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# Improving the Performance of Planning and Controlling Raw Material Inventory in Food Industry

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## Abstract

This paper discusses the inefficient and inaccurate raw material supply at a food company which results in a backlog. This means the overstock occurs so that the improvement of inventory control needs to be done. ABC classification is firstly utilized as input for Material Requirements Planning (MRP). This paper focuses on four products which are classified into A class. Then, this paper discusses the Triple Exponential Smoothing (TES) as the forecasting method. Aggregate planning is also conducted for better production planning. The results of aggregate planning provide solutions to increase the workforce to balance production capacity by the number of demands. Squared Coefficient of Variation (SCV) calculations indicates the demand follows a static pattern. Therefore, the appropriate lot sizing method is the Economic Order Quantity (EOQ) to carry out the production needs. Finally, this paper uses capacity planning using Rough-Cut Capacity Planning (RCCP) and Capacity Requirement Planning (CRP) methods. As a result, the capacity meets the Master Production Schedule (MPS) as well as MRP and they are feasible to be implemented.

**Keywords:** ABC classification, Inventory control, Capacity planning.

## 1 | Introduction

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As technology advances in the field of industry, of course, it will lead to intense competition in the business world. The company will do various ways to satisfy the consumer by trying to produce a high-quality product [1] with a competitive price, provide a good service [2] and the timeliness in the delivery. Real-time demand data could further improve the timeliness of deliveries and reduce inventory levels [3]. Hence, the company needs to run an effective production system by making excellent planning and control start from managing the raw material inventory to the valuable final product [4]. Inventory is the stock of any goods or resources used in a company or organization. The inventory system is a set of policies and controls that are used in production and logistics networks to coordinate supply cycles overseeing the level of inventory to be refilled, the number of orders that must be regulated to reduce risks associated with uncertainty [5], [6]. All manufacturing industries must have a supply of raw materials for production needs.

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The importance of inventory management in industrial applications derives from the effect of out-of-stock in the levels of customer satisfaction and the impact of stock in the economic balance of companies [6]. It is also useful to satisfy safety requirements, in cases where the availability of hazardous raw materials can be replaced with inventory of its products [6]. Furthermore, inventory also plays an important role in the coordination of maintenance turnarounds between various facilities across a site [6].

This research is conducted in the company producing the instant noodle. The manufacturing industry produces a wide range of brands and flavor variants. The company has 6 brands of products with 18 flavors. Instant noodle consists of some raw materials such as raw noodle that comes from flour. Flour is the main raw material in the instant noodles manufacturing, along with spices, seasoning oil, and package which are the compilers and complementary materials. A real-world problem may deal with an inventory shortage [7]. Currently, the company still have the raw materials issue caused by the delay in raw materials receipt (backlog) and the realization of the delivery of raw materials is not following the planned number. This condition implies the overstock and losses on high costs incurred. The backlog and overstock data for all 18 flavor variants in 2017 are shown in *Fig. 1*.

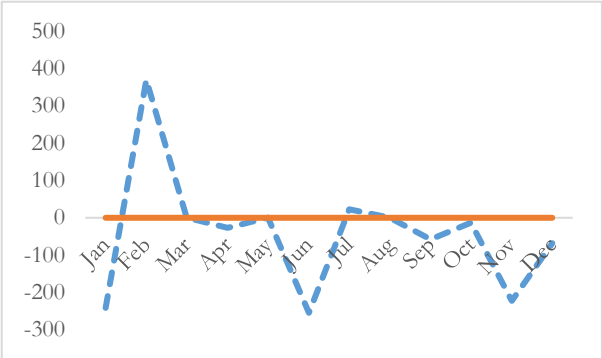


**Fig. 1. Backlog and overstock.**

The previous research showed that the over-supply or over-demand should be avoided and recommended a strong need for a precise forecasting [8]. In the supply chain, it is assumed that each member of the chain owns a warehouse and uses a specific replenishment policy to control inventory to meet the demands of its customers appropriately [9]. To address the mismatch between supply availability, service time, and demand in integrated production networks, inventory is held at different stages of the process [6], [10], [11]. The uncertainties increase the required practical production planning decisions [12]. However, in practice warehouses are actually managed in terms of policies, which are simple rules that dictate when to replenish an inventory with the corresponding amount [10]. The inventory policies considered are the (r,Q) and (s,S) policies [10]. On one hand, the (r,Q) inventory policy and order for Q units is placed every time the inventory level reaches level r [10] to minimize the expected cost of replenishment and out-of-stock [6]. On the other hand, the (s,S) policy the inventory is reviewed in predefined intervals [10].

Previous research utilized Material Requirement Planning (MRP) as the predetermined input by ant colony optimization to improve manufacturing performance [13]. The good manufacturing performance means to produce items with satisfactory and superior quality, accelerate delivery time and offer excellent after-sales service [13].

In short, it is important to make sure the production flow on the shop floor is streamlined. The raw material should be treated as an economical commodity, so the improvement related to the raw material is never ignored by the whole supply chain stakeholders.

