An application of principal component analysis and logistic regression to facilitate production scheduling decision support system: an automotive industry case

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Abstract

Production planning and control (PPC) systems have to deal with rising complexity and dynamics. The complexity of planning tasks is due to some existing multiple variables and dynamic factors derived from uncertainties surrounding the PPC. Although literatures on exact scheduling algorithms, simulation approaches, and heuristic methods are extensive in production planning, they seem to be inefficient because of daily fluctuations in real factories. Decision support systems can provide productive tools for production planners to offer a feasible and prompt decision in effective and robust production planning. In this paper, we propose a robust decision support tool for detailed production planning based on statistical multivariate method including principal component analysis and logistic regression. The proposed approach has been used in a real case in Iranian automotive industry. In the presence of existing multisource uncertainties, the results of applying the proposed method in the selected case show that the accuracy of daily production planning increases in comparison with the existing method.

Keywords

Principal component analysis, Logistic regression, Production planning control, Decision support system

Introduction

Effective planning and control of production processes are usually seen as key to the success of a manufacturing company. During the last 50 years, both academic institutes/universities and industries have put great effort into developing and designing successful approaches and methods for manufacturing planning and control. Indeed, the methods and approaches of how to plan and control production have been changed over time. This occurs in line with changes in customer requirements and technology improvements (Vollmann et al. 2005).

Detailed production scheduling is an extremely complex problem (Brucker 2007) wherein most cases are considered NP-hard (Günther and van Beek 2003). In order to deal with complexities and uncertainties, a detailed production scheduling system should be equipped with all the necessary decision support tools for rendering production problems visible within a planning period and shift dispatching control from the foremen to the planner (Sotiris et al. 2008). According to Simchi-Levi et al. (2008), the decision support system (DSS) is an analytical tool to aid operations and production planning. The DSS can range from simple tools to expert systems. The DSS helps to solve the problems such as network planning to tactical planning all the way to daily operational problems. Thus, the effective DSS can help managers or production planners to manage uncertainties and achieve better results in daily fluctuations.

The stimulus for this work has been to understand whether or not the historical daily shop floor data can be used for creating more robust daily production plan. Moreover, the paper studies the feasibility of using the multivariate statistical analysis of daily shop floor data as an appropriate solver tool for detailed production scheduling decision support system. In order to answer these, we represent an Iranian automotive case of detailed production planning in applied material requirement planning (MRP) system. The results may not be generalized to JIT and lean manufacturing principles which have a pull approach of planning and control of production. The rest of the paper has been organized as follows: in next section, the related literature has been reviewed, whilst the problem has been defined and the selected case has been presented in the 'Case problem statement' section. The 'Methodology of problem analysis' section has outlined the proposed multivariate DSS as subsequent specifications arising from the 'Case problem statement' section. The 'Proposed multivariate DSS method' section has demonstrated the implementation results, and finally, in the 'Conclusions' section, the conclusions have been drawn and further research efforts have been mapped out.

Literature review

The production planning control models can be characterized in a variety of approaches, but most common categorizations are specific to the application areas (Brucker 2007). In this article, we have classified the production planning problem solving approaches in two groups in terms of their environment and condition: unconditional/deterministic analytic production planning and production planning under uncertainties (see Table 1).

Table 1 Classification of related literatures

	Approach					
	Deterministic production planning		Production planning under uncertainties			
	Exact methods	**Heuristic methods**	**Simulation**	**DSS developing**	**Statistical analysis**	**Hybrid/combinational methods**
Literatures	Brucker (2007)	Sotiris et al. (2008)	Aytug et al. (2005)	McKay and Wiers (2003)	Mele et al. (2005)	Cunha and Wiendahl (2005)
	Maravelias and Sung (2009)	Jourdan et al. (2009)	Jahangirian et al. (2010)	Sotiris et al. (2008)	Hatzikonstantinou et al. (2012)	Aytug et al. (2005)
				Farrella and Maness (2005)		
	Framinan and Ruiz (2010)	Ribas et al. (2010)	Volling and Spengler (2011)	Mok (2009)	Peidroa et al. (2009)	Volling and Spengler (2011)
	Ribas et al. (2010)	Jahangirian et al. (2010)	Rolo and Martinez (2012)	Caricato and Grieco (2009)	Verderame and Floudas (2009)	
	Yao et al. (2012)	Ross and Bernardo (2011)		Ko and Wang (2010)	This paper	
Comments	Seldom applicable in actual shop floors since they may only solve small-scale problems with distinct parameters and scale of time	Simulation needs a great deal of efforts to make a practical schedule by some expert and expensive production planners	DSS tools are concerned with complementary applications to ERP/MRP software. They are practical with lack of ERP system		Statistical and hybrid methods are useful to control uncertainties in real condition and improve the effectiveness of both evaluation and decision making; however, they are not independent and complete tools. They have to be designed for each case problem	

DSS, decision support system; MRP, material requirement planning; ERP, enterprise resource planning.

In the case of unconditional analytic models, we are referring to models which are simplifications of a real system in terms of mathematical expressions and can be solved by exact or heuristic methods. The literature on the exact algorithms in scheduling and production planning problems is extensive. A thorough review of scheduling problems, modeling approaches, and solution methods can be found in Brucker (2007), Framinan and Ruiz (2010), and Ribas et al. (2010). Whereas fluctuations and uncertainties have key roles in real world, deterministic, or exact approaches, such that branch and bound (Yao et al. 2012) and mixed integer linear programming (Maravelias and Sung 2009) are seldom applicable in actual shop floors since they may only solve small-scale problems with distinct parameters and scale of time.

