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Decision Support Tool for Dynamic Inventory Management using Machine Learning, Time Series and Combinatorial Optimization

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Abstract

Nowadays, the imbalance between supply and demand increases the volatility of many raw materials for both production and consumption. In this regard, stock management inventory would be necessary in order to limit losses and increase margins.
It this perspective, we propose through this article, the development of a model combining time series, machine learning algorithm and combinatorial optimization in order to identify the opportunities to buy stock at a lower cost and to sale a portion of the unused stock to generate additional profits for the organization.
In this model, we use machine learning models and time series to predict stock prices and demand forecast of stock to ensure the production and then integrate them into a combinatorial optimization algorithm to help making the best decision (Buy, Sell or Hold), and the exact quantities to buy or to sell in order to maximize earnings without risks.

Keywords: Inventory management; Machine Learning; Demand forecasting; XGboost; Decision tool; ARIMA; NARNN

1. Introduction

Inventory management is the process of seeking to acquire stocks that are essential for the activity from suppliers at the right time and at the best cost in order to ensure the production and delivery of the end products. The inventory

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can be any item or resources used in the organization. “There are three types of manufacturing inventories: raw materials, work in progress and finished goods” [1].

The purpose of inventory management is to satisfy demand, generate more profits and also to ensure the proper running of the company. it is a crucial function for the competitiveness of the company. [3]

The stocks are operating values required to be managed, however, there are costs associated with their existence. When supplies are less important, the company is threatened with a stock-outs that can disrupt the production process. This disruption creates additional costs and can damage the brand image of the company. On the other hand, when the supplies are too important, they constitute fixed assets which inflate the cost price and disturb the cash flow balance. This is what makes inventory management a challenging problem in supply chain management [2] [4].

Due to the huge amount of real data available today, companies are increasingly abandoning traditional model-based inventory management approaches and turning to data-driven models because it is less time consuming and also easy to implement [5] [6].

In this paper a new approach is proposed for inventory management that combine model-based approach and data-driven methods. This is a model that determine the right time to buy stocks and the right moment to make additional profit by selling unused stocks. The proposed model use a statistical model to forecast the price of raw materials based on historical data, a machine learning algorithm to forecast demand and finally a combinatorial optimization model is used in order to find the best decision to make for inventory management.

This paper is organized in six section. Following the introduction, the related literatures are reviewed in Section 2. In Section 3 the architecture of the proposed model is presented; the methodology to implement the model is presented in Section 4. To show the applicability of the proposed model, results are presented in Section 5. Finally, the conclusion is presented in Section 6.

2. Literature Review

Confronting an environment that is becoming increasingly competitive, companies today do not allow any mistakes in supply management. Many researchers are interested in inventory problem and it has been studied from various perspectives.

Hadley and Whitin [1] studied basic problems of inventory system. Peterson and Silver [2] studied standard problems of inventory management such as Just-in-Time Manufacturing and Kanban. Those model are time independent and does not include demand variability. Chen [3] developed a model of inventory system with cost-dependent demand and included production cost in proposed model. Zhao et al. [4] suggested an analytical model to quantify the cost savings of an early order commitment in a two-level supply chain where demand is serially correlated. Kong and Jirimutu [5] researched the inventory optimization under stochastic demand based on Monte Carlo simulation. Bertsimas and Thiele [6] proposed a general methodology based on robust optimization to address the problem of optically controlling supply chain subject to stochastic demand in discrete time by taking into account the uncertainty of the demand. Olsen and Parker [7] investigate consumer behavior of potentially leaving the firm’s market when he encounters an inventory stock out at a retailer under the stochastic demand distribution in a time-dynamic context. Huang [8] proposes an optimal integrated vendor-buyer inventory policy in a just-in-time manufacturing environment where the objective is to minimize the total joint annual costs incurred by the vendor and the buyer.

Demand cycles of these customers are different and the demand rate of every customer is also varying, therefore it is difficult to predict the exact quantity of inventory that companies need. The model proposed in this paper is a decision support tool with a new policy of inventory management. Beside the fact that the model allows to optimize the inventory management and also give the right time to sell unused stock every month in order to increase profits.

3. Proposed model

In the decision support tool, we use ARIMA (autoregressive integrated moving average) model to forecast the price of raw materials based on historical data. Then, we use the XGBoost (eXtreme Gradient Boosting) regression model to perform demand forecasting. Finally, we integrate different variables into a combinatorial optimization model in order to help making the best decision. See Fig. 1.

