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Rolling Forecast as an Alternative Tool for Short Term Production Planning: A Case Study of Bicycle Manufacturer

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Abstract: The accuracy of production planning is crucial that must be achieved by manufacturing companies. Production planning is sensitive to sales patterns and the availability of raw materials. Production planning must be in line with raw material planning. To ensure that the raw materials are available, production planning has to be deed in advance. In the waiting period for these raw materials, sales patterns may change so that the forecast and actual value deviations differ significantly. A dynamic mechanism of calculating the value of safety stock is carried out and carrying out the correction function of forecasting value by rolling forecast for overcoming it. Rolling forecasts allow forecasts of updated forecasting due to changes in sales patterns detected from actual sales value renewal. Using a rolling forecast as an alternative tool in forecast correction can reduce excess inventory by up to fifty-seven percent.

INTRODUCTION

Production planning and inventory control have an essential role in the manufacturing industry. Production planning activities include determining the number of products to produce, the number of raw materials needed, preparation of sources needed, and schedule when the product will finish. Production control activities include evaluating production planning and doing improvement plans if pro-duction does not go as planned.

A bicycle manufacturer has various kinds of products. The problem is that every group product has different pro-duct characteristics that create a different demand pat-tern. Each model also tends to specific sales trends based on variations in the SKU (Stock Keeping Units). The other problem is the availability of raw materials. The availability of raw materials is an absolute issue that should achieve in production activity. Before a manufacturer does the production planning, raw materials should be already on hand. It will not be accessible if raw materials' lead time is more extended than production. The manufacturer needs three months to prepare the raw materials. On the other hand, the production lead time is two weeks. Based on these conditions, the manu-facturer should plan the production activity three months earlier so that the availability of the raw materials can be ensured.

Within the waiting time of raw materials, the production and sales keep running. The actual sales number changes every day. It means, within the waiting time, changes in sales patterns can occur. When the sales pattern changes, the forecast number must follow the changes. Discrepancies that occur in a certain period affect the requisition of the next period, so it is necessary to take the decision-making tool to be immediately resolved and reduce potential costs. The rolling forecast can be used as one alternative of dynamic changes of demands, however, this one is not always successful. Massum *et al*. [1] found that single point rolling forecast for time series forecasting strategy provides somewhat deceptive outcome. Wang *et al*. [2] developed rolling forecast models to deal with customer demand uncertainty, inaccurate demand forecasting, and inventory wastes. They applied ARIMA dan LSTM techniques and found that the models improve the accuracy and efficiency of demand and inventory forecasting. The forecasting rolling mechanism was widely used, especially for reducing forecasting error such application of rolling forecasts for electricity demand forecasting of Turkey [3]. In terms of correlation of rolling forecast with other functions in industry, rolling forecast is one of useful tool to reduce inventory management, Accurate rolling forecast will reduce inventory cost [4].

METHODS

The method used in this research is statistical data analysis. The steps are data collection, data filtering, data plotting, and data grouping. After the data had been grouped, forecasting will conduct. The rolling forecast will be conducted as an advanced evaluation phase of forecasting. The notations used in this method are as shown in Table 1.

TABLE 1. List of notations

Notation	**Description**
t	Time period
m	Seasonal period
n	Total period number
F	Forecast demand
A	Actual demand
FIT	Fit value
α	Level index
β	Trend index
γ	Seasonality index

This research was conducted in a specific condition. It cannot accommodate one hundred per-cent of the manufacturer's problems. The limitation in this research is: (1) The product observed in this research are only two models of mountain-bike: Ruby and Jade. (2) The product observed in this research is only for two model years, which are "R" and "S." (3) Data sales of the Ruby model used in this research from May 2017 until December 2019. (4) Data sales of the Jade model used in this research from July 2017 until December 2019. (5) The data processed is until June 2019, and the rest will use for validating. (6) All the mathematical processes in this research had been done using R version 4.00 and Microsoft Excel 2019 version.

