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Smart Material Planning Optimization Problem Analysis

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Abstract

Mostly, the concept of smart manufacturing is addressed based upon how to effectively facilitate the production activities by using the automation equipment; however, causing the fluctuation of production may frequently root to the uncertain incoming sales orders. These uncertain factors may be influenced by various economic parameters, such as changes within trade regulations, competitor innovations, and changes within the market. In order to reduce the difference between the forecasted demand versus actual demand and to minimize risk, these factors need to be taken into account and be fully investigated. The current widely applied forecast methods are factory capacity-driven and based on the trend against the activity history. When the uncertainty comes from the external, then the forecasts derived from these models cannot provide convincing insights to let the firms make decisions confidently. Many previous prestigious studies focused on the problem-solving optimization mathematic methods and articulated the causality among latent factors; few have addressed to a holistic framework that the firms can practice on. This study presents a clear operable step-by-step framework to manage and cushion the impact from the external uncertain factors. It also introduces three novel and feasible production planning models with the consideration of the economic parameters. The empirical case was a multi-nation machinery-making firm who has adopted the proposed framework to optimize the material forecasts pursuing their smart manufacturing goals.

Keywords: material planning, supply chain management, smart manufacturing, advanced analytics, AI application

1. Introduction

In the pursuit of smart manufacturing, to satisfy the customer needs with quality, responsiveness and cost-effectiveness become the major challenge of nowadays factories [1]. The market demands are uncertain [2] and prone to be influenced by the composite effects of the driven forces, including the following: **Market saturation**: most known potential customers have already had the similar kind of product, and the new market segments are still not thriving to prove be the promising revenue fountain [3]. **Product innovation**: the customers hardly pay more for these products with slim marginal utility [4]. **Product differentiation**: most product features are common with the rivals, and the price-cutting thus becomes the inevitable survival strategy [5]. **Rival initiative**: in facing the same situation of demand slump, all rivals are endeavoring to stimulate the demand on their products to gain

the shrinking profit [6]. **Customized features**: in the business-to-business (B2B) model, the purpose-intended design is the key to make the customers' final product differentiable to their rivals. While in the business-to-consumer (B2C) market, the customers are willing to pay more for those personalized products [7].

To effectively fulfill the business model of uncertain sales orders ensuring the product responsive delivery, the factory must prepare adequate resources, including the material and the workforce in advance. The more prepared resources are in advance, the more cost will be incurred; thus the revenue shrinks [8]. In the manufacturing practice, the bill of material (BOM) is an information to keep the product structural data of materials, such as part numbers, the quantity of need, and the associated specification [9]. To manage the material requisition, the total material needed shall be aggregated by the queued sales orders; the minimal quantity of a material is the required product quantities multiply the usage of that material in the BOM, respectively. The supplier material replenishment schedule may not be equivalent to one another due to their various conditions of production and delivery [10]. In most cases, the procurement of material in an economic scale will impact the production cost. This implies that the factory needs provision more and in advance for those materials that have greater variability in delivering.

Of those manufacturing automation equipment products, the sales may not aware of the gaps between the customer's expectations and the equipment limitations, including the required working environment, the excess inputs, and the unsynchronized outputs to the next step of productions. The factory product development team must customize the equipment in order to fit in the customer's application. The dilemma is whether the development team just tweaks the design for this specific case or puts more efforts on triggering the whole engineering change process to enhance the product features. If the decision is to enhance the product, that means a new BOM will be created, and some parts must be replaced; inevitably, the development team will commence a series of rigorous test on this design change; some tests take time. Consequently, the objective of material planning is to find the appropriate cost-effective solution under the constraints of order fulfillment and economic scale of the procurement.

The objective of this chapter is to articulate how the firm's material forecasting under the uncertain business environment can be improved from both management and advanced analytics perspectives.

2. Framing the problem

Apparently, it is a challenge to articulate the overall processes in which the aforementioned uncertainties might occur. Without a comprehensive expression, the firm cannot effectively collaborate on and make contribution to solve the problem. Thus, this chapter applied the problem frame analysis framework to disclose the complexity of the material planning in this smart manufacturing theme. Through this framework, all task-related participants can elaborate their actions to improve the forecast within and also look the problems a bigger firm-level picture. Essentially, the material forecast is an overall optimization in the firm. Such an optimization requires the synergy of the participants through the analytical models among tasks.

The problem frame is a method often used in the requirement engineering to describe a complicated problem's boundary and analyze the mutual influences among the problem factors in rigorous mathematic logic expressions [11]. One of the advantages of applying this method is these mathematic logic expressions can be easily transformed into the analytical forecast models. But it also brings its major

disadvantage that the problem frames are not friendly to the business process improvement. Therefore, this chapter seeks to describe the essential framework of the material planning problem (**Figure 1**) in a more intuitive fashion, by using an expanded "Business Process Model and Notation" (BPMN).

The sales orders usually are not placed at the same time, but in a certain "random" way instead. If the materials take longer time in preparation than the order requested delivery time, consequently, the requested orders cannot be fulfilled, and the business responsiveness (one of the essentials of the smart manufacturing) will be compromised. Therefore, the factory must procure these materials in advance based on the market forecast. This forecast must be able to reflect the confidence level on the estimated quantities of the following: (1) **Mature products**: the firm's major revenue source, with a long, steady predictable sales history, usually adopted by a solid customer base. (2) **Adaptive products**: these are the extended or enhanced version of mature products or the long tail ones. (3) **Long-tailed products**: used by the existing customers for a period of time, but the demand is getting slim. (4) **New products**: used as the market penetration tool to explore the niche market.