Several heuristics and hybrid methods are recommended in the literature (Jourdan et al. 2009). Ribas et al. (2010) have classified the approximate methods into constructive and improvement heuristics. However, the application of heuristic algorithms is believed to be more applicable for real shop floors due to their lower computations, but they are still limited by the dimension of problems and uncertainties. Therefore, their implementation should be coupled with some decision support tools to aid the production planners (Ross and Bernardo 2011; Sotiris et al. 2008).

To cope with uncertainties in production control, it is worth to investigate a new customized framework for planning and scheduling under uncertainty. Another challenging issue is to investigate the ways of controlling a large number of uncertain parameters. Hence, scheduling under uncertainty has received a lot of attention in recent years (e.g., Hatzikonstantinou et al. 2012; Vargas and Metters 2011; Torabi et al. 2010; Verderame and Floudas 2009). Uncertainty can be derived from many aspects, such as demand or product orders, alternation or priority of orders, equipment failures, resource changes, and processing time variability. To adapt uncertainties during the manufacturing process, the proposed methods are divided into two main groups: reactive scheduling and preventive scheduling (Aytug et al. 2005). Simulation approach is able to analyze the behavior of the environment when it is characterized by several constraints and uncertainties (Rolo and Martinez 2012; Volling and Spengler 2011; Jahangirian et al. 2010). In these approaches, the outcomes of the simulation software can be used in preventive scheduling and decision support systems, but they need a great deal of efforts to make a practical schedule by some expert production planners.

By the emersion of enterprise resource planning (ERP) systems, the utilization of data becomes more important in production planning and control (PPC). The incredible wealth of available data in SCM and PPC software raises the question of how to help decision makers in harnessing the organization. The answer to this question has defined the production activity control (PAC) subsystem at the lowest level of MRPII (Vollmann et al. 2005). By means of the PAC system, the sequence of the orders is defined with their release and due times. In fact, PAC cannot take into account the real state of the production environment, and it may produce unrealistic or impractical production plan.

Whereas the MRP-based system cannot follow the large number of shop floor fluctuations, production managers bow to the inevitable complex task of scheduling/rescheduling at the shop floor control. Poor production control may cause serious problems to a firm's ability to meet production requirements and constraints. Many researches have focused on developing DSS tools to face this problem (e.g., Ko and Wang 2010; Caricato and Grieco 2009; Mok 2009; Farrella and Maness 2005; McKay and Wiers 2003). These tools are concerned as complementary applications to the ERP/MRP software.

Unfortunately, few success stories have been reported on creating production planning and logistics in a real factory, and there are still many challenges that remain (McKay and Black 2007). In the absence of one sole issue for PPS success or failure (McKay and Wiers 2003, 2004), one potential issue related to the failure of a planning system is the lack of information system and DSS tools for detailed production planning. This was the first insight obtained from this case study (see Table 1).

Meanwhile, combination use of statistical analysis with other methods to control the uncertainties in real condition decision making has been proposed by some literatures (Mele et al. 2005). Cunha and Wiendahl (2005) have proposed an evaluation method based on the use of multivariate techniques: principal component analysis (PCA) and cluster analysis (CA) to improve the effectiveness of evaluation and decision making, monitoring and manufacturing control. The idea of using multivariate statistical analysis to develop existing DSS is the second and major contribution of this study. The proposed method in this paper is based on the use of multivariate techniques on shop floor data. We intend to improve the effectiveness of the decision-making tasks undertaken when dealing with detailed production plans in an uncertain condition.

Case problem statement

The case study of detailed production planning has been done in an Iranian automotive manufacturing company. SAIPA Corporation (Tehran, Iran) is a holding company that assembles several types of passenger cars, vans, minibuses, buses, and trucks. As with any other car manufacturing company, the production process followed has a high degree of complexity, coupling the complex bill of materials (BOMs) with equally complex routings that transgress the shop floor boundaries.

The main problem of the selected case has been inferred from logistics staff answers to a set of questions and interviews. It is reported that the accuracy of daily production plans is directly affected by some alternate constraints and probable parameters. Hence, either the rescheduling or planning diversity and related extra material handling or extra/shortage parts and production line stop are enviable tasks every day. By their complaint about the alternate decisions to manage stochastic or abnormal events, we have made inferences about the lack of DSS tools to provide a practical detailed production planning.

Methodology of problem analysis

The following three aspects of the problem have been specified in the analysis of the current situation:

- *Layout and physical constraint*. It focuses on the production flow and is concerned with constraints of layout and any physical limitation in the production lines.
- *Production planning and control system.* It is concerned with the daily activities of the production planners during their detailed production planning in the shop floor control process. Shop floor data in a multi period range was gathered from this aspect of analysis.
- *Uncertainties and stochastic factors.* It is concerned with the source of uncertainties and stochastic factors.

To investigate the mentioned aspects, a mixture of interviews and observation has been applied. The major part of observation and a small part of the meetings were concerned with information about the production process and the production planning control.

In the following two subsections, the basic results concerning the first two aspects of the case problem analysis have been presented. These results are normally used to design the system architecture and functionality as well as the shop floor model of the plant. The results of the third aspect, namely uncertainties, are used to construct a multivariate analysis tool of simplified real production.

Layout and physical constraints

A trim shop is located at the end of the production process. Therefore, it has the highest level of complexity in comparison with subsequent production activity control processes. The main assembly production line is equipped with a conveyor. According to production rate and types of products (seven types), the length of production line is not quite enough for assigning individual locations to keep the minimum stock level of all parts according to the type of product BOM. The logistic area is not available near the line far distance from the main warehouses; thus, the order of completion lead time is long and is influenced by probable accidents.