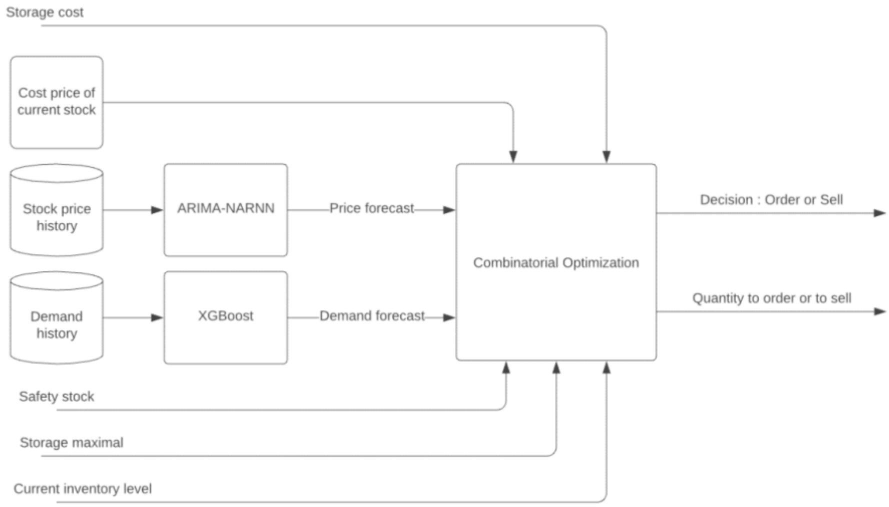

Fig. 1. Architecture of the Decision Support Tool for Dynamic Inventory Management

3.1. ARIMA-NARNN

ARIMA, is a statistical analysis model that uses time series data to predict future trends. The model has been originated from the combination of autoregressive model (AR), the moving average model (MA). It is only used for stationary time series data specified by three order parameters: *p, d, q*, where *p* stands for the order of auto regressive model, *d* is the degree of differencing and *q* represents the order of moving average. The procedure to find the value of those parameters is referred as the Box- Jenkins method [9]. NARNN is called nonlinear autoregressive neural network [10]. It is a model that can continuously learn and train based on past values of a given time series to predict future values. In this paper, we use ARIMA-NARNN, it is a combination of ARIMA model and NARNN model in order to improve the accuracy of forecasting. Many studies shows that ARIMA-NARNN outperforms the ARIMA and NARNN models in terms of the prediction accuracy [11] [12].

3.2. XGBoost

In this decision support tool, we use XGBoost model for demand forecasting. It is a supervised learning algorithm that combines the results of several simpler and weaker models to provide better forecasting. The data of sales request history is a structured data and in prediction problems, decision tree-based algorithms are more efficient than neural network-based algorithms [13]. Sometimes it is not enough to rely on the results of a single machine learning model. XGboost offers a systematic solution to combine the predictive power of multiple learners. The result is a single model that gives the aggregated output of several models.

3.3. Combinatorial Optimization

The aim of this sub-model is to ensure, for a given period, the best possible decision for the management of the stocks. The envisaged decisions are taken according to the maximization of the profit and the minimization of the risk. The model give us one of the three output: “Sell” or “Buy” or “Hold”. For a given period we have:

- P = price of the stock in the market
- K = cost price of the inventory
- C = storage cost
- S_0 = safety stock

- D = demand
- S_{max} = maximum storage capacity
- Q = current inventory level

If $Q \geq D$, three decisions are possible and the best choice is according to the net profit. However, if Q <S, we have two possible decisions: "Buy" or "Hold". The problem can be mathematically modelled by the following equation (1):

$$\begin{cases} \text{Max}[(P-K-C)x_1 + (K-P-C)x_2 - Cx_3] & \\ x_1 + x_2 + x_3 = 1 & \text{(Decision constraint)} \\ (D-Q)x_1 + (S_0 - Q)x_3 \leq 0 & \text{(Quantity constraint)} \\ x_1, x_2 \text{ et } x_3 \in \{0,1\} & \end{cases} \quad (1)$$

$$x_1 = \begin{cases} 1 & \text{if the decision is to "}Sell\text{"} \\ 0 & \text{if not} \end{cases} \qquad x_2 = \begin{cases} 1 & \text{if the decision is to "}Buy\text{"} \\ 0 & \text{if not} \end{cases}$$

$$x_3 = \begin{cases} 1 & \text{if the decision is to "}Hold\text{"} \\ 0 & \text{if not} \end{cases}$$