Each product type may share common parts (materials) with one another. For example, if a new product is an enhanced version of the existing mature product, it will share many common parts with its predecessor. As product versions upgraded, a long-tailed product line is formed, the common parts usually will gradually decrease through generations. To keep as many common parts as possible in the new product design so that the material requisition planning can be further optimized is the key to lower the overstock risk. Nevertheless, in many occasions, the suppliers may discontinue to supply their legacy materials that will force the firm to change the design accordingly.

After the material preparation process completes, the inventory should be adequate to support the following procedures, including the production, shipping products as the sales orders requested, and deploying the products to the customers.

Formula (1) depicts the $qty(i)_{sales}$ which is the total requested quantity of a product aggregated from a group of sales orders; **Formula (2)** depicts the $qty(i)_{forecast}$ which consists of two parts, namely $qty(i)_{mature}$ and $qty(i)_{new}$; and **Formula (3)** depicts the $qty(i)_{total}$ which is the overall quantity at that batch. It is worth noting that the $qty(i)_{mature}$ can be either subjectively determined by the executives or conformed by a series of probabilistic-driven formulae over time.
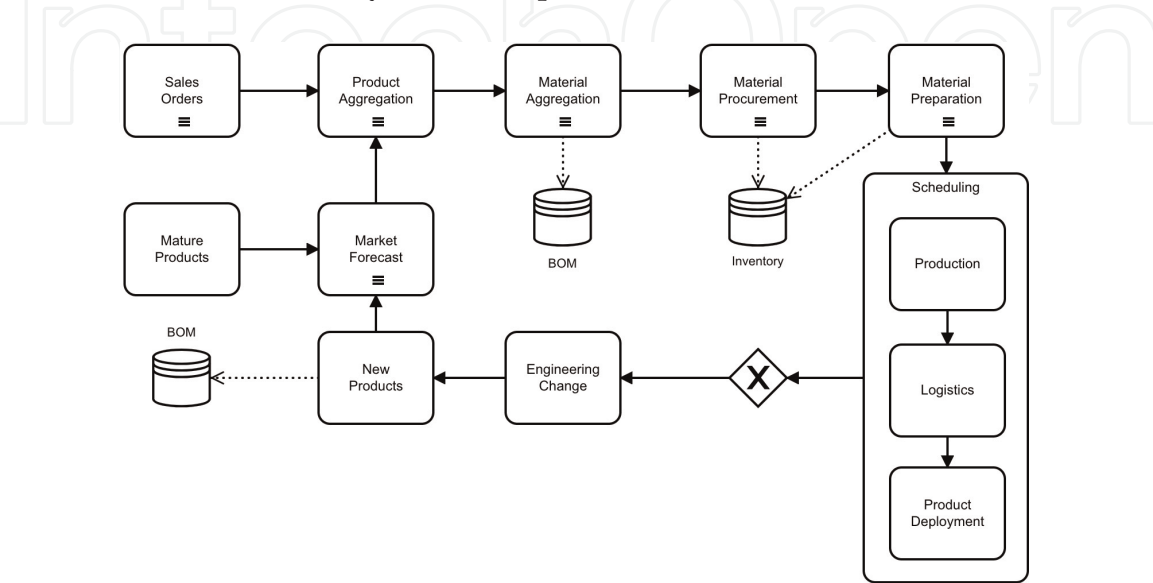
Figure 1.
Material planning problem frame.

The material aggregation is to calculate the required quantity for each material in the BOM; this chapter uses the column vector notation of $X_i = [x_{1 \cdots p} \in P_i]$ to represent the materials that belong to the product P_i. Thus, the total required material quantities to fulfill the batch is also a column vector of $qty(i)_{total} * X_i$. Let X_i^s represents the quantities of these materials in the stock; therefore, the batch demand of these materials is $qty(i)_{total} * X_i - X_i^s$. But it is common that the material procurement should be in an economic scale denoted as X_i^p; the factor often considers the minimal purchase quantity for an order, the strategy of quantity-price advantage, and the safety quantity in stock. **Formula (4)** shows the total procured quantities of the materials in that batch which is a column vector of X_i^r:

$$qty(i)_{sales} = \sum_{j=1}^{n} (order_{i,j}) \tag{1}$$

$$qty(i)_{forecast} = qty(i)_{mature} + qty(i)_{new} \tag{2}$$

$$qty(i)_{total} = qty(i)_{sales} + qty(i)_{forecast} \tag{3}$$

$$X_i^r = \min \left[qty(i)_{total} * X_i - X_i^s, X_i^p \right] \tag{4}$$

Using common parts across the BOMs is a key to manage the risk and costs; this means, in the simplest case of two products P_i and P_j, the common parts X_{ij} will exist in the material vectors X_i and X_j. Either of the $qty(i)_{forecast}$ does not occur, and more $qty(j)_{sales}$ arrive or customers cancel orders causing the $qty(i)_{sales}$ drops and $qty(j)_{forecast}$ is doing well beyond the expectation, the X_{ij} can be used to support the business. The worst case is neither sales orders arrive, nor the forecasted market blooms as expected. The more common parts of X_{ij} have, the more flexible the product will be.