There is a painted body (PB) stock at the end of the paint shop process. The stock of PB is the same as a single line queue before the entrance of the trim shop, and each PB can be transferred to the trim shop by the sequence of its location. Incapability of selecting the desired PB from the PB stock constrains the production planner to make a daily plan according to the PB color and type sequence. Although the elimination of the layout and physical constraints have been investigated in recent years, due to outstanding required cost and time, the progress of development is not noticeable.

Production planning and control system

Although KANBAN cards and pull production control system have been tried to be applied by production planning and the logistic department, the production control system is still MRP-based. A hierarchical two-level planning framework is used prior to the detailed production scheduling. At the top level, aggregate production planning which controls demand management with a yearly time horizon, has been located. The second planning level which is called midterm planning incorporates a hybrid MRP-PBC approach.

Master production schedule (MPS) outcomes are used to calculate components and material requirements. The final plan is made by revision on a weekly basis using the feedback from the detailed scheduling module. The weekly plan is released by PAC, and detailed production planning is issued as the daily schedule. The daily schedule is derived from a complicated decision-making process which uses shop floor data, inventory status data, BOM, and sequence of PB in stock. Figure 1 demonstrates this process.

Figure 1 The current MRP-based PPC process.

PPC suffers from several sources of inconsistencies as a consequence of incomplete ERP implementation. As a result of its complex production process and lack of information technology (IT) infrastructure, the presented case study during the last few years faced numerous problems concerning violated due dates, accumulated late orders, supernumerary production orders, excessive component inventory, poor releasing policies, and low shop floor visibility. The lack of online and integrated information may cause a misunderstanding of the real condition; thus, the production planner faces some unknown parameters in daily scheduling. In this situation, it is not weird if the daily schedule encounters some mistakes. Although the design and implementation of the ERP software is in progress, production planners cannot wait and do not get along with increasing complexity. They really need some practical tools to help them in perfect decision making.

Uncertainties and stochastic factors

Since there are some line-side space constraints, mixed production suffers from lots of problems and obstacles and forces managers to act on the basis of batch production. Meanwhile, there are many sources of stochastic events and uncertainties that batch production such as demand, process, and supply uncertainties (Peidroa et al. 2009). One of the main sources of stochastic factors that have been identified in this study is derived from the paint shop process and PB stock constraint. Due to some small defects on bodies, some of the PBs are selected to go into a touch-up area, and after doing all necessary reworks, they are transferred to the PB stock line. Almost all of the procedures in the defect inspection process are performed manually through human vision and influenced by stochastic factors. On the other hand, the required rework process times depend on the type and the level of defects which are not really exact and deterministic. Hence, the sequence of painted bodies in the queue of stock line cannot be absolutely defined. Meanwhile, supply uncertainties have a key role in unreliability of the production schedule. Each type of products has special parts which are from different suppliers. The availability of all special parts related to the desired type of products is the other vital information for the production planner to make the daily production schedule. According to our observation, the stock levels of these items are not expected to follow exact patterns.

Proposed multivariate DSS method

The complexity of production planning and control process, stochastic factors, physical constraint, uncertainties, and the shortcomings of the underlying IT infrastructure would pose significant drawbacks to the current detailed production scheduling. In this light, to the aforementioned production planning process and fully interoperable, both with the PPC system and existing software package, the proposed approach has been developed on the basis of a custom-built DSS using statistical multivariate techniques.

The integrated approach that will be presented introduces facilities to analyze data which are directly unavailable from the current planning system. This approach is introduced through the use of PCA to decrease the dimension of input-independent variables (Aguilera et al. 2006) and the use of logistic regression (LR) to predict the first priority of available and suitable type of product which can be selected to make a practical and effective detailed production schedule. These are used at different steps as shown in Figure 2.

Figure 2 Process of establishing a multivariate statistical tool for DSS development.

Shop floor and production plan historical data acquisition

The manner and logical behavior of the production planner to create a weekly plan or change daily detailed scheduling is an important factor through the practical decision-making process which can be used for finding an effective DSS tool. As answer to the main question of this research, the objective has been to find the statistical analysis appropriate for reducing this logical behavior. Hence, it has been required to collect daily shop floor data and historical data of the daily schedule issued by the production planner. The historical data of PB stock, existing PB quantity, and PB types in paint shop, sale online requests, inventory data, MRP weekly plan, released daily production schedule, and related orders with actual production were the main fields of data that have been collected for this analysis.

Reduction of inventory data by PCA

In this study, the collected inventory data sets (warehouse and line side separately) have at least 40 fields related to each types of products. This high volume and dimension of data matrix increase the complexity of analysis. If a substantial amount of the total variance in these data is accounted for by a few (preferably far fewer) principal components or new variables, then these few principal components can be used for interpretational purposes or in further analysis of the data instead of the original variables. PCA can be viewed as a dimensional reduction technique (Sharma 1996), and it is the appropriate technique for achieving the mentioned objective.

The core idea of PCA is to reduce the dimensionality of a data set comprising a large number of interrelated variables while retaining as much as possible the data set variance (Jolliffe 2002). This is obtained by transforming original variables to a new set of variables or principal components (ξ_i) which are a linear combination of original (p) variables. Due to their properties, they are uncorrelated and are ordered such that the first ($m \leq p$) that are retained contain most of the variation presented in the original data:

$$\mathrm{PC} = \{\xi_1 \ldots \xi_m\};\ \xi_i = w_{i1}x_1 + w_{i2}x_2 + \ldots + w_{ip}x_p,$$

where principal component (PC) = $\{\xi_1 \ldots \xi_m\}$ are the m principal components and w_{ij} is the weight of the jth variable for the ith principal component.

The reduction in complexity is achieved by performing PCA on collected inventory data. Thus, the original data of inventory can be substituted by PCs, and the new matching table of the shop floor data and corresponding production schedule is established as a contingency table.