## 2 | Literature Review



A previous study suggested to utilize the green manufacturing including the inventory control process to achieve environmentally-friendly activities and achieve better performance as well [14]. The ABC classification is an effective technique to develop a mechanism for identifying inventory items that not only has a significant impact on the total inventory cost [15]. This technique classifies items into three classes, A, B, and C depends on certain characteristics. Previous research utilized the ABC classification in dynamic storage assignment problem and used the order frequency as the criterion [16]. Meanwhile, a research classified them according to the item's annual consumption value [17]. Another paper classified the inventories into A, B, and C types, based on picking frequency [18]. In this paper, a percentage of stored goods are used.

Several studies combined and improved this technique. A study improved this technique in determining weights using Shannon entropy [15]. A periodic review policy based on the ABC classification was conducted in order to control the raw materials inventory [17].

Since the expected service time is normally much smaller than the production lead time, the demand of a customer must be anticipated through a forecast [10]. An accurate forecast results in establishing appropriate operational practices where the forecast inaccuracies have significant implications [19]. But, the main difficulty is that a forecast is an estimation since demands are uncertain [10], which leads to both out-of-stock and excessive stock situations [20].

This uncertainties issue has been tackled through stochastic programming model to point out the nature of inventory policy [6]. Seasonal future demand was estimated using the multiplicative seasonal method [12]. Previous study tried to estimate and predict the demand of new product through machine learning [21]. Other study presented a forecasting model to estimate the demand based on big data technologies [22]. Three stages were used such as a cluster analysis to classify traffic patterns, and a relational analysis to identify influential factors, and a decision tree to establish classification criteria [22]. Other study utilized the Root Mean Squared Error (RMSE) to measure the demand accuracy [8], while this paper use Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), and Mean Squared Deviation (MSD) at the same time.

Aggregate planning is a fundamental decision model in supply chain management, refers to the determination of production, inventory, capacity and labor usage levels in the medium term [23]. In general, the benefits of inventories derive from their ability to reduce the interdependence of processing units, to mitigate the effects of bottlenecks, and to facilitate capacity utilization [6]. In this paper, the demand as well as the production capacity for this aggregate product in different periods of the planning horizon is given [11]. To plan the aggregate accurately, the first decision is the detail forecasts of each product [21]. One challenge we must address that arises from this decision is how to apply inventory constraints [21], such as production and resources capacity [6]. An aggregate planning model is developed to balance the demand and production capacity simultaneously [11]. The aggregate planning should make sure the objective and the constraints are satisfied by adjusting output rates, inventory levels, backorders and the other controllable variables [11]. The controllable variables are inventory costs, ordering costs, training costs, and worker hiring and firing costs [24]. Another study added some important variables such as transportation cost of the vehicles and the energy cost to keep the cold storage temperature [25]. These variables are the important factors in terms of conversion of raw materials into final products, their maintenance, and distribution to end customers [26]. Therefore, aggregate planning plays a major role in shaping the Master Production Scheduling (MPS) and consequently the shop floor scheduling operations [27].

MPS is generally specifies the production quantity of each finished good during each planning horizon period of multiple weeks and is based on estimated or known demands [20], [28]. The MPS is constrained by the decisions regarding capacity and the targets in terms of inventory levels [29]. To be

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able to cope with the differences between the forecast and the actual orders, overtime is allowed [29]. Since overtime is limited, we also consider backorders as well ensuring feasibility [29]. Because MPS does not plan product types but product family, the target inventory level has to be disaggregated [29].

Although other research tried to integrate the aggregate production planning and MPS [29], this paper solve them gradually. This paper constantly pay attention to the quality of solution by making sure they are feasible to run in minimizing inventory costs [30].

Making good use of the material requirements plan result can increase inventory turnover, improve procurement quality, increase productivity, and increase customer satisfaction [13]. As a result, the rapid and correct implementation of the material requirement plan will have a better effect on the efforts of the whole company [13].

According to the structure of the MRP system, it must complete the following three main functions: parts demand calculation, inventory calculation, and purchase calculation [13]. By using product structure (of the raw material list, product material list) and the scheduled completion date of each component combination, the MRP system could complete these three functions after getting the amount of product demand [13]. To accomplish these three functions, the input items of the MRP system are product structure, inventory status, lot sizing rule, and Master Production Schedule (MPS) [13]. The output items are the number of components that should be ordered, the capacity demands and the manufacturing demands [13].

The demand deployment of the MRP system is based on the final project [13]. It calculates from top to bottom and traces back from the bottom to top to meet the production of the final project and obtains the number of components needed [13].

In the MRP system, the material requirement file is established for each item of the main production schedule, and the final product requirement in MPS is converted to the gross requirement [13]. The net requirement is calculated from the gross requirement [13]. Then, the planned order receipts for each period of the total product or material are obtained by production or purchase, and the lot size of each item in each period must be calculated by the batch rule [13]. The planned order quantity for each period of the material item is equal to the planned order quantity for each period of the material item unless the lead time for each period of the material item is non-zero [13]. The gross demand at the next level of the structure is determined by the number of planned orders issued during each period of the material items [13].

Bill of Material (BOM), also known as the product structure table or material structure, which is the most paramount foundation to compose the product information [13]. It records all parts of the component and interrelated information of a product, such as the kind of component and the required quantity to meet the final production from the BOM [13]. Generally, BOM data contain various attributes such as part number, quantity, and specification, etc. [13].