Furthermore, in some cases, the material x_i is a substitutable part-set with priorities, $x_i = \{x_i^k, k = 1 \cdots m\}$, and usually, the priority implies the material received order, first-in-first-served (FIFS), or the release versions of parts, which serves the lower version part first. It will make the material planning more challenge when those legacy products are still in service at the customers' sites.

3. Supply chain optimization

In the smart manufacturing theme, the production planning is a multiperiod, multiproduct problem; the factory makes appropriate schedules based on a scenario tree containing all possible combinations to build the products optimally under the resource constraints. Both demand and supply uncertainties are driven by dynamic stochastic processes. The optimality is to satisfy the minimal resource consumed and the stochastic uncertainty of changes [12]. When multiple manufacturers at different sites collaborate to build products, the uncertainty may root from various external changes, illustrated in **Table 1**.

This problem can be resolved as multiobjective linear programming functions to minimize the total costs of supply chain and the total order fulfillment gaps across the factory sites [13]. However, both aforementioned approaches did not answer the fundamental question: how to determine the uncertainty of each forecast? This uncertainty causing the poor performance may be attributed from (1) over- or underprovisions on the different market demand prospects; (2) planning with the limited information; (3) misperception of customers' operating environment; and (4) quality of decision-making [14]. Therefore, this chapter incorporates the concepts from the multiobjective method with the consideration of overcoming the information asymmetry to present a novel approach as follows to tackle the problem.

| Source of change	Reasons
Workforce size	The suppliers shrank their operation and impacted the replenishment, or the workers went on the strike
Production rate	Additional or unexpected cost incurred, the suppliers increased their material prices, or the rival lowered down their market prices
Seasonal overstocked	Based on the previous experience on business cycle, the firms had overprovisioned their resources than expected
Back orders	The suppliers canceled the procurement orders owing to their poor capacity planning, or the customers postponed the purchase plans for business reasons; and these numbers were counted in the forecast
Regulations	The authorities imposed new regulations that increased the firm additional costs, such as taxation or the equipment replacement
Extreme weather	There is no doubt that the extreme weather, including heavy snow, flood, or tsunami, has impacted the economic growth globally

Table 1.
The uncertain change sources.

The participants in the supply chain can reach the consensus about the market demand prospects of coming period, if information visibility is improved. This improved visibility will also relieve the information asymmetry side effect on the participants' planning. Fully documented product specifications and well-trained field engineers will overcome the deployment obstacles at customers' operating environment. The consented market demand prospect and the visible information are the tangible artifacts of the decision-making which is a collaborative process within the factory's departments and even with the external participants of the supply chain. Therefore, the more effective collaboration in improving the quality of decision-making, the less uncertainty bias shall be incurred.

4. Collaborative decision-making

The objective of conducting the collaborative decision-making process is to reach the consensus on the scale of the demand forecast in the next period. The diversity of this collaborative team is essential. The team members should cover the roles from (1) **material planner**, to report the current inventory status; (2) **procurement**, to report the collected forecasts from the suppliers; (3) **sales**, to present the products' front log with their selling confidence levels for each customer, respectively; (4) **channel**, to present the products' front log with their selling confidence levels for each distributor, respectively; (5) **marketing**, to disclose the overall demand from the external professional analysis and the competitor's recent launched initiatives; (6) **finance**, to present the current cash flow status and the capital capacity of procurement and suggest the forecast quantity based on the analysis of management accounting; and (7) **data analyst**, a critical role in the forecasting under the uncertainty, who designs the analytical process, including constructing the optimization formulae, collecting and compiling the datasets, disclosing the insight about how and where the inaccuracy of previous forecasts came from, and, the most importantly, making the prediction closer to the coming business reality.

