3rd Central & Eastern European LUMEN International Conference
New Approaches in Social and Humanistic Sciences | NASHS 2017 |
Chisinau, Republic of Moldova | June 8-10, 2017

New Approaches in Social and Humanistic Sciences

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<https://doi.org/10.18662/lumproc.nashs2017.51>

How to cite: Zota, R. D. & Al Hadad, Y. (2018). Inventory Management Using Cross Prediction. In V. Manolachi, C.M. Rus, S. Rusnac (eds.), New Approaches in Social and Humanistic Sciences (pp. 575-585). Iasi, Romania: LUMEN Proceedings.
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Inventory Management Using Cross Prediction

Răzvan Daniel ZOTA¹, Yasser AL HADAD²

Abstract

Inventory management involves determining optimum inventory stock that should be held. It is necessary to introduce a set of policies and controls that establish and track levels of inventory and determine when stock should be refilled. At a firm level, identifying all opportunities for optimizing the value chain and lowering the warehouse cost is a main requirement for an efficient stock management. In this paper a supply chain application is modelled to support and optimize the stock management activity. This topic is addressed by using autoregressive method to model a supply chain application. Also, the potential of cross prediction is tested for increasing the performance of the auto regression method. SQL server Analysis services and visual basic for application is used for implementing the supply chain application.

Keywords: *Inventory management, BI (Business intelligence), SAS (SQL analysis services), cross prediction, Data analysis.*

1. Introduction

Inventory can be defined as a physical stock of items that are stored for the functioning of a business. It is required to ease transactions and avoid any wait time due to lead time of procurement orders. Inventory management is defined as a set of controls and policies that monitor levels of inventory. It determines the levels of inventory maintained, the size of orders, and when stock should be replenished [1]. Holding inventory can

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<https://doi.org/10.18662/lumproc.nashs2017.51>

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Selection and peer-review under responsibility of the Organizing Committee of the conference

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protect against any price fluctuation of raw materials. The objective of an inventory management system is to minimize the inventory investment and to provide optimum customer service. Inventory management has become a leading issue for maximizing the productivity of the operations. It is necessary for each company to assess both methods and financial results in each financial year in order to minimize risks and maximize profits. Company management can take specific procedures to increase or decrease the investment of stocks in order to make the investment more profitable. Stocks must be maintained at an optimum level and should meet the needs of the company. Analysing the status of stocks by using approaches and techniques contribute to the diagnosis of the various phenomena in managing the stocks. Maintaining large inventory is difficult to control and the risk of deterioration of inventory increases. On the other hand, insufficient supplying will disrupt business continuity. Holding inventory is an important factor that contributes to the over-all performance of a business activity.

2. Problem Statement

Inventory management involves determining optimum inventory stock to be held. The stock level is influenced by sales estimation, production lead time, transport time, etc. The maximum stock limit is the quantity of inventory which must not be exceeded without certain instructions from the management. The minimum level of a certain item is called threshold inventory quantity, a level below which the number of items should not be allowed to fall [2]. An efficient stock management of inventories includes usage of proper control methods. 'Lean Concept' and 'Just-in-Time' inventory management were applied to adapt inventory movements in order to maximize the efficiency of the retail operating process at [3]. It aims to reduce inventory as much as possible in order to decrease the cost of holding inventory. This approach requires essential conditions to be applied properly such as reliable suppliers, high-quality workmanship, and steady production at the plant [4]. These conditions are difficult to meet, especially with the absence of appropriate infrastructure and cooperation with unreliable medium and small suppliers.

The specialized literature includes descriptions of cases where the Monte Carlo method is used in stock management control. The method helps in creating various supply scenarios for forecasting demand in the area of automotive aftermarket inventories [5]. The Monte Carlo method has some limitations, and the most important issue in our case is that it requires

a large data set for training. Consequently, it cannot produce satisfactory results unless a considerable amount of empirical data has been collected [6].

In this paper, the problem of lack of empirical data regarding inventory management is studied. The problem is investigated through creating a general regression model that can fill the gap of information shortage with regard to any individual product to enhance the entire performance of inventory management application.

3. Research Questions/Aims of the research

The purpose of the paper is to model a stock management application as part of a supply chain analytics application of business intelligence system by the means of data mining algorithms. The proposed application aims to enhance the ordering process and decrease the possibility of over-estimation and under-estimation of the demand level. When handling a large number and/or wide variety of products, a large body of input data is required in order to get a satisfactory result. Within this context, we investigate the applicability of cross prediction features in solving the problem of data shortage. Finally, a supply chain application is presented to support the stock management activity. The dataset of a Timber Export Company will be used for testing and validating the selected model.

4. Research Methods

Cross prediction is the process of predicting one series using the data of other correlated series. Cross prediction is an additional feature that aims to enhance the performance of time series method in case of data shortage. In this chapter, the potential of cross prediction feature is tested by comparing the results between simple time series and time series with cross prediction feature. The dataset of a Timber Export Company is used as case study. Microsoft time series algorithms that is part of SQL server Business intelligence platform is used for implementing the proposed application.