There are three data are used in this research. Those are sales data, actual production data, and inventory data. The sales data contains information on how many products are sold in a month. It is collected from the marketing department's monthly report. Data actual production collected from the database contains infor-ma-tion on the amount produced for every SKU every day. Data inventory is calculated from the total difference between pro-duct produced and product sold.

Each data comes from different departments and has a different form, so it needs to edit. The editing process has been done through two phases. The first phase consists of defining the limitation, then transforming it into a uniform format. The second phase is filtering data. The data which are not included in this research should be filtered. The amount of SKU in every data has to be the same. The filtering process is done by defining the intersects of data sales, data actual production, and data inventory.

A plot is a graphical technique for representing a data set. The plot created is a time series plot where time measures (in the month) on the x-axis and the sales value on the y-axis. The aim of creating a time series plot is to see is there any trend, cycle, or seasonality. The plot is also used to define the group product. The data that has the same pattern, combined into a group.

The data decompositions have been done by using STL (A Seasonal-Trend Decomposition Procedure Based on Loess) method that was introduced by Cleveland in 1990. STL is a procedure for decomposing a time series data into a trend, seasonal, and remainder components.

Forecasting is a project of predicting the future by doing statistical data analysis and mathematical processes [5 2]. Forecasting methods can be grouped into four. (1) Simple Moving Average, which is used for short-term forecasting with weekly stationer data. (2) Weighted Moving Average, which is used for short-term forecasting with monthly stationer data. (3) Holt Exponential Smoothing, which is used for forecasting time series data that exhibits a trend. (4) Linear Regression, which is used for short-term to medium-term forecasting. (5) Trend and Seasonal Model, which is used for short-term to medium-term forecasting, with data containing trends and seasonal.

Holt Exponential Smoothing Method

Holt exponential smoothing is an extended method of exponential smoothing of data with trends. This method is widely used in many areas such as customer transaction forecasting in a store [6] and housing price [7]. _This method involve two smoothing parameters which are one for the level (α) and the other one (β) for the trend. The Holt method is presented in the following equations.

$$FIT = F_t + T_t \tag{1}$$

Estimate of the level at time t

$$F_t = \alpha(A_{t-1}) + (1-\alpha)(F_{t-1} + T_{t-1}) \tag{2}$$

Estimate of the trend at time t

$$T_t = \beta(F_t + F_{t-1}) + (1-\beta)T_{t-1} \tag{3}$$

Holt-Winters Method

Holt-Winters method is a time series forecasting method by considering the seasonal factor. This method is an improved method of the Holt Exponential Smoothing method. This method involves three smoothing parameters: one for the level, one for the trend, and the other one for the seasonality. The Holt-Winters method has two variations of the model, and those are additive Holt-Winters and multiplicative Holt-Winters. Additive Holt-Winters is useful to use when the number changes regularly. Otherwise, multiplicative Holt-Winters is useful to use when the number changes increasingly [8]. Some research tried to combine the application of Holt Winter with other methods to improve result quality such as combination with extreme learning machine [9] and bootstrap aggregating [8].

Additive Holt-Winters

The additive Holt-Winters method is presented in the following equations.

$$FIT = F_t + T_t + S_t \tag{4}$$

Estimate of the level at time t

$$F_t = \alpha(A_{t-1} - S_{t-m}) + (1-\alpha)(F_{t-1} + T_{t-1}) \tag{5}$$

Estimate of the trend at time t

$$T_t = \beta(F_t + F_{t-1}) + (1-\beta)T_{t-1} \tag{6}$$

Estimate of the seasonal at time t

$$S_t = \gamma(A_{t-1} - F_t) + (1-\gamma)S_{t-m} \tag{7}$$

Multiplicative Holt-Winters

The multiplicative Holt-Winters method is presented in the following equations.

$$FIT = (F_t + T_t)S_t \tag{8}$$

Estimate of the level at time t

$$F_t = \frac{\alpha}{S_{t-m}}(A_{t-1}) + (1-\alpha)(F_{t-1} + T_{t-1}) \tag{9}$$