The Squared Coefficient of Variation (SCV) calculations are utilized to measure the variability of the demand pattern. SCV formula can be seen in the *Eq. (1)* [31]. If SCV < 0.2, use a simple EOQ and utilize a heuristic if $SCV \geq 0.2$ [31]. The total cost can be obtained from *Eq. (2)* [32].

$$\text{SCV} = \frac{\text{Variance of demand per period}}{\text{Square of average demand per period}}. \tag{1}$$

$$\text{Total cost} = (D)(C) + \left(\frac{D}{Q^*}\right)(S) + \left(\frac{Q^*}{2}\right)H. \tag{2}$$

where:

D: Annual demand of the product.

C: Cost per unit of product.

Q*: EOQ.

S: Fixed cost incurred per order.

H: Holding cost per unit per year.

## 3 | Research Methodology

This paper tries to solve the problem of excess or shortage of raw materials through serial stages, starting from the ABC classification, along with forecasting, aggregate planning, and capacity planning. ABC analysis is a technique for prioritizing the management of inventory as shown in *Fig. 2*. Inventories are categorized into three classes - A, B, and C. Most management efforts and oversights are expended on managing A items while C items get the least attention and B items are in-between [33]. Forecasting predicts the demands which are a crucial step in production planning schedule to satisfy customer needs on time [34]. At this stage, the Holt-Winters exponential smoothing is used as an appropriate and popular approach for predicting seasonal time series. The discussion continues on the aggregate planning stage. Aggregate planning is a process which helps companies to provide better service level with smaller preparations, to shorten customer lead times, to stabilize production levels, and to give control from top management in managing the business [5]. MPS is a production planning with a planned time to produce each finished product [5]. The production capacity is closely related to the MPS, which describes what and how many items should be produced in a given period. The problem that often occurs is a delay in raw material shipment. This is due to the lack of careful planning for the production process. To overcome these problems, we require production capacity planning using Rough Cut Capacity Planning (RCCP). RCCP is the second priority in the planning hierarchy, and is used to evaluate the resource usage of the MPS [35]. Material Requirements Planning (MRP) is a well-known approach to inventory management of dependent demand items. Items that are independently demanded are typically finished goods, while dependently demanded items are typically components and subassemblies that are related to an end item by a BOM [13]. CRP is increasingly close to the success of planning and capacity measurement due to the existence of time standards and route information settings. CRP usually does not provide information to change the MPS because it is easier to change capacity by using overtime, subcontract and additional manpower. At the end, the objective function is to minimize the cost [11]. The two types of data used in this research are primary and secondary data. The primary data was obtained verbally in the interview session with the supervisor, mentor, operators, and administrators. The secondary data was obtained from written documents such as company data, companies' documents, journals, articles, and others.

## 4 | Result and Discussion

In this section, the discussion covers the ABC classification and followed by the most appropriate forecasting method. After that, aggregate planning is performed before heading to the stage of making a MPS. The production capacity at the MPS stage will be checked using Rough-Cut Capacity Planning (RCCP). The output from the MPS is treated as the input for MRP. The production capacity on the MRP is then checked using the Capacity Requirement Planning (CRP).

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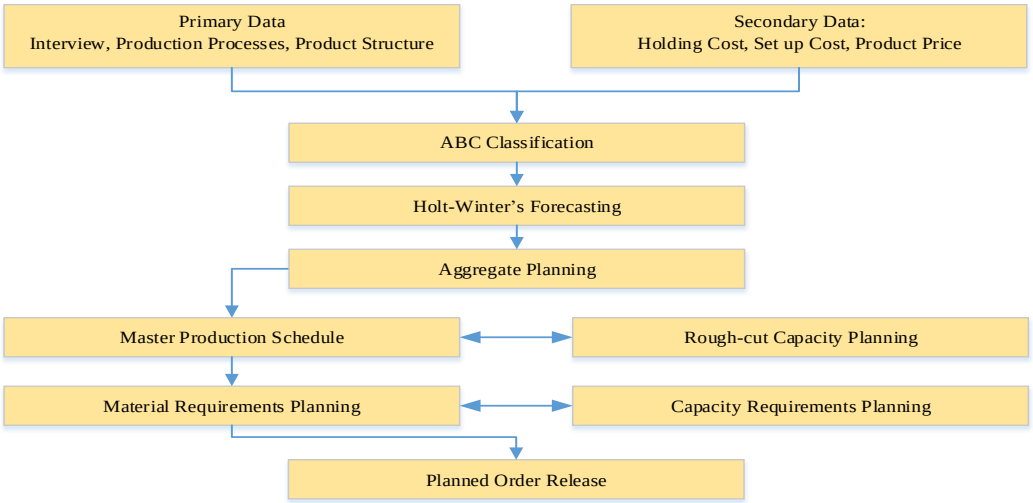


**Fig. 2. Research flow chart.**

## 4.1 | ABC Classification

There are 18 product variants and four of them are classified as the "A" category, coded in IGB, ISM, IAB, and IKA as shown in *Table 1*. These items are classified as the "A" category because they serve 20% of storage. Six items coded in IGRS, PMAB, PMBS, IKALA, and ISL are classified as the "B" category since the company holds them as 30% of the whole inventory. Finally, the rest are classified as the "C" items as they occupy 50% of the storage. Hence, the attention in terms of inventory is focused on the "A" category. Later, these items are forecasted to predict their future demand.

