400	206,380
15	Product 15	0	2200	4400	5280	880	4840	5280	2860	4840	4400	2772	440	38,192
16	Product 16	0	0	0	0	1826	0	0	1826	0	0	253	0	3905
17	Product 17	0	9845	0	0	8500	0	0	10,200	0	0	1640	0	30,185
18	Product 18	0	2060	0	0	1660	0	0	1660	0	0	630	0	6010
19	Product 20	60	2200	1760	2200	2200	2200	2640	1386	2266	1826	1386	2200	22,324
20	Product 21	1873	1826	1386	1826	1826	1826	2266	1826	1826	1826	1386	1826	21,519
21	Product 22	0	15,200	10,000	11,944	10,856	13,200	15,600	10,200	11,000	7900	7330	7400	120,630
22	Product 24	0	0	0	0	0	0	68,341	52,000	72,000	84,000	68,000	80,000	424,341

Appendix B:. Detailed results of Plan-I

After solving the data set of Plan-I optimally, the following results were obtained. Table B1 shows the production plan for each product during each production period. Table B2 shows the inventory levels at the end of each period. Table B3 shows the subcontracting levels for each product, the other non-listed products have zero levels. Table B4 shows the number of shifts required

Table B2
The optimal inventory levels for Plan-I.

#	Product	Jan.	Feb.	Mar.	Apr.	May.	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
1	Product 1	2050	880	880	880	880	440	440	440	440	440	440	440
2	Product 2	8053	1760	4400	3960	1320	1320	1980	3960	2640	2640	2200	1540
3	Product 3	30,539	22,000	21,200	16,303	12,800	12,400	14,292	23,029	21,769	24,000	11,000	11,000
4	Product 4	4258	880	880	880	440	440	440	440	880	880	880	440
5	Product 5	8104	1760	660	880	880	880	1760	1760	1760	1760	880	880
6	Product 6	21,410	14,800	12,400	7400	8000	8000	13,819	8000	18,800	18,800	18,800	9400
7	Product 7	18,313	5200	5200	2600	2300	2300	4600	2300	5200	5200	4593	2600
8	Product 8	70,549	32,365	20,100	42,200	21,100	21,100	20,100	20,100	21,100	42,200	21,100	21,100
9	Product 9	9051	2040	1020	2040	2040	2040	2040	2040	2040	4080	4080	1020
10	Product 10	10,213	2040	1020	4080	2040	2040	2040	2040	1020	2040	1020	1020
11	Product 11	36,588	40,200	20,100	21,100	21,100	21,100	20,100	20,100	21,100	21,100	21,100	21,100
12	Product 12	10,970	4080	2040	3060	4080	4080	4080	4080	3060	3060	3060	2040
13	Product 13	32,550	26,000	18,792	17,156	17,714	20,228	16,636	15,000	14,000	14,000	13,000	13,000
14	Product 14	4500	6800	6400	3800	7600	3800	3800	7600	7200	7200	7200	3200
15	Product 15	25,500	880	880	880	1760	440	880	1760	1320	1760	1760	880
16	Product 16	7000	7000	880	880	880	880	880	880	880	880	880	220
17	Product 17	355	355	1700	1700	1700	1700	1700	1700	3400	3400	3400	840
18	Product 18	0	0	400	400	400	400	400	400	400	400	400	200
19	Product 20	3020	880	880	440	440	440	440	880	440	880	880	440
20	Product 21	833	880	880	440	440	440	440	880	880	880	880	440
21	Product 22	23,763	4400	5600	2600	3544	2400	2600	5200	4400	4400	4000	2200
22	Product 24	1659	1659	1659	1659	1659	1659	1659	20,000	12,000	14,000	28,000	16,000

Table B3
The obtained subcontract levels for Plan-I.

Product	Jan.	Feb.	Mar.	Apr.	May.	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
Product 4	0	0	0	374	374	374	374	0	0	374	374	0
Product 13	0	3044	12,750	11,900	11,900	12,750	12,750	8386	11,342	3386	6342	0
Product 14	0	0	0	0	0	0	0	0	0	0	2720	0
Product 15	0	0	0	0	0	0	0	0	0	0	748	0
Product 16	0	0	0	0	374	0	0	374	0	0	187	0
Product 18	0	340	0	0	340	0	0	340	0	0	170	0
Product 20	0	0	0	0	0	0	0	374	374	374	374	0
Product 21	374	374	374	374	374	374	374	374	374	374	374	374
Product 22	0	0	0	0	0	0	0	0	0	1700	1870	0

Table B4
Number of shifts to be worked for Plan-I.