After identifying the best decision to make, the next problem to be solved consist on determining the right quantity to buy or to sell. Let q_1 is the maximal quantity to sell and q_2 is the maximal quantity to buy according to the decision made for the inventory management. Then $q_1$and q_2 are solutions of the following linear program:

$$\begin{cases} \text{Max}[(P-K-C)q_1 + (K-P-C)q_2] & \\ 0 \leq q_1 \leq \text{Max}(0, \text{Q} - \text{S}) & \text{(Constraint of quantity to sell)} \\ \text{Max}(0, S_0 - \text{Q}) \leq q_2 \leq S_{max} - \text{Q} & \text{(Constraint of quantity to buy)} \\ q_1 \text{ et } q_2 \in \mathbb{N} & \end{cases} \quad (2)$$

The equation (2) determine the optimum quantity of stock to order or to sell.

4. Methodology

The study used a two-year stock data from a private company that produce and distribute automotive engine oils. The raw material used for their production is the Base Oil. History of base oil prices were used in ARIMA-NARNN and history of demand were used for XGboost. Python were used for developing the models.

4.1. Base Oil forecasting using ARIMA-NARNN

4.1.1. ARIMA

ARIMA can only be applied on a stationary and univariate time series [9]. To do so, it is essential to make the data used stationary with a finite difference “d” and to determine the number of autoregressive terms "p" and the number of lagged forecast errors in the prediction equation "q".
ARIMA forecasting model includes the moving average process (MA) and the autoregressive process (AR) [11]. A pth-order autoregressive process: AR (p) is expressed as follows:

$$M_t = \text{c} + v_t + \sum_{i=1}^{p} \emptyset_i M_{t-i} \quad (3)$$

Where, c is a constant term; v_t is a white noise; $\emptyset_i$ are the moving average coefficient; M_{t-i} are regressors;

A qth-order moving average process: MA (q) is expressed as follows:

$$M_t = \text{u} + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \quad (4)$$

Where, u is a constant term; ε_t is a white noise; θ_i are the moving average coefficient;

ARMA (p,q) is obtained by merging (3) and (4) :

$$M_t = \mathrm{c} + \varepsilon_t + \sum_{i=1}^{p} \emptyset_i M_{t-i} + \sum_{i=1}^{q} \varepsilon_i M_{t-i} \quad (5)$$

In order to estimate the parameter of the ARIMA model, we used the function *auto_arima()* in python. This function provide the most optimal p,q and d values suitable for the data set.

4.1.2. NARNN

In this paper, we have used the same NARNN model used by Shouwen in [11] and Lingling in [14]. NARNN model is used to predict the same time series of base oil price Y_t as ARIMA. It is composed of a default two-layer of feed-forward back propagation, with a sigmoid transfer function in the hidden layer and a linear transfer function in the output layer. The algorithm incorporates the output to the input of the network (through delays) as shown in Fig. 2.

Fig. 2. Configuration of NARNN model for demand forecasting

The data history were divided randomly into two parts: 90% were used for training the network and 10% remaining were used for the testing of the network.

Base oil price time series can be modeled by combining the linear autocorrelation M_t and Y_t the nonlinear model as seen previously. The price of base oil P_t can be expressed using ARIMA-NARNN as:

$$P_t = M_t + Y_t \ (6)$$

4.2. Demand forecasting using XGBoost

XGBoost is essentially a method based on gradient boosted tree. The trees are built sequentially so that each subsequent tree aims to reduce the errors of the previous one. XGBoost follows three steps. A first model is defined to predict the demand. This model will be associated with an initial residual. Then, a new model is fit to the residuals from the previous step. After that, the algorithm combine the two first model in order the boost the initial model defined to predict demand. This new model decrease the squared error. This three steps are repeated until error is improved [15]. The result of the prediction is the sum of the scores predicted by trees, as shown in the formula below:

$$P_t = \sum_{k=1}^{K} f_k(x_i), f_k \in F \quad (7)$$

Where x_i is *i*-th of the training sample, $f_k(x_i)$ is the score for the *k*-th tree, and *F* is the space of functions containing all gradient boosted trees.
To implement the XGBoost model, the python library XGBoost were used in order to perform demand forecasting.

5. Experimental Results

By combining all of the sub-models and introducing the different variables into the combinatorial optimization model, we obtain a decision tool for inventory management that can be used to optimize the cycle of the stock by maximizing the profit while avoiding stock shortage as much as possible as seen in Fig. 3.