**Table 1. ABC classification result.**

| No. | Flavor Variants | Available Inventory | Percentage of Stored Goods |
|---|---|---|---|
| 1 | IGB | 19200 | 20% |
| 2 | IAB | 16400 | |
| 3 | ISM | 14600 | |
| 4 | IKA | 10800 | |
| 5 | IGRS | 9600 | 30% |
| 6 | PMAB | 4480 | |
| 7 | PMBS | 3920 | |
| 8 | IKALA | 7200 | |
| 9 | ISL | 7000 | |
| 10 | MTK | 5400 | 50% |
| 11 | SAB | 4788 | |
| 12 | SUSD | 3564 | |
| 13 | SAK | 2142 | |
| 14 | PMMAB | 2415 | |
| 15 | SUAB | 1836 | |
| 16 | SUGOPANG | 1404 | |
| 17 | SAGOR | 750 | |
| 18 | SAKBS | 300 | |
| Total | | 115799 | |

## 4.2 | Holt-Winters Forecasting Analysis

The historical data patterns on each product can be seen from *Fig. 3* to *Fig. 6*. June and December are the common peak seasons in all the "A" products. In detail, the data pattern for product IGB has peak seasons in March, June, and December as shown in *Fig. 3*. *Fig. 4* tells us the peak seasons for product IAB are in May, June, September, November, and December. Meanwhile, product ISM has only peak seasons in two months, which are June and December as manifested in *Fig. 5*. Lastly, *Fig. 6* denotes the peak seasons for product IKA in five months, such as February, May, June, November, and December. Besides, in terms

of trend analysis, these products also indicate uptrend throughout the year. Therefore, this paper proposes that the forecasting method should consider seasonality and trend conditions. A previous study have shown that the Holt-Winters exponential smoothing method is able to provide suitable forecasts on seasonal and trend demand patterns [36]. This paper also presents the Holt-Winters exponential smoothing as an appropriate method. This paper runs nine different scenarios in terms of smoothing constant, as shown in *Table 2*. It turns out that different smoothing constant works divergently. The results show that product IGB, IAB, and IKA performs well with the smoothing constant $a = 0.9$, $\gamma = 0.1$, $\beta = 0.1$. The performance indicator is MAPE and MAD. Regarding these three products, the forecasted data fluctuates with the higher α results in the smaller MAPE and MAD. The other product, which is ISM, fits with the smoothing constant $a = 0.1$, $\gamma = 0.1$, $\beta = 0.1$ and follows the lower α results in the smaller MAPE and MAD. *Table 3* refers the forecasting results that have been selected based on the most suitable smoothing constant on the product IGB, ISM, IAB, and IKA. These data are the inputs for aggregate planning stage.