#	Product	Jan.	Feb.	Mar.	Apr.	May.	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
1	Product 1	0.085	0.000	0.000	0.000	0.145	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2	Product 2	0.000	1.246	0.780	0.338	0.544	0.900	0.980	0.436	0.563	0.417	0.600	0.309
3	Product 3	1.916	2.384	2.438	2.578	2.541	2.808	3.000	2.505	2.652	1.732	2.344	1.774
4	Product 4	0.000	0.395	0.357	0.232	0.296	0.306	0.296	0.428	0.369	0.296	0.232	0.357
5	Product 5	0.000	0.100	0.191	0.188	0.181	0.225	0.181	0.181	0.188	0.145	0.188	0.181
6	Product 6	0.748	0.779	0.788	1.033	0.985	1.166	0.841	1.423	1.196	1.157	0.956	0.684
7	Product 7	0.000	0.354	0.256	0.285	0.283	0.351	0.226	0.391	0.331	0.305	0.280	0.217
8	Product 8	0.993	1.557	2.034	1.390	1.682	1.639	1.602	1.698	2.085	1.345	1.738	1.682
9	Product 9	0.000	0.186	0.252	0.435	0.421	0.435	0.421	0.421	0.522	0.421	0.087	0.210
10	Product 10	0.000	0.186	0.547	0.348	0.421	0.435	0.421	0.168	0.261	0.168	0.217	0.210
11	Product 11	2.288	1.956	2.340	2.395	2.318	2.259	2.208	2.340	2.395	2.318	2.395	2.318
12	Product 12	0.362	0.988	1.785	2.420	2.231	2.305	2.231	1.562	1.729	1.673	1.037	1.115
13	Product 13	2.893	3.000	3.000	3.000	3.000	3.000	3.000	3.000	3.000	3.000	3.000	2.326
14	Product 14	2.388	2.137	2.029	2.915	1.881	2.429	2.821	2.178	2.301	2.227	1.187	1.534
15	Product 15	0.000	0.301	0.544	0.675	0.109	0.619	0.653	0.354	0.619	0.544	0.354	0.054
16	Product 16	0.000	0.000	0.000	0.000	0.226	0.000	0.000	0.226	0.000	0.000	0.032	0.000
17	Product 17	0.000	1.349	0.000	0.000	1.052	0.000	0.000	1.262	0.000	0.000	0.210	0.000
18	Product 18	0.000	0.447	0.000	0.000	0.325	0.000	0.000	0.325	0.000	0.000	0.128	0.000
19	Product 20	0.015	0.603	0.436	0.563	0.544	0.563	0.653	0.343	0.579	0.452	0.354	0.544
20	Product 21	0.267	0.288	0.197	0.269	0.260	0.269	0.323	0.260	0.269	0.260	0.204	0.260
21	Product 22	0.000	0.833	0.495	0.611	0.537	0.675	0.772	0.505	0.563	0.391	0.375	0.366
22	Product 24	0.000	0.000	0.000	0.000	0.000	0.000	1.682	1.280	1.832	2.068	1.730	1.969

for the production of each product during each period t. This number of shifts is real to be used in computing the total product-machine loading for the corresponding period. By comparing Tables B3 and B4 especially for product 13, one can conclude that this product has the maximum levels of subcontracting in reasons of machine capacity shortage. As listed, the number of worked

Table B5
Results of workforce for Plan-I.

	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
Permanent workers	760	720	760	747	787	805	845	885	906	866	826	786
Overtime hours of permanent workers worked at normal working days	0.0	0.0	623.9	586.3	610.5	689.0	689.0	6372.0	7047.9	5699.9	5929.7	0.0
Overtime hours of permanent workers worked at days-off	0.0	0.0	0.0	0.0	0.0	0.0	0.0	31.4	0.0	0.0	0.0	0.0
Part-time workers	0	80	80	80	80	80	80	80	0	0	0	0
Hiring of part-time workers	0	80	0	0	0	0	0	0	0	0	0	0
Firing of part-time workers	0	0	0	0	0	0	0	80	0	0	0	0
Overtime hours of part-time workers worked at normal working days	0.0	0.0	623.9	576.0	600.0	624.0	624.0	576.0	0.0	0.0	0.0	0.0
Overtime hours of part-time workers worked at days-off	0.0	0.0	0.0	0.0	0.0	0.0	0.0	31.4	0.0	0.0	0.0	0.0

shifts is the maximum (3 shifts). Table B5 shows the data associated with permanent and non-permanent workforce.

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