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Understanding Future Performance of Warehouse using Key Performance Indicator Forecasting

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Abstract

Improving supply chain performance has become one of the critical issues for gaining competitive advantages in companies. Usage of key performance indicators (KPIs) are one of the methods to determine if the supply chain is functioning properly. Different warehouses have different KPIs, hence for better functioning of the warehouses, improved strategies based on future requirements need to be formulated. The existing KPIs do not provide solutions for developing future strategies hence in this paper new KPIs are designed in such a way that it helps in predicting future performances and in providing insights for decision making to the managers and stakeholders. The newly designed KPIs are stock index for determining safety stock, defective cost index for measuring defective products, operator productivity for efficient functioning of logistics, efficiency of machinery for measuring machines efficiency. Based on the data collected, KPIs are forecasted for the year 2022 and insights based on the analysis is delivered. Measures for improving the performance of the warehouse can be formulated using the insights.

Keywords

Key performance indicators, Holt-Winters triple exponential smoothing, ARIMA model, Time series forecasting

Introduction

Supply chain management is a methodology for improving business processes, making them more resilient, more agile and as a result, more competitive [1]. Improving the supply chain is one of the opportunities for saving costs in the upcoming competitive world [2]. The success of a supply chain is dependent on the planning and execution of the strategies. To deal with this, tools based on the KPIs concept were developed [3]. The strategies can be developed using KPIs. In certain organizations, KPIs are used from manufacturing of a product to delivery of the product, which covers every department. The strategies of the warehouse are also dependent on the effect of the KPIs [4]. Hence a lot of KPIs have been built to determine the functioning of the warehouses [5]. It is not possible to develop a new KPIs every time. The existing KPIs provides the measure of whether the warehouse is functioning well or not, they analyze the present situation of a warehouse. These KPIs give the measure based on the available data, they do not provide suggestions or solutions for making future strategies [6]. This paper discusses the designing of KPIs that can be used in the supply chain which can predict the future performance of the warehouse. The KPIs are designed in such a way that it can be model into time series, and further predict future performances [7].

In this paper, time series models like Holt-Winters triple exponential smoothing and ARIMA models were fitted to all the KPIs, and the best model fit was considered to forecast the KPIs [8]. Holt-Winters triple exponential smoothing is a way to model three aspects of the time series: average value, a trend present in the data, and seasonality present in the data. ARIMA or an autoregressive integrated moving average is a statistical analysis model that uses time series data to either better understand the data set or to predict future trends [9]. This research paper gives us a systematic approach that helps us to analyze the KPIs and predict the future values, which helps the decision makers of the organization to understand the future predictions and make strategies accordingly to gain profits in the market.

Materials and Methods

Secondary data was considered for the analysis. Five years of daily data from 2017 to 2021 was collected for the analysis. Secondary data consisted of the variables based on the requirement for all four KPIs. The variables used were remaining stock in a day, total demand, number of defective units, number of scrapped units, cost to repair a product, cost to scrap a defective product, actual stock unloaded in a day, expected cost to be unloaded in a day, number of manufactured products, expected cost to manufacture a product, electricity cost of the machine, and maintenance cost of the machine. Using this data, all the four newly designed KPIs: stock index, defective cost index, operator productivity, and efficiency of machinery were calculated. To prepare future strategies, time series models like Holt-Winters triple exponential smoothing and ARIMA were fitted to all four KPIs and the best model was used to predict the future values of KPIs. These future predictions were then used to design strategies for the warehouse.

Results and Discussion

In this section, explanation of each newly designed KPI along with the analysis to forecast the future KPI values was explained. The first KPI was the stock index which was calculated as shown in equation (1).

$$Stock\ Index = \frac{remaining\ stock}{Total\ demand}\ x\ 100 \quad (1)$$

The data was collected for variables total stocks and demand of units. The warehouse stores have safety stock value. The safety stock value of the warehouse was 20 units, so the stock index value for the warehouse should lie between 0.3778 to 2.2272 for efficient functioning. The time series plot for stock index was plotted in figure 2. The second KPI was defective cost index which was calculated as shown in equation (2).

$$Defective\ Cost\ Index = \frac{cd*d+cs*s}{Total\ production\ cost}\ x\ 100 \quad (2)$$

Where, cd = expected cost to rework a unit; d = number of defective units; cs = expected cost to scrap a unit; s = number of scrap units.