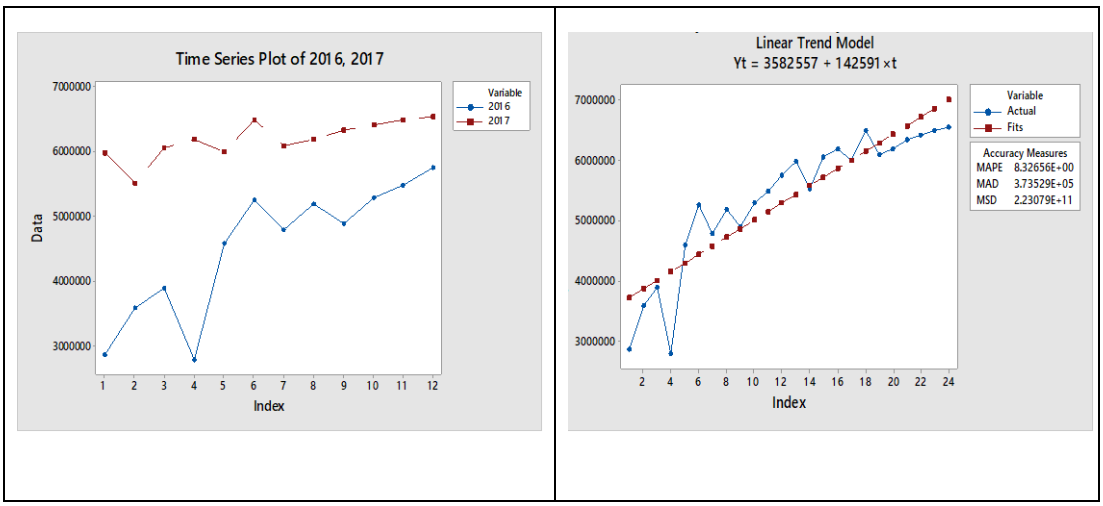


**Fig. 3. Seasonal pattern and trend analysis for IGB.**

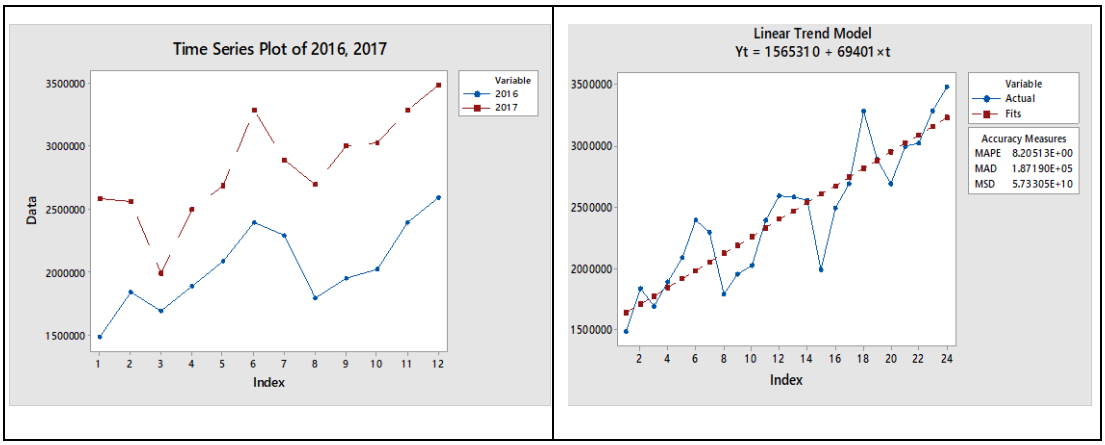


**Fig. 4. Seasonal pattern and trend analysis for IAB.**

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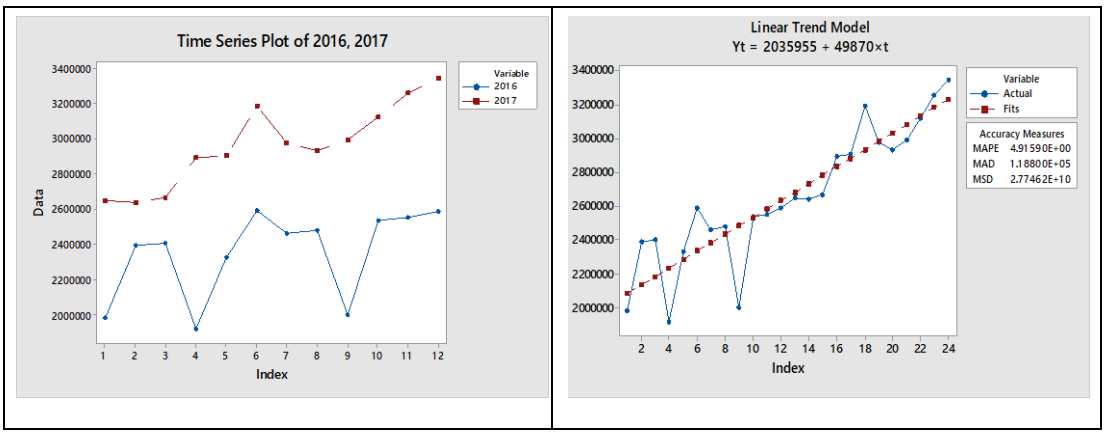


Fig. 5. Seasonal pattern and trend analysis for ISM.

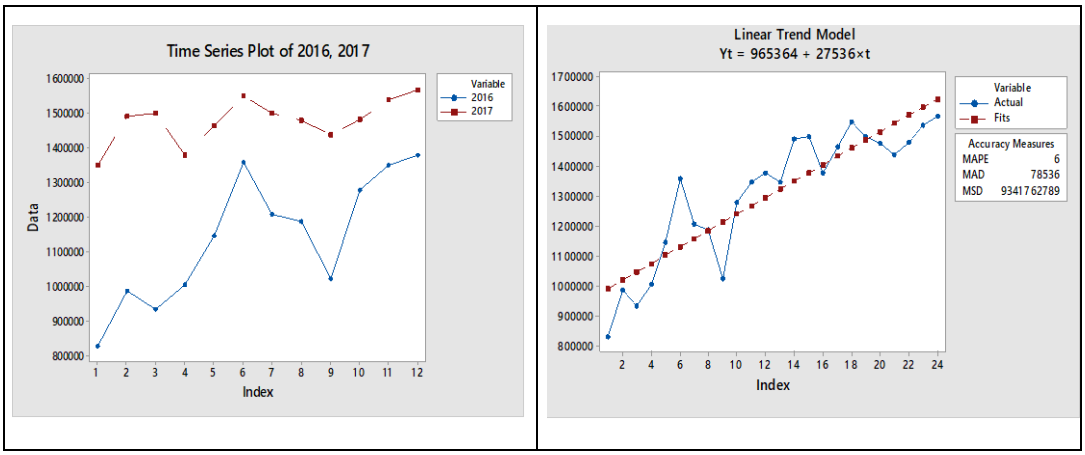


Fig. 6. Seasonal pattern and trend analysis for IKA.

Table 2. Smoothing constant scenarios.

| Scenario | Smoothing Constant | Fit for Specific Product |
|---|---|---|
| 1 | $\alpha = 0.1$ $\gamma = 0.1$ $\beta = 0.1$ | ISM |
| 2 | $\alpha = 0.2$ $\gamma = 0.1$ $\beta = 0.9$ | |
| 3 | $\alpha = 0.3$ $\gamma = 0.9$ $\beta = 0.1$ | |
| 4 | $\alpha = 0.4$ $\gamma = 0.9$ $\beta = 0.9$ | |
| 5 | $\alpha = 0.5$ $\gamma = 0.1$ $\beta = 0.1$ | |
| 6 | $\alpha = 0.6$ $\gamma = 0.1$ $\beta = 0.9$ | |
| 7 | $\alpha = 0.7$ $\gamma = 0.9$ $\beta = 0.1$ | |
| 8 | $\alpha = 0.8$ $\gamma = 0.9$ $\beta = 0.9$ | |
| 9 | $\alpha = 0.9$ $\gamma = 0.1$ $\beta = 0.1$ | IGB, IAB, IKA |