Figure 2 illustrates this collaborative decision process; after the group decision reaches the consensus on the material planning, the participants draft a couple of proposals and submit it to the material planning committee composed of the firm executives, the decision group participants, and the external industry professionals.
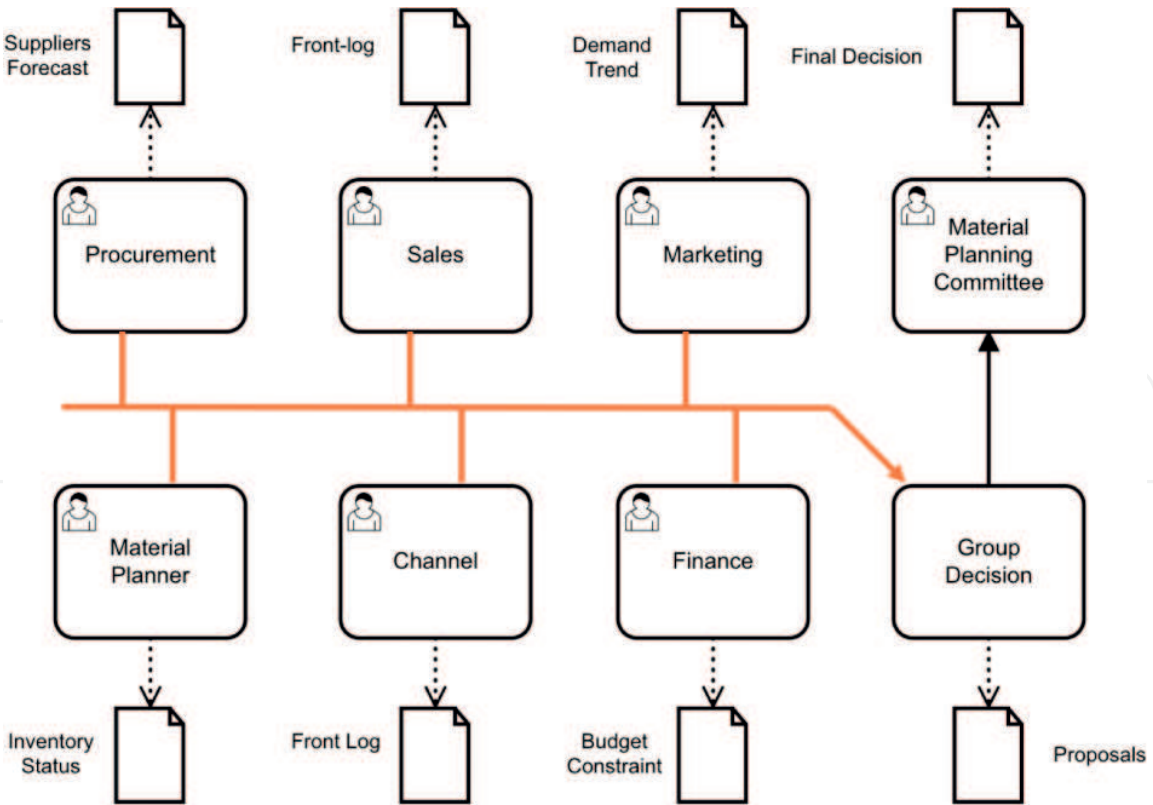
Figure 2.
Collaborative decision process.

The committee will make the final decision on the material planning. It is worth noting that the data analyst plays the backbone role facilitating the tasks of other participants throughout the process.

5. Effective elaboration

To make the aforementioned collaboration more effectively to elaborate the material planning proposals, this chapter presents a generic form for the group decision participants to discuss with. **Table 2** illustrates a sample form for the forecasting. The form consists of two portions, the target product and its critical components.

In this sample form, the product *PD* portion, which belongs to *CA* category, currently has *PI* units in stock, its last period's turnover rate ($\Delta out/\Delta in$) is *PT*, the maximal can-build quantity is *BQ* units under current on hand material status, previous forecast accuracy rates, calculated by $\left(F_{previous} - \widehat{F_{actual}} \right)/\widehat{F_{actual}}$, were *AM*, *AS*, *AC*, *AP*, and *AF*, and the forecasted quantities are *FM*, *FS*, *FC*, *FP*, and *FF*.

Category/product		Inventory	Turnover	Build/suppler	Accuracy/forecast		Source
CA	**PD**	**PI**	**PT**	**BQ**	**AM**	**FM**	**Marketing**
MR_1		MI_1	MT_1	MS_1	AS	FS	Sales
MR_2		MI_2	MT_2	MS2	AC	FC	Channels
MR_3		MI_3	MT_3	MS_3	AP	FP	Suppliers
MR_4		MI_4	MT_4	MS_4	AF	FF	Finance

Table 2.
Material forecast sample form.

The critical components section contains four major parts—$MR_{1...4}$, inventory levels are denoted by $MI_{1...4}$, turnover rates denoted by $MT_{1...4}$, and the suppliers of critical components are denoted by $MS_{1...4}$ respectively. It is worth noting that all the figures in the form depend on the information capability of firm, especially the BQ quantity which must be iteratively calculated during the process.

The final agreed decision on the forecast of the product can be systematically measured by **Formula (5)**. The outer summation adds up the forecast of the five groups and multiplies by their w_i weights, respectively. The inner summation adds up the group's forecast decision. Each group has the p_i participants, and there is also a θ_j weight for every participant's $forecast_{i,j}$ quantity:

$$Forecast_{final} = \sum_{i=1}^{5} \left[w_i \sum_{j=1}^{p_i} \left(\theta_j * forecast_{i,j} \right) \right] \tag{5}$$

The reason why previous forecast accuracy rates were excluded from $Forecast_{final}$ is because the participants will adjust their forecast rates accordingly, based on assigned weights by their group leaders. The purpose of this form is to give a template for the group discussion; it can help the participants make their forecasts not relying on the hunches but based on the fact of tangible numbers.

6. Material dynamics

The material readiness is essential to the production, especially for those scarce and/or valuable ones. There are several reasons causing the material scarcity: (1) usually these are subcomponents which required the outsourcing, customized design; (2) those materials are provided by the single source or the oligopoly market; and (3) the materials are common but essential in many products, and when these products are hot in the market, these materials become very difficult to acquire the adequate quantities to support the firm's production. To prevent the shortage of materials, reserving and maintaining the materials at some level of quantities in stock are common measures in practice.