Estimate of the trend at time t

$$T_t = \beta(F_t + F_{t-1}) + (1-\beta)T_{t-1} \tag{10}$$

Estimate of the seasonal at time t

$$S_t = \gamma\left(\frac{A_{t-1}}{F_t}\right) + (1-\gamma)S_{t-m} \tag{11}$$

Trigonometric Seasonality, Box-Cox Transformations, ARMA Errors, and Seasonal Components (TBATS)

This model is developing the exponential smoothing method and combined with the Box-Cox transformation, which is fully automated calculated through the "TBATS" package available in the R. As with other models that are developed automatically, it is possible to occur a significant inaccuracy. Application of TBATS lonely or combination with other methods is widely used in many areas such as chili price forecasting [10], electricity price forecasting [11], and web traffic [3]. To overcome this, it is strongly recommended to use short.

Rolling Forecast

Rolling forecasts were initially made to bridge the frequency of updating actual values and different forecast horizons. Generally, the actual value is updated faster than the updated forecast value. So, the actual value is more sensitive to change. Thus, a rolling forecast is best used to accommodate forecasting with a continuous planning horizon. The rolling forecast itself can be done using many different methods, but the datasets are available using an automated forecast is the best choice.

RESULTS AND DISCUSSIONS

The data shows that there are 102 SKU (Stock Keeping Units) that can be used as the research objects. Those SKU can be grouped in Ruby, Jade A, and Jade B, however, in this paper we only discuss Ruby. The grouping was made based on the similarity of sales patterns and product characteristics (Fig. 1).

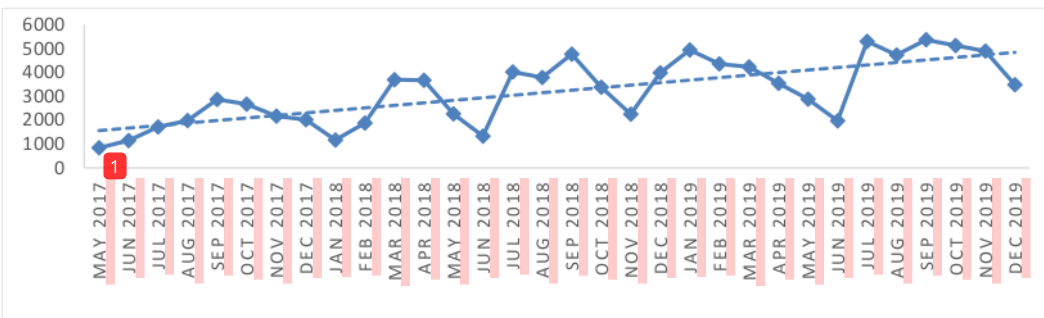

FIGURE 1. Ruby group sales pattern

Forecasting Model

Before determining the appropriate method to be used in the forecasting process, decomposition of the time sequence data is performed first. Data decomposition is carried out to determine the description of trends, seasonality, and remainder of the data. (Fig. 2). The decompositions show that every group product has a trend and seasonal pattern to forecast using an exponential smoothing forecast method and its variations. Ruby group's sales season recurs every six months.

To define which forecast method is the best, we use the error level as the comparison. The method with the lowest error level is the best. Every method has three parameters, and we experimented to define the best combination of those parameters. In the first experiment is, we use a balanced point to define the parameter combination. The second experiment is defining a minimum number of a parameter. The second experiment is repeated for every parameter. The comparison of each method that was tested is shown in Table 2. The results show that the Holt-Winter is the best for MAPE, and Multiplicative Holt-Winter has the best value of MASE and RMSE. Therefore, every method is compared by defining tracking the signal numbers to conclude which method is given a more stable outcome. The method which is compared is the method highlighted in yellow. Table 3 shows tracking signal comparison of Additive Holt-

Winter and are Multiplicative Holt Winter. Tracking signal numbers that are considered stable is not out of control limits (between four and minus four). The tracking signals that out of control limits are marked in red letters. According to that rules, the forecasting method is used for Ruby is multiplicative Holt-Winters with parameters $\alpha, \beta, \gamma = (8x10^{-3},\ 7x10^{-3}, 0.016)$.