Table 3. Forecasting results.

| Month | Forecast 2018 Products and Flavor Variants | | | |
|---|---|---|---|---|
| | IGB | ISM | IAB | IKA |
| January | 5060530 | 2881919 | 2527841 | 1233181 |
| February | 5226143 | 3156213 | 2755404 | 1403308 |
| March | 5725059 | 3199771 | 2326878 | 1379124 |
| April | 5136889 | 3039112 | 2779493 | 1358891 |
| May | 6138679 | 3334205 | 3052584 | 1492097 |
| June | 6836712 | 3705005 | 3648850 | 1668667 |
| July | 6340171 | 3509641 | 3354610 | 1554897 |
| August | 6659845 | 3514955 | 2908532 | 1533844 |
| September | 6573141 | 3251536 | 3229894 | 1417749 |
| October | 6879614 | 3720932 | 3318849 | 1597274 |
| November | 7058026 | 3841887 | 3758560 | 1674710 |
| December | 7271099 | 3947656 | 4041331 | 1713318 |

## 4.3 | Aggregate Planning

After performing the forecasting analysis, the next step is to conduct the aggregate planning. This step aims to plan production quantities based on forecasting results and to determine the number of workers to minimize related costs production. At this stage, this paper performs linear programming to produce the global optimal aggregate planning subject to cost structure as shown in *Table 4*. From there, the process proceeds to the total cost calculation for 1 year ahead. The total cost for product IGB, IAB, ISM, and IKA are IDR 143,010,336,000, IDR 71,604,692,000, IDR 77,286,664,000, and IDR 34.385.446.000 respectively.

**Table 4. Cost structure.**

| Cost (IDR) | |
|---|---|
| Regular Cost | 5500000/month |
| Overtime | 230000/overtime |
| Hiring | 500000/hiring |
| Layoff | 3000000/layoff |
| Inventory Cost | 100/pcs |
| Backorder | 800/pcs |
| Cost of Goods Sold | 2000/pcs |
| Subcontract | 2200/pcs |

## 4.4 | MPS and RCCP

The succeeding stage is to create a MPS which will be implemented based on the production lot sizes and the remaining stock from the previous period. In this paper, the MPS is made for 52 weeks from January to December 2018. *Table 5* shows the MPS raw data of each flavor variant. *Table 6* denotes an example of the calculation for the IGB flavor variant.

**Table 5. MPS data.**

| Product | IGB | ISM | IAB | IKA |
|---|---|---|---|---|
| Lead Time | 0 | 0 | 0 | 0 |
| On Hand | 3538490 | 2550000 | 1977690 | 898087 |
| Lot Size | 1000000 | 500000 | 500000 | 250000 |

The MPS is further tested with the RCCP method to check the feasibility and make headway to the MRP stage. If the RCCP results in the available capacity are greater than the required capacity, it means MPS deserves to be continued to the MRP stage. For simplicity, the calculation is done only for IGB at this stage. For the first six months, *Table 7* presents its available capacity while *Table 8* and *Table 9* together point its required capacity using two different approaches. *Table 8* and *Table 9* utilize the Capacity Planning Overall Factor (CPOF) and Bill of Labor Approach (BOLA) respectively. Altogether, the favorable outcome shows the capacity available for IGB, ISM, IAB, and IKA is satisfactory, indicates the MPS is feasible to run.

## 4.5 | Material Requirements Planning and CRP

Based on the forecasting results, the SCV calculations are performed to measure the variability of the demand pattern. SCV formula can be seen in *Eq. (1)* [31]. *Table 10* shows the future demand for all "A" items are static because of SCV < 0.2, meaning the EOQ method can be applied.

IGB has four components of raw materials at once forming its BOM such as TPG, ETK, BM, and MBM, as presented in *Fig. 7*. *Table 11* shows the cost of MRP calculation results. TPG is processed through the serial process on work station 1B, 2B, 3B, 4B, 5B, 6B, and 3A. ETK processing is completed by using work station 2A, while BM and MBM go to work station 1A. The highest EOQ is presented

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by ETK as it has the highest total inventory. From the total cost point of view, MBM denotes the highest value.

**Table 6. MPS calculation for January and February.**

| Month (2018) | Past | January | | | | February | | | |
|---|---|---|---|---|---|---|---|---|---|
| Week | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| Sales Forecast | | 1265133 | 1265133 | 1265132 | 1265132 | 1306536 | 1306536 | 1306536 | 1306535 |
| Actual Orders | | 1645850 | 1645850 | 1645850 | 1645850 | 1599748 | 1599748 | 1599748 | 1599748 |
| Projected Available Balances (PAB) | 3538490 | 3538490 | 1892640 | 246790 | 600940 | 955090 | 355342 | 755594 | 155846 |
| Available to Promise (ATP) | | | | 600940 | 955090 | 355342 | 755594 | 155846 | 556098 |
| MPS | | | | 1399060 | 1044910 | 644658 | 1244406 | 844154 | 1443902 |
| MPS with LS | | | | 2000000 | 2000000 | 1000000 | 2000000 | 1000000 | 2000000 |