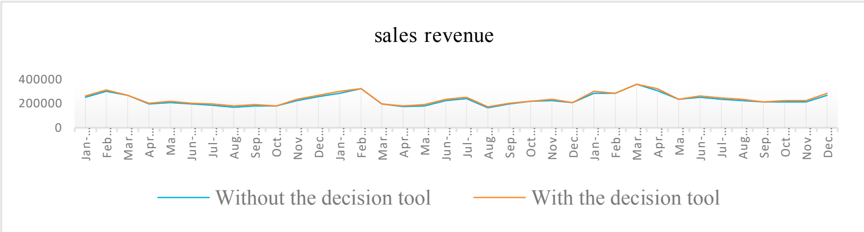

Fig. 3. Comparison between the inventory management with and without the decision tool proposed

The new policy of inventory management allowed the company to detect the right moments to sell the extra stock of raw materials. On each month the model suggest first the quantities of inventory to buy in order to ensure the production of the final product, then propose the right quantities of remaining stock of base oil to sell in the market. This increased the turnover by 1.3% in two years, compared to the company's current policy.

6. Conclusion

The implementation of this decision support tool can help any company that manages inventories. Forecasting demand will help maintain a well-managed inventory as well as minimizing the risk of stock-outs. It also helps to avoid overstocking which increases acquisitions cost. In addition, the price forecast of the inventory combined with the combinatorial optimization model give us the right time to buy or sell the unused inventory in order to maximize the gains. The difficulty remains in the implementation of this new inventory management policy and also to find buyers of the unused stocks.

References

[1] G. Hadley and T. M. Whitin. (1963) "Analysis of Inventory Systems", *Prentice-Hall International Series in Management*, New York, USA.

[2] R. Peterson and E. A. Silver. (1985) "Decision Systems for Inventory Management and Production Planning" *John Wiley & Sons*, New York, USA, 2nd edition.

[3] T. C. E. Cheng. (1991) "Economic order quantity model with demand-dependent unit production cost and imperfect production processes" *IIE Transactions*, vol. 23, no. 1, pp. 23–28.

[4] X. Zhao, J. Xie, and J. C. Wei. (2007) "The value of early order commitment in a two-level supply chain" *European Journal of Operational Research*, vol. 180, no. 1, pp. 194–214.

[5] F. L. Kong and Jirimutu. (2013) "A research on inventory optimization with random demand based on Monte Carlo simulation" *Statistics & Decisions,* no. 8, pp. 36–38.

[6] D. Bertsimas and A. Thiele. (2006) "A Robust Optimization Approach to Inventory Theory", *Operations Research Volume* 54, pp 150–168.

[7] T. L. Olsen and R. P. Parker. (2008) "Inventory management under market size dynamics," *Management Science*, vol. 54, no. 10, pp. 1805–1821.

[8] C. K. Huang. (2004) "An optimal policy for a single-vendor single-buyer integrated production-inventory problem with process unreliability consideration," *International Journal of Production Economics*, vol. 91, no. 1, pp. 91–98.

[9] G.E.P. Box and G.M. Jenkins. (1970) "Time series analysis: forecasting and control", Holden Day.

[10] E. Cadenas, W. Rivera, R. Campos-Amezcua, and C. Heard. (2016) "Wind speed prediction using a univariate ARIMA model and a multivariate NARX model," *Energies*, vol. 9, no. 2, pp. 1–15.

[11] L. Maobin, J. Shouwen and L. Gang. (2018) "Forecasting of Chinese E-Commerce Sales: An Empirical Comparison of ARIMA, Nonlinear Autoregressive Neural Network, and a Combined ARIMA-NARNN Model", *Mathematical Problems in Engineering*, Article ID 6924960, Hindawi.

[12] G. Ren and J. GAO. (2019) "Comparison of NARNN and ARIMA Models for Short-Term Metro Passenger Flow Forecasting*", 19th COTA International Conference of Transportation Professionals*. Nanjing, China

[13] Z. Yingrui, L. Taiyong, S. Jiayi and Q. Zijie. (2019) "A CEEMDAN and XGBOOST-Based Approach to Forecast Crude Oil Prices", *Complexity*, Article ID 4392785, Hindawi.

[14] Z. Lingling, Z. Ping, W. Dongdong, C. Cheng and H. Huang. (2018) "Time series model for forecasting the number of new admission inpatients", *Medical Informatics and Decision Making*, pp. 18-39.

[15] T. Chen and C. Guestrin. (2016) "XGBoost: a scalable tree boosting system," *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, KDD 2016, pp. 785–794, ACM, New York, USA.