Logistic regression model fitting, validation, and review to improvement

The fundamental question in this research motivated us to understand the logical behavior of the production planner in the decision-making process through daily production scheduling. As illustrated in Figure 2, the historical input/output of the decision process is analyzed and the relationship among them is discovered by logistic regression. In the remainder of this section, we briefly discuss about the basic concept and details of developing the logistic regression model and, finally, the validation procedure and review method for the improvement of this model.

Definition of variables

To simplify the discussion and interpretation of estimation model, the notation is introduced and variables are defined which can be recognized from collected data. Table 2 shows a code sheet for definition of preliminary selected variables from collected data.

Table 2 Description of variables

Variable	Description	Code/values
TYP	Compressed natural gas equipped	CNG
	CNG and hydraulic steering wheel	CNG-H
	Hydraulic steering wheel	HYD
	SABA simple injection system	GLXi
	Reinforced new body	X132
	Morvarid hatchback	DM
	Other new models	NEW
CLR	Color production plan	W = white G = gray B = black R = red S = silver
PBS	Painted body stock	0-400
SEQ	Compatibility of PB sequence	1 = Low compatibility 2 = Fair compatibility 3 = Good compatibility 4 = High compatibility
INV1	Warehouse and line-side inventory PC 1	0 to 2,000
INV2	Warehouse and line-side inventory PC 2	0 to 1,000
SRT	Scheduled receipt	0 to 1,000
ACP	Available colored parts	0 to 1,000
RWP	Remainder quantity of weekly plan	0 to 5,000
ESD	Emergency sales/demand	1 = Critical 2 = Urgent 3 = Normal 4 = Non-emergency
ADP	Actual daily product	0 to 1,100
DPP	Daily production plan	0 to 1,100
DPC	*Daily production plan capability*	*0 = No* *1 = Yes*

Basic theory on logistic regression

There are two models of logistic regression to contain binomial/binary logistic regression and multinomial logistic regression. Binary logistic regression is typically utilized when the dependent variable is dichotomous and the independent variables are either categorical or continuous variables (Sharma 1996). Logistic regression is the best to use in this condition. The result of this type of regression can be expressed by a logit function as follows:

$$\text{logit}\left(p\right)=\text{Ln}\left(\frac{p}{1-p}\right)=\beta_0+\beta_1*x_1+\beta_2*x_2+\ldots+\beta_k*x_k=\beta_0+XB, \quad (1)$$

where $\left(\dfrac{p}{1-p}\right)$ is the odds.

The model can either be interpreted using the logit scale, or the log of odds (the relative probability) can be converted back to the probability such that

$$p = \exp\frac{\beta_0 + XB}{1 + \exp(\beta_0 + XB)} \tag{2}$$

In order to calculate the parameters β_0, β_1, β_2,…, β_k, the logistic regression transforms the dependent into a logit variable and then uses maximum likelihood estimation. In this paper, logistic regression is used to estimate the daily production planning capability (DPC) from the shop floor data. According to the variables summarized in Table 2, the logit can be defined for this case as follows:

$$\begin{aligned}\text{logit} = {} & \beta_0 + \beta_1 * \mathbf{TYP}(\mathbf{1}) + \beta_2 * \mathbf{TYP}(\mathbf{2}) + \beta_3 * \mathbf{TYP}(\mathbf{3}) + \beta_4 * \mathbf{TYP}(\mathbf{4}) + \beta_5 * \mathbf{TYP}(\mathbf{5}) + \beta_6 * \mathbf{TYP}(\mathbf{6}) + \beta_7 * \mathbf{INV1} + \beta_8 * \mathbf{INV2} \\ & + \beta_9 * \mathbf{CLR}(\mathbf{1}) + \beta_{10} * \mathbf{CLR}(\mathbf{2}) + \beta_{11} * \mathbf{CLR}(\mathbf{2}) + \beta_{12} * \mathbf{CLR}(\mathbf{3}) + \beta_{13} * \mathbf{CLR}(\mathbf{4}) + \beta_{14} * \mathbf{DPP} + \beta_{15} * \mathbf{PBS} + \beta_{16} * \mathbf{SEQ(1)} \\ & + \beta_{17} * \mathbf{SEQ(2)} + \beta_{18} * \mathbf{SEQ(3)} - \beta_{19} * \mathbf{SRT} + \beta_{20} * \mathbf{ACP} - \beta_{21} * \mathrm{RWP} - \beta_{22} * \mathbf{ESD(1)} + \beta_{23} * \mathbf{ESD(2)} - \beta_{24} * \mathbf{ESD(3).}\end{aligned} \tag{3}$$

To find out how effective the model expressed in Equation 3 is, the statistical significance of individual regression coefficients is tested using the Wald chi-square statistic. Goodness-of-fit test assesses the fitness of a logistic model against actual outcomes. Hosmer-Lemeshow test is an inferential goodness-of-fit test which is utilized in this paper. Meanwhile, the consequent predicted probabilities can be revalidated with the actual outcome to determine if high probabilities are indeed associated with events and low probabilities with non-events. The readers are referred to Bewick et al. (2005) and Hosmer and Lemeshow (2000) for more information about the assessment of fitted model.