**Table 7. Available capacity for IGB.**

| Work Center (WC) | Month (Working Days) | | | | | |
|---|---|---|---|---|---|---|
| | January (26) | February (23) | March (25) | April (24) | May (24) | June (20) |
| WC-1 (units) | 2742.01 | 2425.63 | 2636.55 | 2531.09 | 2531.09 | 2109.24 |
| WC-2 (units) | 1371.01 | 1212.81 | 1318.28 | 1265.54 | 1265.54 | 1054.62 |
| WC-3 (units) | 2742.01 | 2425.63 | 2636.55 | 2531.09 | 2531.09 | 2109.24 |
| WC-4 (units) | 1371.01 | 1212.81 | 1318.28 | 1265.54 | 1265.54 | 1054.62 |
| WC-5 (units) | 2742.01 | 2425.63 | 2636.55 | 2531.09 | 2531.09 | 2109.24 |
| WC-6 (units) | 5484.02 | 4851.25 | 5273.10 | 5062.18 | 5062.18 | 4218.48 |
| WC-7 (units) | 2742.01 | 2425.63 | 2636.55 | 2531.09 | 2531.09 | 2109.24 |

**Table 8. Required capacity for IGB using CPOF.**

| Work Center (WC) | Historical Proportion | Month (Working Days) | | | | | |
|---|---|---|---|---|---|---|---|
| | | January (26) | February (23) | March (25) | April (24) | May (24) | June (20) |
| WC-1 | 0.22 | 950 | 1425 | 1425 | 1187.5 | 1425 | 1662.5 |
| WC-2 | 0.03 | 111.11 | 166.67 | 166.67 | 138.89 | 166.67 | 194.44 |
| WC-3 | 0.21 | 888.89 | 1333.33 | 1333.33 | 1111.11 | 1333.33 | 1555.56 |
| WC-4 | 0.01 | 55.56 | 83.33 | 83.33 | 69.44 | 83.33 | 97.22 |
| WC-5 | 0.20 | 833.33 | 1250 | 1250 | 1041.667 | 1250 | 1458.33 |
| WC-6 | 0.20 | 833.33 | 1250 | 1250 | 1041.667 | 1250 | 1458.33 |
| WC-7 | 0.13 | 555.56 | 833.33 | 833.33 | 694.44 | 833.33 | 972.22 |

**Table 9. Required capacity for IGB using Bill of Labor Approach (BOLA).**

| Work Center (WC) | Historical Proportion | Month (Working Days) | | | | | |
|---|---|---|---|---|---|---|---|
| | | January (26) | February (23) | March (25) | April (24) | May (24) | June (20) |
| WC-1 | 0.010 | 950 | 1425 | 1425 | 1187.5 | 1425 | 1662.5 |
| WC-2 | 0.001 | 111.11 | 166.67 | 166.67 | 138.89 | 166.67 | 194.44 |
| WC-3 | 0.009 | 888.89 | 1333.33 | 1333.33 | 1111.11 | 1333.33 | 1555.56 |
| WC-4 | 0.001 | 55.56 | 83.33 | 83.33 | 69.44 | 83.33 | 97.22 |
| WC-5 | 0.008 | 833.33 | 1250 | 1250 | 1041.67 | 1250 | 1458.33 |
| WC-6 | 0.008 | 833.33 | 1250 | 1250 | 1041.67 | 1250 | 1458.33 |
| WC-7 | 0.006 | 555.56 | 833.33 | 833.33 | 694.44 | 833.33 | 972.22 |

MRP needs to be verified whether the number of orders with the existing lead time satisfactory or not. If the available resource capacity is greater of the required capacity, then MRP can be implemented, as shown in *Table 12*.



**Table 10. SCV results.**

| | IGB | IAB | ISM | IKA |
|---|---|---|---|---|
| Variance of Demand per Period | (5.59) ($10^{11}$) | (2.43) ($10^{11}$) | (1.03) ($10^{11}$) | (2.00) ($10^{10}$) |
| Squared of Average Demand per period | (3.90) ($10^{13}$) | (9.87) ($10^{12}$) | (1.17) ($10^{13}$) | (2.26) ($10^{10}$) |
| SCV | 0.014 | 0.025 | 0.009 | 0.009 |

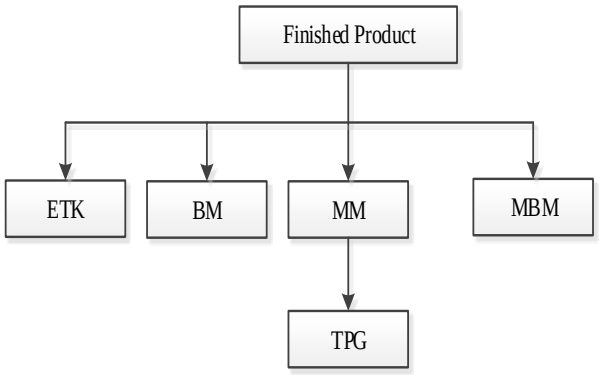


**Fig. 7. Product structure.**

**Table 11. Total inventory costs for IGB.**

| Component Name | WC | EOQ | Total Inventory | Total Planned Order | Material Cost (Rp) | Ordering Cost (Rp) | Holding Cost (Rp) | Total Cost (Rp) |
|---|---|---|---|---|---|---|---|---|
| TPG | 1B | 612 | 21374 | 11628 | 1,150 | 12,500 | 800 | 30,708,900 |
| | 2B | | | | | | | |
| | 3B | | | | | | | |
| | 4B | | | | | | | |
| | 5B | | | | | | | |
| | 6B | | | | | | | |
| | 3A | | | | | | | |
| ETK | 2A | 122,720 | 35,698,000 | 75,000,000 | 250. | 10,000 | 100 | 22,320,300,000 |
| BM | 1A | 86,780 | 35,360,000 | 75,000,000 | 350 | 10,000 | 200 | 33,322,500,000 |
| MBM | 1A | 86,780 | 35,360,000 | 75,000,000 | 400 | 10,000 | 200 | 37,072,500,000 |