The challenge of making the decision on the quantities of these safe stocks is that the procurement and the planner must be aware of the supply market's movements and take action in a proactive manner at all times. **Formula (6)** illustrates the general material acquired function; when qty_{need} is a negative value, it means the reserved stock is no longer able to support the production, and thus the further procurement is needed. Each material more or less will have waste during the production; it can be attributed to the poor quality or mishandling by the workers. The $\omega\%$ is the additional ratio—can be an average number from the past—to compensate the production loss. **Formula (7)** shows the total quantity of use qty_{use} which is the multiplication of the loss and the summation of total p forecast products' used quantities qty_i in BOM_i, respectively:

$$qty_{need} = qty_{stock} - \left(qty_{use} + qty_{safety} \right) \tag{6}$$

$$qty_{use} = (1 + \omega\%) \sum_{i=1}^{p} \left[qty_i * BOM_i \right] \tag{7}$$

$$qty_{safety} = MA \left(qty_{use}, \kappa \right) * \left(\frac{e^{-\mu} * \mu^{qty_{order}}}{qty_{order}!} \right) \tag{8}$$

The estimation of qty_{safety} plays a significant role in the forecast accuracy. If the safety stock is overestimated, it will incur the additional financial pressure or discontinues the production due to the shortage of supply if the safety stock is underestimated. This chapter proposes a generic function: $qty_{safety} = MA(qty_{use}, \kappa) * \varphi\%$, it is based on the moving-average of the material in the past κ terms and multiplied with a given weight for that material. Furthermore, **Formula (8)** presents more aggressive idea on the estimation of $\varphi\%$ by applying the Poisson probability distribution subject to the product orders that use this material [16, 17].

7. Uncertain demand

The "bullwhip effect" is a classic problem in the supply chain management; the obvious symptom is the overstocking in the whole supply chain. When the market demand declines not as the forecast expected, it will potentially impose the financial risk significantly. More overproduced products will push to the distribution channels, and the channels might sacrifice their margin in order to attract the consumers to buy more until the demand has saturated. Both the product and the material inventory levels will hike and thus incur the warehouse management cost and the value depreciation. This symptom will impact more when the optimistic supply chain tiers are deep. It is simply because the suppliers in each tier might magnify their forecasts under the asymmetric market demand information [18]. The root cause of this effect is that the market demand does not always follow the trend derived from the past. It is very challenging to forecast the demand of the individual product because the order quantity is slim. But the products in the same category may share a common component structure in the majority. In the configure-to-order model, let the consumer to optionally select the components from the configuration of the product; the differences among these products can be as simple as just a few components vary than one another [19]. This implies that the forecast model can be applied to reduce the inventory overstock and understock risk, as long as the quantity volatile product demands shares common materials.

The increasing economic disturbance such as the trade barriers has annoyingly amplified the market demand uncertainty. For instances, recently, the US-China trade tensions [20] and the Brexit [21] are the perfect examples of this. In order to assess business potential risk, we must consider the big picture and be aware of the impact of various economic parameter through the use of PEST analysis: (1) **political harmony**, such as shared visions, diplomatic situation, polarization; (2) **economic factors**, such as disposable income, interest rate, wealth inequality; (3) **social trend**, such as product adoption preferences, living style expectation, stability of community; and (4) **technology novelty**, such as the maturity of supply chain, innovation capability. Certainly, the firm can consider more perspectives than PEST or apply other perspectives that are more comprehensive to the firm's business environment.

This chapter proposes the material planning committee to set the confidence levels (a sort of weights) on these firm external perspectives to adjust the demand forecast. The p_i is the confidence level of a perspective; as **Formula (9)** suggests, $p_i \Downarrow$ is set when the committee think the forecast is too optimistic; or giving $p_i \Uparrow$ to amplify the scale of business otherwise. A new scoring scheme is presented in this chapter, as illustrated in **Formula (10)**:

$$p_i \in \Re, 0.0 < p_i \Downarrow < 1.0 < p_i \Uparrow < 2.0 \qquad (9)$$

$$\tau(p) = \left[\sum_{i=1}^{n} p_i^2 + \sum_{i=1}^{n-1} \sum_{j=i+1}^{n-i} \left(p_i * p_j \right) \right] * \tau^{-1}(p = \{1.0_{1..n}\}) \qquad (10)$$

where $\tau(p)$ is the forecast adjustment coefficient, $0.0 < \tau(p) < 2.0$. $p = \{1.0_{1..n}\}$ means the set containing n perspectives, and each $p_i = 1.0$ which is the expected value of no adjustment to the forecast.