Predicting capability of daily production planning

The fitted model, which has successfully passed the goodness-of-fit tests, can be used to calculate the predicted Logit (probability) of DPC for a given value of shop floor data. For example, assume that at the end of the working day, the production planner wants to make a decision about tomorrow's production plan and would like to predict the capability of a given production schedule. At first, using the PCA method ('Reduction of inventory data by PCA' section), the inventory level of line-side and related warehouses can be estimated by two principal components (INV1 and INV2), and then, according to the shop floor data, the amount of other independent variables (TYP, PBS, RWP, ESD, and DPP) are defined. Therefore, the probably of response variable (DPC) can be calculated by Equation 4:

$$p = \frac{e^{\left(\begin{smallmatrix}\beta_0+\beta_1*\mathrm{TYP}(1)+\beta_2*\mathrm{TYP}(2)+\beta_3*\mathrm{TYP}(3)+\beta_4*\mathrm{TYP}(4)+\beta_5*\mathrm{TYP}(5)+\beta_6*\mathrm{TYP}(6)+\beta_7*\mathrm{INV1}+\beta_8*\mathrm{INV\,2}+\beta_9*\mathrm{CLR}(1)+\beta_{10}*\mathrm{CLR}(2)+\beta_{11}*\mathrm{CLR}(3) \\ +\beta_{12}*\mathrm{CLR}(4)+\beta_{13}*\mathrm{DPP}+\beta_{14}*\mathrm{PBS}+\beta_{15}*\mathrm{SEQ}(1)+\beta_{16}*\mathrm{SEQ}(2)+\beta_{17}*\mathrm{SEQ}(3)+\beta_{18}*\mathrm{SRT}+\beta_{19}*\mathrm{ACP}+\beta_{20}*\mathrm{RWP}+\beta_{21}*\mathrm{ESD}(1)+\beta_{22}*\mathrm{ESD}(2)+\beta_{23}*\mathrm{ESD}(3)\end{smallmatrix}\right)}}{1+e^{\left(\begin{smallmatrix}\beta_0+\beta_1*\mathrm{TYP}(1)+\beta_2*\mathrm{TYP}(2)+\beta_3*\mathrm{TYP}(3)+\beta_4*\mathrm{TYP}(4)+\beta_5*\mathrm{TYP}(5)+\beta_6*\mathrm{TYP}(6)+\beta_7*\mathrm{INV1}+\beta_8*\mathrm{INV\,2}+\beta_9*\mathrm{CLR}(1)+\beta_{10}*\mathrm{CLR}(2)+\beta_{11}*\mathrm{CLR}(3) \\ +\beta_{12}*\mathrm{CLR}(4)+\beta_{13}*\mathrm{DPP}+\beta_{14}*\mathrm{PBS}+\beta_{15}*\mathrm{SEQ}(1)+\beta_{16}*\mathrm{SEQ}(2)+\beta_{17}*\mathrm{SEQ}(3)+\beta_{18}*\mathrm{SRT}+\beta_{19}*\mathrm{ACP}+\beta_{20}*\mathrm{RWP}+\beta_{21}*\mathrm{ESD}(1)+\beta_{22}*\mathrm{ESD}(2)+\beta_{23}*\mathrm{ESD}(3)\end{smallmatrix}\right)}}, \tag{4}$$

or $p = \dfrac{\exp(\text{logit})}{1+\exp(\text{logit})}$.

Customized DSS to facilitate detailed production scheduling

Predicting the capability of daily production planning facilitates the decision making of the PPC system, and as a result, the customized DSS can be defined and applied. The new hierarchical planning framework is depicted in Figure 3. The main procedural sequence does not exhibit any remarkable change in comparison with the current PPC process (Figure 1). The MPS calculates long-term end item needs and feeds the PPC system which creates the production order backlog according to MRP procedures. The weekly production plans are issued by the MRP module and feeds detailed scheduling.

Figure 3 Role of the proposed method in the production planning control framework.

The proposed multivariate method contributes in the DSS module which is denoted in Figure 3 in the dashed box. As we have described in the previous sections, the online shop floor data is used by this customized DSS tool and the predicted amount of DPC index is calculated. This production planning capability index can facilitate the decision-making process of detailed scheduling. The production planner can typically run this customized DSS at the beginning of each planning period (commonly one working day), and after making the decision about final changes on the detailed schedule, data of production order is extracted. When detailed scheduling is finalized, the production orders are handed down to the foremen for beginning of production. If dynamic events take place (e.g., a machine breaks down, a rush order arrives, or a subcontractor violates due dates), the planner reschedules to accommodate them.

Numerical experiment and results

According to the defined variables, the 42-week shop floor and inventory data have been collected. Every day, the line-side inventory level of special and important parts as well as warehouse inventory level have been recorded. Table 3 illustrates the sample data which were recorded on the first and second days in the warehouse. Data were collected over a period of 8 months and included PB stock, sale online requests, inventory data, MRP weekly plan, inventory status data schedule, and actual production.

Table 3 Sample data format of warehouse and line-side inventory levels

Date	TYP	ENGN	AXLE	PIPE	CONT	BODY	DASH	ECUT	STWL	EXST	TRIM	WIRE	SNSR	DMPR	CNGK	HYDK	SUB
09/01	CNG	138	154	129	102	158	96	404	251	157	259	250	451	253	320	-	306
09/01	DM	63	66	67	-	94	41	80	83	46	91	42	88	93	-	49	73
09/01	GLXi	189	159	156	-	150	103	153	-	123	229	266	157	126	-	-	100
09/01	HYD	46	60	72	-	104	48	117	98	69	108	185	205	170	-	27	139
09/01	NEW	27	112	122	-	180	43	174	-	119	164	185	285	219	-	-	142
09/01	X132	127	310	128	-	137	246	256	220	181	250	255	263	268	-	267	302
09/02	CNG	106	153	129	95	152	96	403	250	154	259	259	457	255	300	-	314
09/02	CNG-H	65	62	65	57	75	50	124	126	156	81	167	182	130	236	219	110
09/02	DM	63	64	64	-	139	39	73	81	52	176	49	87	85	-	91	77
09/02	GLXi	171	151	159	-	155	102	158	-	129	266	253	155	126	-	-	104
09/02	NEW	23	117	124	-	184	53	168	-	124	163	182	285	222	-	-	142
09/02	X132	120	243	121	-	139	246	255	223	181	258	259	266	268	-	271	300

ENGN, engine; AXLE, rear axle; PIPE, fuel pipe set; CONT, compressed net gas container; BODY special parts of body; DASH, dashboard or instrument panel; ECUT, electronic central unit; STWL, steering wheel; EXST, exhaust; TRIM, trim parts; WIRE, wiring set; SNSR sensors set; DMPR, dampers set; SNGK, compressed net gas kit; HYDK, hydraulic kit; SUB, sub assembly required parts.