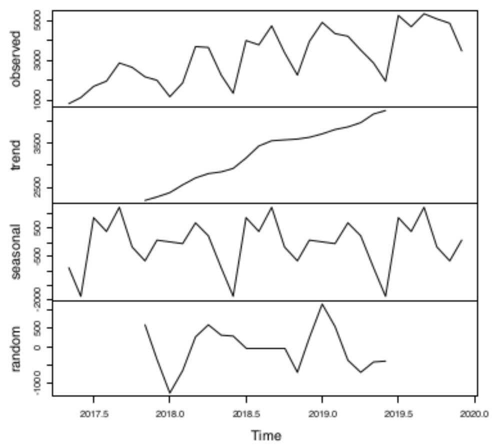

FIGURE 2. Data decomposition Ruby group

TABLE 2. Forecasting error comparison for Ruby

Method	Parameters	MASE	RMSE	MAPE
Additive Holt-Winters	$\alpha, \beta, \gamma = (10^{-4}, 10^{-4}, 0.93)$	0.308	797.575	16.956
Additive Holt-Winters	$\alpha, \beta, \gamma = (10^{-4}, 10^{-4}, 0.65)$	0.391	799.904	17.307
Additive Holt-Winters	$\alpha, \beta, \gamma = (10^{-4}, 10^{-4}, 0.99)$	0.397	791.218	17.951
Additive Holt-Winters	$\alpha, \beta, \gamma = (10^{-4}, 10^{-4}, 10^{-4})$	0.402	822.367	18.259
Multiplicative Holt-Winters	$\alpha, \beta, \gamma = (10^{-4}, 10^{-4}, 10^{-4})$	0.373	639.189	19.281
Multiplicative Holt-Winters	$\alpha, \beta, \gamma = (10^{-4}, 10^{-4}, 0.05)$	0.436	832.845	19.767
Multiplicative Holt-Winters	$\alpha, \beta, \gamma = (10^{-4}, 10^{-4}, 10^{-4})$	0.327	537.033	19.437
Multiplicative Holt-Winters	$\alpha, \beta, \gamma = (4x10^{-3}, 4x10^{-3}, 10^{-4})$	0.357	582.161	20.13
Multiplicative Holt-Winters	$\alpha, \beta, \gamma = (8x10^{-3}, 7x10^{-3}, 0.016)$	0.307	518.389	19.152

At the beginning of the observation period, the error generated by the multiplicative Holt-Winters looks greater when compared to the additive Holt-Winters. However, Multiplicative Holt Winter is better at the end periods. Multiplicative Holt Winter also has a more stable error since it has a better tracking signal. Both methods show that the tracking signal number is out of the range of tolerance in the Ruby group. However, the better method is the multiplicative Holt-Winters. The forecasting with multiplicative Holt-Winters method shows less period that is out of the range than the forecast with additive Holt-Winters method. The other reason is the tracking signal, which is out of range of tolerance is a positive number. It means the forecast result is larger than the approximately of actual sales number. In production planning, having an inventory is better than losing sales.

Rolling Forecast

In ideal conditions, data sales must be up to date. The importance of updating data is to detect whenever there is a change in the sales pattern. We never know how long the forecasting model can be relevant to the current situation. So, the sales data need to be updated. It can prevent planning mistakes due to changes in the sales pattern that are not eligible. The sales pattern changing can be detected when the tracking signal is out of control for more than three months.

The forecasting method used is the method that has a minimum error level as already calculated before. When sales data are updated, the forecast value can be changed so that the calculation of safety stock, place orders, and expectations of the amount of inventory at the end of the period is also updated. In this research, the software is developed as a tool to calculate demand forecasting and make changes depending on the actual sales data. When the data input is updated, a forecasting number will be updated. It causes the change of amount production planning, and an estimate of the inventory amount can also be updated. How the forecasting value changes as shown in Table 4.