**Table 12. CRP for IGB.**

| Work Center | Capacity | Months (Working Days) January (26) | February (23) | March (25) | April (24) | May (24) | June (20) |
|---|---|---|---|---|---|---|---|
| 1B | Available | 2742.012 | 2425.626 | 2636.55 | 2531.088 | 2531.088 | 2109.24 |
| | Required | 1666.875 | 1190.625 | 1428.75 | 1428.75 | 1428.75 | 1666.875 |
| 2B | Available | 1371.006 | 1212.813 | 1318.275 | 1265.544 | 1265.544 | 1054.62 |
| | Required | 198.8194444 | 142.0138889 | 170.4166667 | 170.4166667 | 170.4166667 | 198.8194444 |
| 3B | Available | 2742.012 | 2425.626 | 2636.55 | 2531.088 | 2531.088 | 2109.24 |
| | Required | 1559.930556 | 1114.236111 | 1337.083333 | 1337.083333 | 1337.083333 | 1559.930556 |
| 4B | Available | 1371.006 | 1212.813 | 1318.275 | 1265.544 | 1265.544 | 1054.62 |
| | Required | 101.5972222 | 72.56944444 | 87.08333333 | 87.08333333 | 87.08333333 | 101.5972222 |
| 5B | Available | 2742.012 | 2425.626 | 2636.55 | 2531.088 | 2531.088 | 2109.24 |
| | Required | 1462.708333 | 1044.791667 | 1253.75 | 1253.75 | 1253.75 | 1462.708333 |
| 6B | Available | 5484.024 | 4851.252 | 5273.1 | 5062.176 | 5062.176 | 4218.48 |
| | Required | 1462.708333 | 1044.791667 | 1253.75 | 1253.75 | 1253.75 | 1462.708333 |
| 3A | Available | 2742.012 | 2425.626 | 2636.55 | 2531.088 | 2531.088 | 2109.24 |
| | Required | 976.5972222 | 697.5694444 | 837.0833333 | 837.0833333 | 837.0833333 | 976.5972222 |
| 2A | Available | 1828.008 | 1617.084 | 1757.7 | 1687.392 | 1687.392 | 1406.16 |
| | Required | 441.875 | 315.625 | 378.75 | 378.75 | 378.75 | 441.875 |
| 1A | Available | 1828.008 | 1617.084 | 1757.7 | 1687.392 | 1687.392 | 1406.16 |
| | Required | 927.5 | 662.5 | 795 | 795 | 795 | 927.5 |

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## 5 | Conclusion

The ABC classification results of 18 taste variants are IGB, ISM, IAB, and IKA for class A with the percentage of goods saved by 20%. IGRS, PMAB, PMBS, IKALA, and ISL for class B with the percentage of goods stored by 30%. MTK, SAB, SUSD, SAK, PMMAB, SUAB, SUGOPANG, SAGOR and SAKBS for class C with the percentage of goods stored at 50%. So, the attention and the inventory control are preferred for class "A" namely IGB, ISM, IAB, and IKA. The forecasting method is applied using Triple Exponential Smoothing (TES) because the data has a trend and seasonal with the smallest error rate that is $a = 0.9$, $\gamma = 0.1$ and $\beta = 0.1$ for three products, such as IGB, IAB, and IKA. The value of $a = 0.1$, $\gamma = 0.1$ and $\beta = 0.1$ is fit for ISM. The results of aggregate planning can run efficiently while balancing the workforce and the amount of production. The aggregate planning indicates that the company should require a lot workforce to balance the amount of production with the production capacity of labor. The total cost for product IGB, IAB, ISM, and IKA are IDR 143,010,336,000, IDR 71,604,692,000, IDR 77,286,664,000, and IDR 34.385.446.000 respectively. RCCP under CPOF and BOLA both indicates that MPS is feasible to be implemented because the available capacity in each production line is enough to fulfill the required demand. RCCP is based on MPS lot size data with lot size already according to the lot size determined by the 52 weeks made up to 12 months, machine time processing data and historical proportions machine. Based on the SCV analysis and calculations, Economic Order Quantity (EOQ) is the selected lot-sizing technique to perform the MRP calculation. The CRP result shows the MRP is feasible for product all "A" products. CRP is based on planned order release data from MRP each raw material for 52 weeks which is made 12 months based on lot size, data setup time, run time, operation time and setup time/lot size.

Future study could utilize the regression tree since it was claimed more effective than other regression methods in predicting demand [21]. Under uncertainty where statistical data are either not that reliable or not even available, MPS model can be developed [37] as one of the unique characteristics in the further study.

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