According to the data reduction method described in the ‘Reduction of inventory data by PCA’ section, the following PC scores can be derived by applying PCA. In this study, the result of PCA shows that the first two principal component variables account for about 90% of the total variance of data, and the screen plot shows that the appropriate number of PCs is two. Using these PCA scores, the PC formulas are defined, and then the amount of PCs by the exact amount of each variable every morning can be calculated.

By the results of data reduction, we can make a new shop floor control (SFC) data which can be used for calculating logit more easily and practically. Table 4 shows the sample format of SFC data table which must be created for logistic regression analysis. Using Equation 4, the probable response variable (DPC) can be calculated by the coefficients derived from logistic regression analysis.

Table 4 SFC table data format: -input of LR analysis

Week	Working day	TYP	PCs		Daily plan		PBS	SEQ	SRT	ACP	RWP	ESD	ADP	DPC
			INV1	INV2	CLR	DPP								
1	1	CNG	316	166	W	450	180	3	400	385	968	3	446	1
	1	DM	157	44	R	50	50	4	100	86	300	1	51	1
	1	GLXi	127	255	S	100	80	4	100	85	500	3	98	1
	1	HYD	171	36	G	100	80	3	100	65	200	3	105	1
	1	NEW	79	195	S	150	100	1	100	0	430	4	131	0
	1	X132	417	192	W	250	200	2	300	85	1,400	4	212	0
1	2	CNG	293	136	B	200	50	1	100	20	522	2	154	0
	2	CNG-H	208	67	S	150	100	2	150	150	350	3	132	0
	2	DM	253	56	B	250	131	3	130	100	252	3	248	1
	2	GLXi	185	262	W	150	100	4	100	100	395	4	153	1
	2	NEW	66	195	W	100	55	3	100	83	330	4	82	0
	2	X132	409	199	G	250	250	4	400	186	1,105	2	253	1
↓	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓
↓	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓

$$\text{logit} = 0.93153 - 0.39432 * \mathbf{TYP(1)} - 0.56284 * \mathbf{TYP(2)} - 0.7653 * \mathbf{TYP(3)} - 0.56226 * \mathbf{TYP(4)} - 2.28933 * \mathbf{TYP(5)} - 1.43129 * \mathbf{TYP(6)} - 0.00502 * \mathbf{INV1} - 0.00157 * \mathbf{INV}2 + 0.21325 * \mathbf{CLR(1)} + 0.29959 * \mathbf{CLR(2)} - 1.13775 * \mathbf{CLR(3)} - 0.44392 * \mathbf{CLR(4)} + 0.01631 * \mathbf{DPP} - 0.00162 * \mathbf{PBS} + 0.2752 * \mathbf{SEQ}(1) + 0.23753 * \mathbf{SEQ(2)} + 0.20142 * \mathbf{SEQ(3)} - 0.00016 * \mathbf{SRT} + 0.00042 * \mathbf{ACP} - 0.00047 * \mathrm{RWP} - 0.01292 * \mathbf{ESD(1)} + 0.48281 * \mathbf{ESD(2)} - 0.02589 * \mathbf{ESD(3)}$$

$$\Rightarrow p = \frac{\exp(\text{logit})}{1+\exp(\text{logit})}. \tag{5}$$

Table 5 summarizes the test results of null hypothesis in which all the coefficients associated with predictors equal 0. The test statistic G = 230.037 with a p-value of 0.000 implies that there is at least one estimated coefficient that is different from 0. The results of Pearson, deviance, and Hosmer-Lemeshow goodness-of-fit tests have been also summarized in Table 5.

Table 5 Goodness-of-fit tests

Test		*df*	*P* value
All slopes are zero (*G*)	230.037	23	0.000
Pearson (χ^2)	514.679	584	0.982
Deviance (χ^2)	631.625	584	0.947
Hosmer-Lemeshow (χ^2)	3. 474	8	0.901

In this study, there is insufficient evidence to claim that the LR model does not fit the data adequately because the *P*-values for all tests are larger than the significance level of 0.05. Therefore, the LR model shown in Equation 5 is appropriate in explaining the DPC prediction.

The association between the response variable and predicted probabilities has been evaluated by some measures such as Somers' *D*, Goodman-Kruskal's gamma, and Kendall's tau-a in our case; the summary of results is listed in Table 6. The measures indicate that there is a close correspondence between DPC and its predicted probabilities.

Table 6 Measures of association

Pairs	Number	Percent	Summary measures	*P* value
Concordant	67,781	84.6	Somers' *D*	0.69
Discordant ties	12,163	15.2	Goodman-Kruskal's gamma	0.70
	151	0.2	Kendall’s tau-a	0.30
Total	80,095	100		

The accuracy of the proposed method

Utilizing the discussed PCA and LR model, 42 working weeks of shop floor data (including 1,256 records) were used to evaluate its prediction quality. In addition to real data, Monte Carlo-based simulated data were generated to extend our samples to 100 weeks. The simulation was run under a variety of conditions such as production line, seasonal demand, and probable disruption in production line. Every 4 weeks (1 month), the outcomes of classical detailed planning were compared with the corresponding outcomes of the proposed method. These results have been reported in Table 7, including 10 instances which have been selected from the worst to the best states.