8. Empirical case and discussion

The empirical case is about a global production automation equipment manufacturer. Their flag-fleet products are the Computer Numerical Control (CNC) category which is widely used in the production to provide more precise, complicated and repeatable control than just manning the equipment. Basically, each CNC consists of five major components: (1) input, receiving the signals/status from the controlled equipment via various handshaking interfaces; (2) output, sending a set of instructions to the equipment to proceed the next action; (3) control, a number of electrical mechanical units to convert or transform the input signals to the processor and translate the electrical magnetic signals into the output instruction set; (4) processor, performing the signal predefined computations accordingly; and (5) human, providing the interface, usually is through keypad panel, to let worker interact or intervene with the control process.
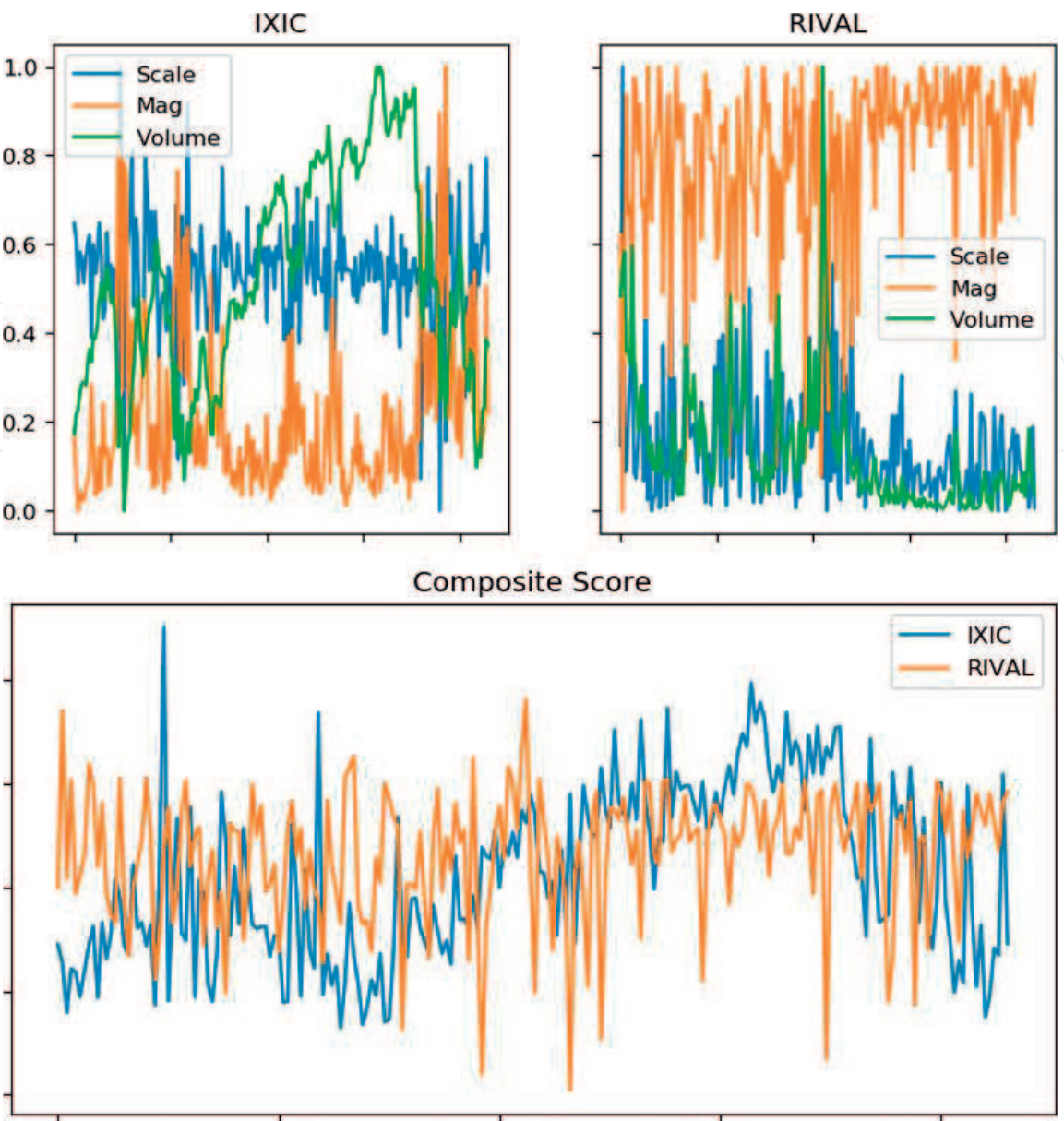
8.1 Economic parameter

The empirical case adopted the stock market performance information as their foundation of setting the $p_{economic}$ parameter, the most significant $w_{economic}$ among all perspectives in the PEST evaluation model. They posit that two stock indices, the NASDAQ and their major rival/benchmark in China, can reflect their business trend.

Figure 3 illustrates a sample economic factor parameter analysis against the stock performance of Nasdaq and the rival's in 2018. The X-axis is the dates and Y-axis is the standardized ratios. The stock index changed is $Scale = Stock_{Close} - Stock_{Open}$, and the maximal fluctuated is $Mag = Stock_{high} - Stock_{low}$. The standardization is to transform the indices in to the values between 0 and 1 by applying $[index - \min(index)]/[\max(index) - \min(index)]$.

Formula 11 defines a composite scoring function for the economic factors. The $\Delta Score_i$ is the first-order difference of the composite scores; by applying the product of these difference vectors, **Formula 12** derives each s_i in the evaluation vector S. The *trend*, showing both indices are moving toward the same direction, is the proportion of all positive s_i in S illustrated in **Formula 13**. Choosing the appropriate stock indices by the data analyst to reflect the current sector's business state will determine the usefulness of this *trend* function. **Formula 14** introduces the matrix cosine similarity method to facilitate this choosing process, especially in targeting the appropriate rivals in the volatile stock market. The committee can reference these figures to determine the comfortable $p_{economic}$ to fit in the group decision model:

$$Score_i = \sqrt{Scale_i^2 + Mag_i^2 + Volume_i^2} \qquad (11)$$

Figure 3.
A sample economic factor parameter analysis.

$$S = \prod_{i=1}^{2} (\Delta Score_i), s_i \in S \qquad (12)$$

$$Trend = \frac{count(S, \forall s_i \geq 0)}{count(S)} \qquad (13)$$

$$Similarity = 1 - \frac{Score_i^T * Score_j}{\|Score_i\| * \|Score_j\|} \qquad (14)$$

8.2 Material requisition models

8.2.1 Fixed input

The proposed fixed input material requisition model (**Figure 5**) makes the following assumptions (1) suppose the sample material fulfillment lead time takes three terms (usually in weeks); (2) suppose the sample material economic scale of supply is 1000 units; (3) the predicted loss ratio is set on 5% of each procurement quantity; (4) when the inventory is below the safety stock, an economic scale

purchase will be made; (5) when the inventory is short to fill the order, a purchase of the lead time multiply the economic scale will be made (3000 units in this model); and (6) the supplier will deliver the sample material after the lead time of the purchase.