TABLE 3. Tracking signal comparison for Ruby

Period	Sales	Additive Holt-Winters	TS	Multiplicative Holt-Winters	TS
May 2017	837	982	1.00	1152	1.00
Jun 2017	1144	1145	2.00	828	0.00
Jul 2017	1708	1709	3.00	2231	1.36
Aug 2017	1977	1978	4.00	2227	2.20
Sep 2017	2867	2868	5.00	2939	2.86
Oct 2017	2663	2664	6.00	2296	1.55
Nov 2017	2169	2169	7.00	1675	-0.05
Dec 2017	2009	2009	8.00	2443	1.20
Jan 2018	1161	1314	9.00	2660	4.04
Feb 2018	1873	1872	9.93	2619	5.31
Mar 2018	3688	3687	10.86	3142	4.18
Apr 2018	3668	3668	11.84	2846	2.43
May 2018	2263	2010	1.12	2043	2.11
Jun 2018	1330	2307	9.35	1443	2.47
Jul 2018	4016	2871	-0.67	3757	2.00
Aug 2018	3784	3140	-3.68	3674	1.85
Sep 2018	4764	4030	-6.28	4758	1.95
Oct 2018	3383	3826	-4.22	3658	2.66
Nov 2018	2253	3332	0.08	2627	3.59
Dec 2018	3983	3172	-2.46	3739	3.05
Jan 2019	4933	2335	-7.91	3985	0.63
Feb 2019	4358	3037	-10.04	3890	-0.47
Mar 2019	4228	4853	-8.58	4645	0.51
Apr 2019	3544	4833	-5.48	4164	1.93
May 2019	2876	3411	-4.42	2945	2.16
Jun 2019	1964	2563	-3.23	2052	2.44

The context of the example shown in Table 3 is the latest data is sales of June 2019. At first, the amount of production planned for July 2019 until October 2019. In the first column data up to June 2019 is used, then the second column using data up to July 2019 column 3 using data up to August 2019. It can be shown that demand forecasts are changing where new data can generate a better result.

The rolling forecast can be an alternative for evaluating a planning activity in short-term production planning. However, this alternative can work optimally if the data is always updated. Rolling forecast will not be relevant if the data are not updated continuously. Rolling forecast is an improved method of the fundamental forecast.

Rolling forecast is sensitive to the change in the sales pattern. The most important thing that must be considered in the forecast process is sales patterns. Once the sales pattern changes, the forecast method might not be relevant. forecast model that does not suit the actual condition can affect the error level.

TABLE 4. The changes of forecast value

Period	Forecast	Forecast $n+1$	Forecast $n+2$
July 2019	5010		
August 2019	4789	4950	
September 2019	6055	6498	6324
October 2019	4478	4996	4805

CONCLUSION

Supply and PPIC (Production Planning and Inventory Control) departments are responsible for determining the company's number of placement orders in bicycle manufacturing. Determination of the number of existing placement orders has not been systematically arranged, so it is not recorded, and it is challenging to evaluate department performance. Those problems are then assisted by a placement order determination system that can be used at a time to assist in planning, recording, and evaluating performance.

The decision-maker tool in the form of a calculation system is made to determine how much quantity of products can be planned for each period. It can also measure the inventory level, whether it is still within the minimum and maximum allowable levels. The system created is very closely related to forecast demand for each product category. Forecast demand is made with past data and then assisted with R 4.0 based data processing. At the same time, the placement order determination system itself is made based on Microsoft Excel 2019.

Based on the experimental results that have been made, forecast demand and the placement order determination system can help maintain inventory levels to not go out of the specified minimum and maximum limits. This system can support data for decision-makers to reduce excess inventory and reduce potential loss of sales. Overall rolling forecast mechanism can reduce the excess inventory. The initial purpose of this research is to plan a monthly amount of production. But, this research also can be applied to weekly production planning.

The system that has been created produces an output, which is the total number of product groups that have been determined in one month. The outputs can be used as a basis for weekly production planning and shared in more detail for each SKU with a user's determined percentage. In using this system, the user must always pay attention to the inventory status so that if the input data is not relevant, it can be updated or added so that the system output's accuracy can be maintained.

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