Table 7 The comparison of DSS method accuracy

Applied methods		Total observations	Actual daily production capability		Predicted daily production capability			Daily planning accuracy (%)
			DPC = 1	DPC = 0	DPC = 1	DPC = 0	Error	
Instance 1	Classic DSS method	124	81	43	124	0	43	65
	Revised proposed method	124	117	7			7	94
Instance 2	Classic DSS method	136	88	48	136	0	48	65
	Revised proposed method	136	127	9			9	93
Instance 3	Classic DSS method	110	81	32	110	0	32	74
	Revised proposed method	110	105	5			5	95
Instance 4	Classic DSS method	116	93	23	116	0	23	80
	Revised proposed method	116	109	7			7	94
Instance 5	Classic DSS method	84	62	22	64	0	25	74
	Revised proposed method	84	76	8			8	90
Instance 6	Classic DSS method	64	39	25	64	0	25	61
	Revised proposed method	64	55	9			9	86
Instance 7	Classic DSS method	88	75	13	88	0	13	74
	Revised proposed method	88	86	2			2	98
Instance 8	Classic DSS method	101	66	35	101	0	66	74
	Revised proposed method	101	95	6			6	94
Instance 9	Classic DSS method	76	33	43	76	0	43	43

	Revised proposed method	76	69	7			7	91
Instance 10	Classic DSS method	121	80	41	121	0	41	66
	Revised proposed method	121	120	1			1	99

From the perspective of daily planning accuracy, the logistic regression model correctly identified 109 of 124 observations (refer to instance 1). The accuracy of each method can be simply calculated by dividing the number of observed actual productions, which are respondents of production plans (DPC = 1), to the total number of production plans. As shown in Table 7, by the proposed DSS method, more reliable detailed production plans can be submitted than by the classic method.

Conclusions

This study presents an application of statistical multivariate method together with the solver module in production activity control of an Iranian automotive manufacturer and introduces a revised decision support system which can provide a productive tool for knowledge workers to offer more reliable detailed production plans.

The proposed method is based on the use of principal component analysis to reduce the extensive dimension of shop floor data and logistic regression analysis to make a predictive tool and pre-check of daily production plan capability to improve the effectiveness of decision making. In this case study, it is shown that the revised DSS works more reliably and more accurately.

For future studies, either prediction accuracy or data reduction techniques may be improved by applying other specialized models of logistic regression. Manufacturers can also further adjust the proposed prediction models to accord with their production environments and data availability.

Competing interests

The authors declare that they have no competing interests.

Authors' contributions

SM has made substantial contributions to the concept, design, and acquisition of data and analysis and interpretation of data. MB has been involved with the main idea, drafting the manuscript, revising it critically for important intellectual content, and has given final approval of the version to be published. Both authors read and approved the final manuscript.

Authors' information

SM is a PhD student at Payme Noor University. MB is an associate professor at Shahed University.

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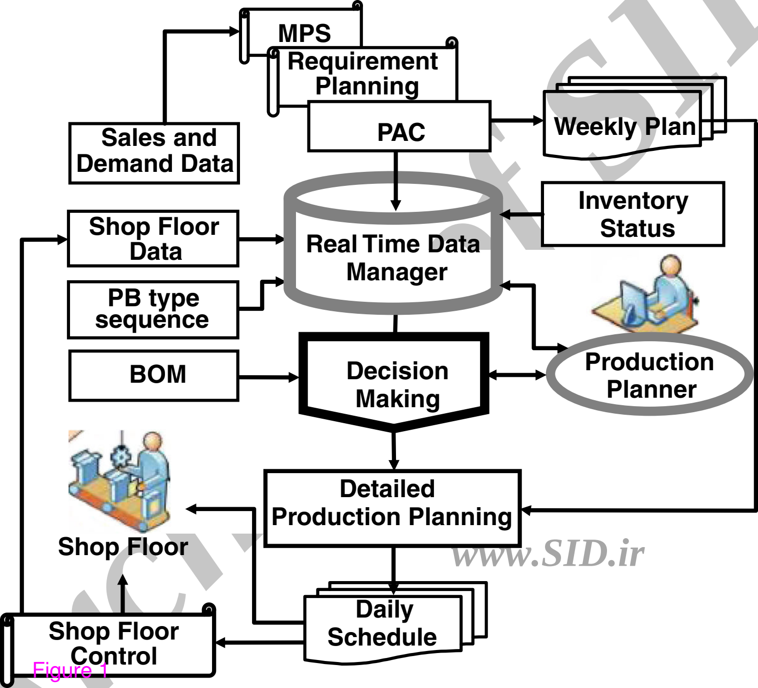

MPS
Requirement Planning
PAC
Weekly Plan
Sales and Demand Data
Inventory Status
Real Time Data Manager
Shop Floor Data
PB type sequence
BOM
Decision Making
Production Planner
Detailed Production Planning
Shop Floor
Daily Schedule
Shop Floor Control