In **Figure 4**, the sales orders related to this sample material have shown the demand, with the star markers, slumped from the expected 1000 units down to near 750. The triangle markers represent the purchases, and the round markers are the remained inventory. The green circle represents the stock on hand at the end of the forecast period. With the exception of the last circle (leftover stock), they coincide with every purchase made (triangle). By applying this model, the production may stop because of the material shortage; finding the sufficient safety stock quantity is a challenge to prevent the disruption of production:

$$params = \left(qty_{order}, qty_{Safety}, qty_{economic}, time_{lead}, qty_{loss}\right) \qquad (15)$$

$$risk_{safety}, stop_{safety} = Model(params) \qquad (16)$$

This chapter applies the iterative method by changing the qty_{Safety}, illustrated in **Formula 16**, and evaluating the return values. The $risk_{safety}$ is the occurrences when inventory is below the qty_{Safety}, and the $stop_{safety}$ is how many times that the product has stopped. The model function $Model(params)$ behavior depends on the settings of the given $qty_{order}, qty_{economic}, time_{lead}, qty_{loss},$ and the variable qty_{Safety}. In the sample material case, the minimal qty_{Safety} to prevent the disruption of product is 1000 units (coincidently matched with the $qty_{economic}$). It is worth noting that if the $qty_{economic}$ is underestimated, the production disruptions are inevitable in this fixed input model.

8.2.2 Variable input

An enhanced variable input of the material requisition model is illustrated in **Figure 5**. It has the same configuration as the fixed input, but (1) suppose the sample material economic scale of supply is per 1000-unit; (2) when the inventory is below the safety stock; an economic scale purchase will be made; (3) when the inventory is short to fill the order; a purchase of the lead time multiply the economic scale will be made; and (4) each purchased quantity will be based on the moving average of the quantities of the previous lead time of the orders, illustrated in

Safety Qty	Risk	Stop
200	4	9
400	13	6
600	21	4
800	29	2
1000	37	0
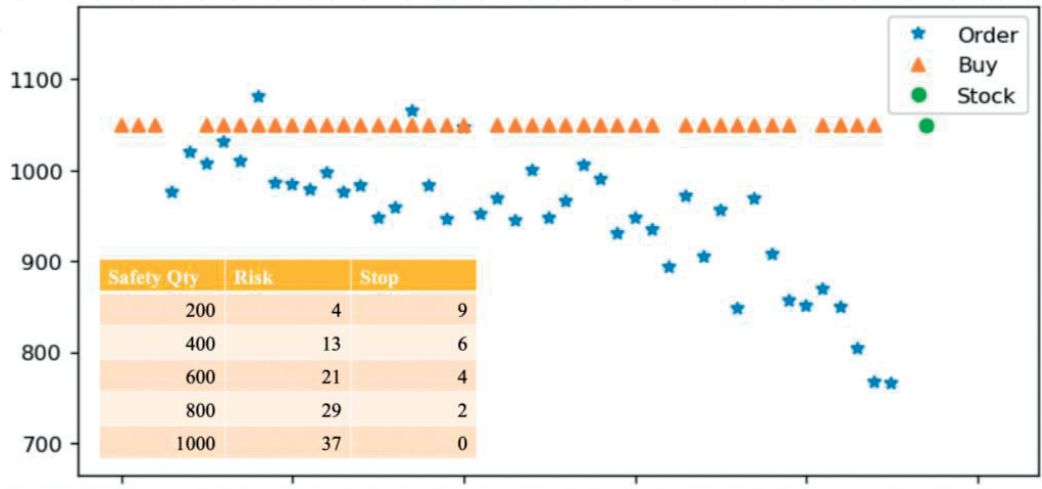
Figure 4.
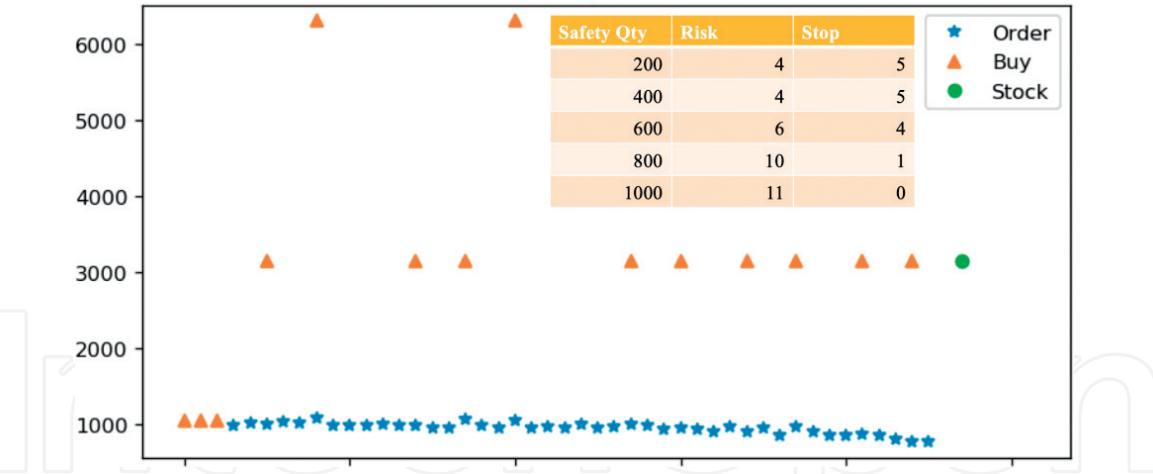*Sample material fixed input requisition model.*