The data was collected for variables number of reworked units, number of scraped units, cost of reworked product, cost of scraped products. The defective cost index should be less than 0.5 for efficient functioning. The time series plot for de-

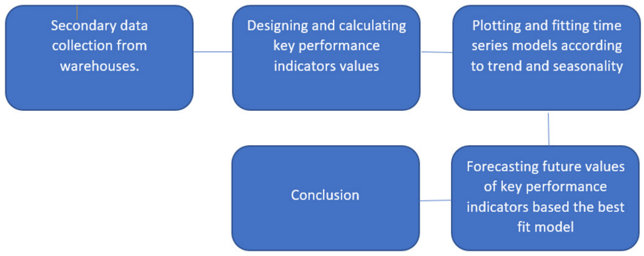

Figure 1: Methodology flowchart.

fective cost index was plotted in figure 2. The third KPI was operator productivity which was calculated as shown in equation (3).

$$Operator\ productivity = \frac{actual\ units\ unloaded}{Expected\ units\ to\ be\ unloaded} \quad (3)$$

The data was collected for actual stocks unloaded and expected stocks to be unloaded. The time series plot for operator productivity was plotted in figure 2. The fourth KPI was the efficiency of machinery which was calculated as shown in equation (4).

$$Efficiency\ of\ machinery = \frac{em*m}{ec+mc} \quad (4)$$

Where, em = expected cost to manufacture a product; m = number of products manufactured; ec = electricity cost; mc = maintenance cost.

The data was collected for the variables number of units manufactured, expected cost to manufacture a product, electricity cost, and maintenance cost efficiency of machinery. The time series plot in figure 2a, shows that the stock index ranges from -14 to 24. The stock index values from -14 to 0 indicate that the warehouse was out of stock on those days. The stock index values from 2.22 to 24 indicate that the warehouse was overstock on those days. The time series plot in figure 2b shows that the defective cost index was more in the months of January to June as compared to July to December. This indicates that there was a certain factor that caused more loss in the period of January to June. The time series plot in figure 2c shows that the operator's productivity fluctuates between 0.8 to 1.15. Overall, it increased from the start of 2018 to the end of 2019 and then decreased from the start of

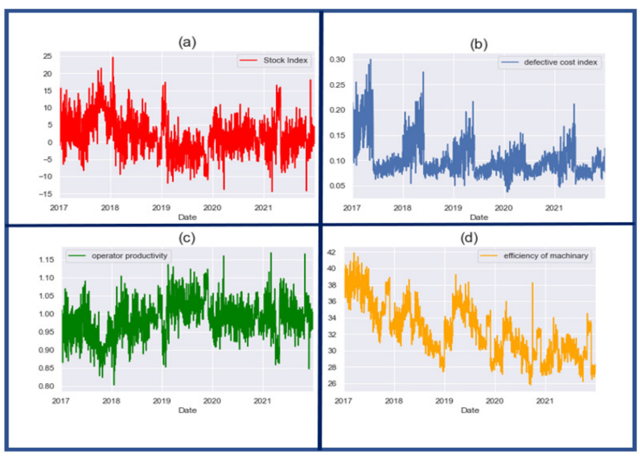

Figure 2: Time series plot for all the KPIs.

2020. The operator productivity greater than 1 indicates that a greater number of units were unloaded than expected on that day. The time series plot in figure 2d shows that the efficiency of the machinery plot was following a downward trend, which implies the efficiency of machinery was decreasing with time.

To study the downfalls and understand the problems in the warehouse, these KPIs were forecasted using time series predictive models. Holt-Winters triple exponential smoothing [3] and ARIMA models were fitted to the data by dividing the dataset into training and test. The training dataset had 80% of the data and the test dataset had 20% of the data. To check which time series model was best fit for the KPIs, various measures like the mean square error (MSE), mean absolute error (MAE), Akaike Information Criterion (AIC) [10, 11], Bayesian Information Criterion (BIC) values were obtained. These measures were calculated by comparing the test values and the predicted values. The lesser these model evaluation metrics, the better the model.

From table 1 it was observed that the AIC and BIC values of Holt-Winters triple exponential smoothing model were less than the ARIMA model hence Holt-Winters triple exponential smoothing model was used for forecasting future values of the stock index. From table 2 it was observed that the AIC and BIC values of Holt-Winters triple exponential smoothing model were less than the ARIMA model hence Holt-Winters triple exponential smoothing model was used for forecasting future values of defective cost index. From table 3 it was observed that the AIC and BIC values of Holt-Winters triple exponential smoothing were less than the ARIMA model hence Holt-Winters triple exponential smoothing model was used for forecasting future values of operator productivity. The AIC and BIC values of Holt-Winters triple exponential smoothing model were less than the ARIMA model hence Holt-Winters triple exponential smoothing model was used for forecasting future values of Efficiency of machinery.