Figure 1

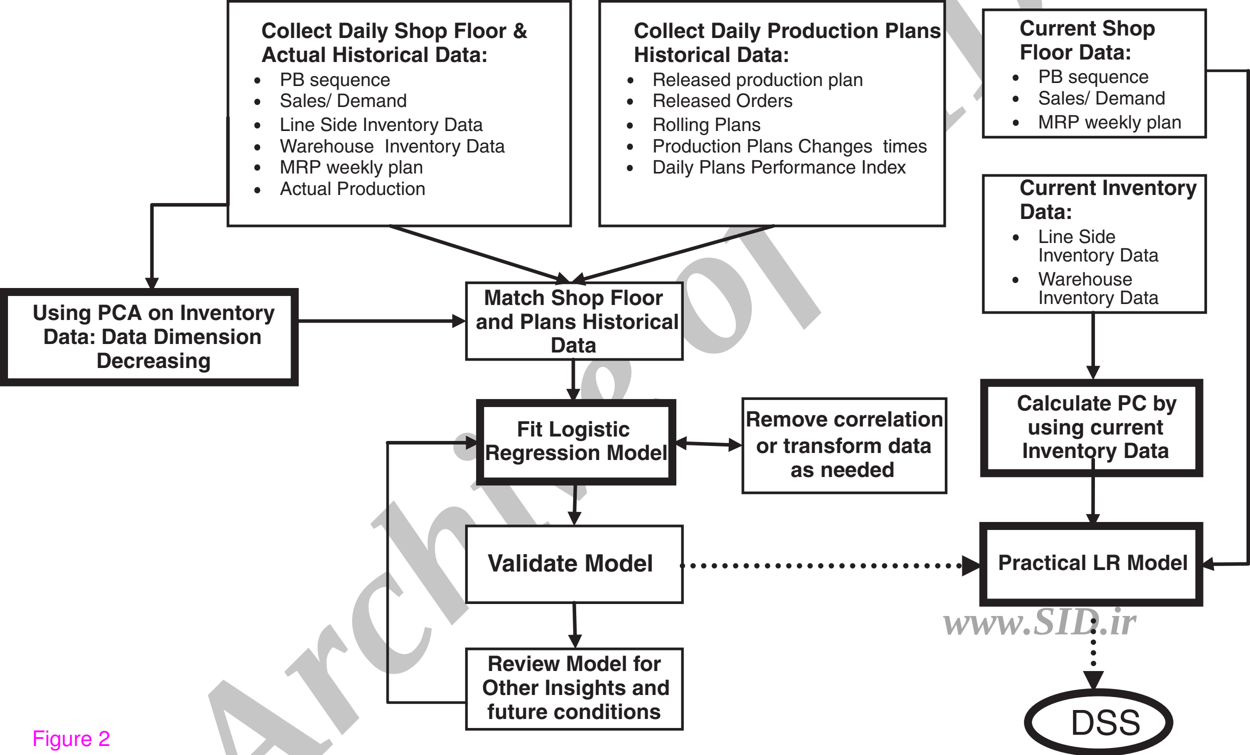
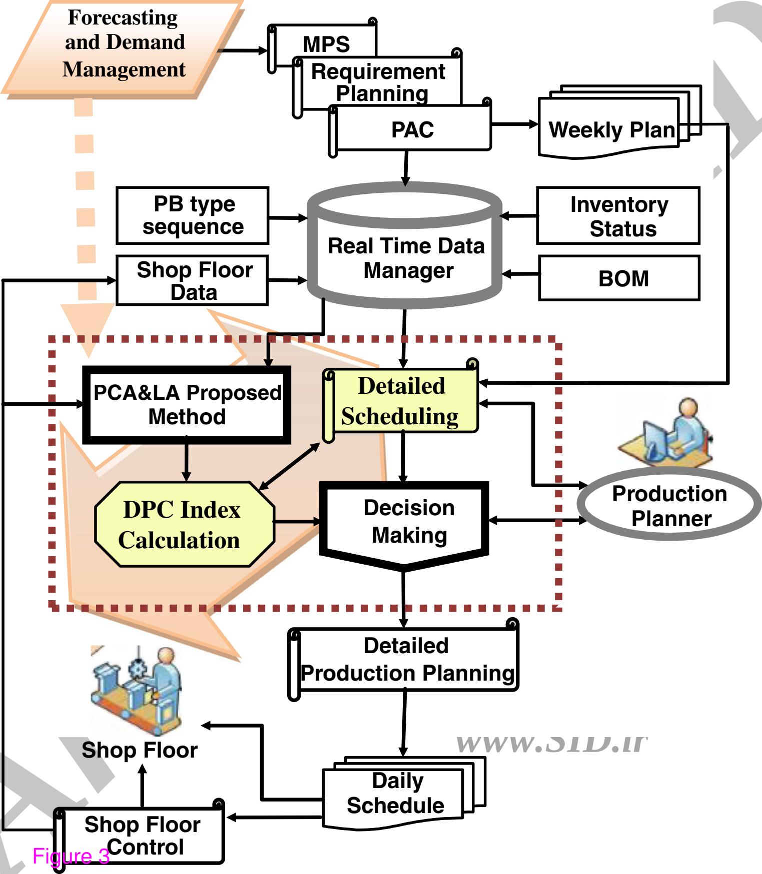

Collect Daily Shop Floor & Actual Historical Data:
PB sequence
Sales/ Demand
Line Side Inventory Data
Warehouse Inventory Data
MRP weekly plan
Actual Production
Collect Daily Production Plans Historical Data:
Released production plan
Released Orders
Rolling Plans
Production Plans Changes times
Daily Plans Performance Index
Current Shop Floor Data:
PB sequence
Sales/ Demand
MRP weekly plan
Current Inventory Data:
Line Side Inventory Data
Warehouse Inventory Data
Using PCA on Inventory Data: Data Dimension Decreasing
Match Shop Floor and Plans Historical Data
Fit Logistic Regression Model
Remove correlation or transform data as needed
Calculate PC by using current Inventory Data
Validate Model
Practical LR Model
Review Model for Other Insights and future conditions
DSS

Figure 2



Forecasting and Demand Management
MPS
Requirement Planning
PAC
Weekly Plan
PB type sequence
Real Time Data Manager
Inventory Status
Shop Floor Data
BOM
PCA&LA Proposed Method
Detailed Scheduling
DPC Index Calculation
Decision Making
Production Planner
Detailed Production Planning
Shop Floor
Daily Schedule
Shop Floor Control

Figure 3