Figure 5.
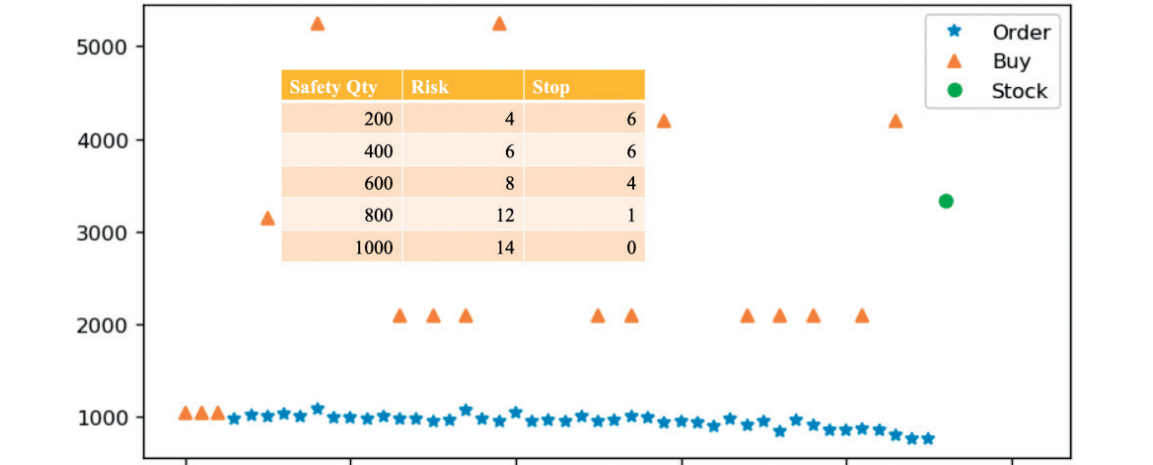*Sample material variable input requisition model.*

Figure 6.
Sample material trend variable input requisition model.

Formula 17. When qty_{Safety} is adequate, the purchase quantities are high, but the frequency is less; however, the production disruption will never occur in this variable input model.

$$qty_{purchase} = MA(qty_{use}, \kappa) * time_{lead} \tag{17}$$

8.2.3 Trend variable input

The final proposed model, illustrated in **Figure 6**, is based on the aforementioned variable input, but each purchased quantity will consider the trend about the previous lead time of qty_{order}. The simplest form of the trend function is shown in **Formula 18**, taking the $MA^{(1)}$ first-order derivative, and if the trend is positive (demand increasing), the purchase will plus one additional average quantity; if the trend is otherwise, the purchase will lessen one additional average quantity instead. Comparing this model with the aforementioned variable input, the inventory levels are constantly lower, and it implies the risk is also less in the case the demand drops drastically. For the long-term observed material, the trend can be estimated by a proper probability distribution or the decision of PEST:

$$qty_{purchase} = MA(qty_{use}, \kappa) * \left[time_{lead} + Trend\left(MA^{(1)}(qty_{use}, \kappa)\right) \right] \tag{18}$$

9. Conclusion

The customers buying preferences stimulate and inspire a new way of manufacturing. It has been a trend that the manufacturers are heading toward their ultimate goals of smart manufacturing. Many firms put the equipment automation as the first step of their smart manufacturing initiatives. But soon they found out that the current business challenge is on the uncertain market demand rather than just focusing on the operation automation. In addition, the smart manufacturing initiative is a sort of business reengineering process; it requires all participants to be aware in the problems in a holistic view. This is where this chapter would like to address.

In the smart manufacturing theme, the material planning is a challenging task under the uncertain demand environment. The task is not just the responsibility of the planner nor the data analyst but the synergy of all related participants. This chapter presents three material requisition models, for those materials having short lead times or being able to apply the pull model (vendor managed inventory, VMI), the fixed input model is adequate enough; for those materials having the same trend for a period of time, the variable input model can compensate the trend difference and prevent the excessive purchase; and for those volatile demand materials, the trend variable input model has the lowest inventory level than the others.

Finally, all proposed modes treat the loss ratio $\omega\%$ as constant for easy to explain, and this ratio should be measured from the production. To manufacture smarter products nowadays, to create a healthy collaborative culture within the firm is above all to enhance the competence of data analysis, and to improve the information systems is the cornerstone of survival and the business success as well.

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