After identifying the best fit model for all KPIs, the KPIs for the year 2022 were predicted using Holt-Winters triple exponential smoothing model for stock index, defective cost index, operator productivity, and efficiency of machinery in figure 3, respectively.

From figure 3a, the stock index values for 2022 were predicted between -5 to 11. This suggests the warehouse manager to identify the reasons for over and under stocking and build strategies to bring the stock index value to lie between 0.3778 to 2.2272. From figure 3b, the predicted defective cost index was less compared to previous years, which gives an insight that the strategies implemented for reducing the defective items was working efficiently, and the same strategy can be continued. From figure 3c it was observed that the predicted operator productivity lies between 0.9 to 1.05. This implies that the operator almost completes the expected work on time and sometimes even works more than expected. From figure 3d, it was observed that the efficiency of machinery will decrease further in the year 2022, hence the manager should make planned strategies for maintenance of machines based on usage of the machines, and production batches should be planned accordingly.

Table 1: Model metrics of stock index.

	Holt-Winters	ARIMA
Mean absolute error	0.045	0.039
Mean Square Error	0.003	0.003
Akaike Information Criterion	-9302	-5255
Bayesian Information Criterion	-7351	-5244

Table 2: Model metrics of defective cost index.

	Holt-Winters	ARIMA
Mean absolute error	0.016	0.02
Mean Square Error	0.0004	0.0006
Akaike Information Criterion	-10884	-8670
Bayesian Information Criterion	-8933	-8653

Table 3: Model metrics of operator productivity.

	Holt-Winters	ARIMA
Mean absolute error	4.308	3.775
Mean Square Error	31.486	24.098
Akaike Information Criterion	4018.472	8065.554
Bayesian Information Criterion	5969.330	8076.127

Table 4: Model metrics of efficiency of machinery.

	Holt-Winters	ARIMA
Mean absolute error	1.627	1.983
Mean Square Error	3.951	6.034
Akaike Information Criterion	290.014	4612.076
Bayesian Information Criterion	2240.871	4622.649

Conclusion

Solutions to improve the functioning of the warehouse were provided. The forecasted value of the stock index suggested the expected value of safety stock be maintained. The forecasted value of the defective cost index suggested that the present strategies are efficiently working in managing the defective products. There is some factor that is responsible for more defects in the month of January to June which suggests the manager identify the reason for defects and formulate more efficient strategies. Operator productivity suggested that the operators were functioning more efficiently than expected

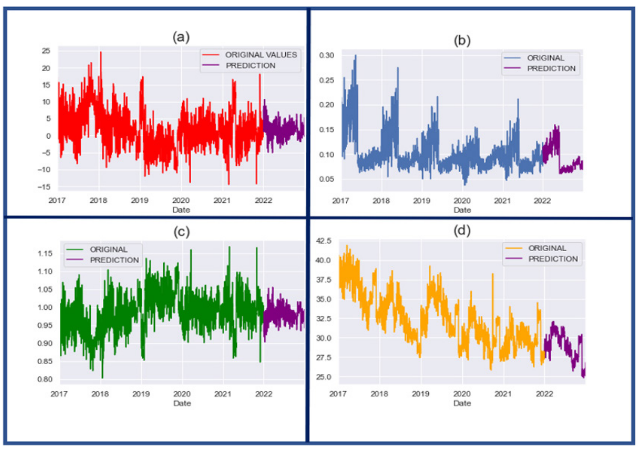

Figure 3: Time series forecasting plot for the KPIs.

on certain days hence if a similar strategy was implemented to other operators functioning then the company can cut expenses by reducing manpower in the operator section. The efficiency of machinery was decreasing which suggests that the manager should make strategies for maintenance of machines based on usage of the machines. The production rate will go up as the machine's efficiency goes down, hence batches should be arranged accordingly. These KPIs can be used in predicting the future performance of warehouses, which helps in formulating better strategies for the future, that will lead to reduced losses. The KPIs score can be used to improve performance of warehouses. The further scope of research is to build models which can combine these factors and give a result on overall performance of warehouse.

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Credit Author Statement

Neha Mumbaikar: Study conception, Design, Data analysis; Purnima Agarwal and Vamsikrishna A: Data analysis, Writing - original draft preparation, Writing - review and editing. All the authors read and approved the manuscript.

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