4.1 Microsoft time series algorithm and cross prediction

Microsoft time series algorithm is one of the methods that are implemented by SQL server analysis services. It provides multiple algorithms for forecasting continuous values such as ARIMA (autoregressive integrated moving average) and ARTXP (Autoregressive Tree Models with Cross Prediction) that have the ability to learn any regular patterns and

periodicity patterns [7]. Time series can be used in many applications such as forecasting sale over time. It doesn't require any additional input fields to predict the sale trend except the historical sale data and other field that is used as key and should be continuous or date-time type fields. The combination of the prediction data and the source data is called a series. Cross prediction refers to the process of predicting one series using the data of other series. It is an important feature that enables the usage of other related series to predict the result of one series based on correlations that exist between them. Cross prediction is useful for creating a general stable series and applying it to other sub series that are affected by high level of fluctuation. For example, the prediction of sale series for a particular product can be unstable due to the lack of enough quality data, so the general series can be used to predict a more stable series for each sale product.

Microsoft time series uses probabilistic methods such as the ARIMA model that is optimized for long-term prediction and ARTXP model that is optimized for short-term prediction. By default, Microsoft time series trains both models separately and then blends them to get a better result. The mixing rate of both methods can be controlled by the "PREDICTION_SMOOTHING" parameter. Also both methods can detect any periodicity that exists by cycling inputs such as field of month input by setting the "PERIODICITY_HINT" parameter. The data of series describes the change of a particular variable over a date or other unique numeric input. Prediction can be performed in several ways:

- Simple prediction – It is performed by training the model using the existing historical data and then using the trained model to forecast the following periods.
- Prediction using "EXTEND MODEL CASES" parameter – This feature enables to feed a model that is already training with new data without training it again, so the model will apply the new data to the previous learned model.
- Cross prediction – It uses a general model or aggregated mining model that keeps the overall trends and applies it to every individual data series to minimize their fluctuations.

4.2 Timber export company dataset as case study

Romania is one of the leading exporters of timber for several countries. Romanian timber exporters are currently facing several challenges that affect their profitability. One of the challenges in the financial markets is

to correlate historical information with forecasting data. At a firm level identifying all opportunities for optimizing the value chain and lowering the warehouse cost is a main requirement for an efficient stock management in the field of timber export. The sales forecast and inventory level were provided by managers and decision makers based on their experience, even though it is time consuming and inefficient with limited information about demand and sales history.

Timber products are characterized by their dimensions (thickness, width and length). The dimensions of timber and the required standard characteristics vary depending on clients and destinations countries. Some products dimensions are standardized and can be prepared in advance. The dataset consists of the transactions of five hundred different products and dimensions during a continuous period of four years.

4.3 Preparing the model

The objective of this section is to build a model that can forecast the sales amount for every product in the following period of time and comparing the predicted values with actual existing stock levels in order to manage the orders' operations. Microsoft time series is used to build the forecasting model that is based on auto regressive model. The historical sales data is used for training the model. The training data should be stable without many fluctuations to assure a good performance of the data mining model. Here we use the transactional data of a timber export company. These are wholesale transactions, so the number of sales transaction is small but their size is large. This characteristic makes the sales graph too fluctuating. In order to make the sales graph more stable, data are aggregated in bimonthly periods (every two months). A stable graph can increase the accuracy of the predicting model. Microsoft time series' auto regressive model named ARTXP algorithm is used. ARTXP algorithm is optimized for short term prediction. In the case of an order management application, we are interested in forecasting the short term sales volume to monitor any inventory shortage. Another way to forecast the sales is by using cross prediction. Cross prediction uses a general model or an aggregated mining model that keeps the overall trends and uses this generic trend to minimize the fluctuations of every individual data series. In our case, cross prediction is involved in building a model that aggregates the sale of all products and then uses the generic trend to decrease the sale fluctuations of every single product. Querying the analysis services is performed by DMX (data mining extension) script language. Computing and

saving results in the database engine can be realized by integration services or by any programming language such as visual basic for application (VBA). Connecting to analysis services and database engine is realized by any suitable connector such as OLE DB connector for windows operating systems.

4.4 Algorithms validation modelling

A data set is divided into two parts: training data that is used in learning the data mining model and testing data that is used for validating the trained model. There are many methods that can be used as performance measure for evaluating and testing the performance of the data mining model. One such method is “Validation standard error of the Mean” called also “Root Mean Squared Error (RMSE)”, see Equation 1 below. RMSE is one of the most popular formulas that are used to measure the error rate of a data mining model or regression model. It compares two models whose errors rates are measured by the same unit.

$$\text{Equation 1 - RMSE} = \sqrt{\frac{\sum_{i=1}^n (p_i - a_i)^2}{n}}$$

p = predicted target, a = actual target, n=number of products (tested items)

As seen on Figure 2, the performance of the model that used auto regressive with cross prediction is better than the simple auto regressive model. The main reason for this is the lack of enough training data for every single product, lack of data which increases the level of fluctuations. The cross prediction can adapt better to such conditions. For our dataset, we were concerned with making short term predictions for two month periods. The output of the forecasting model is compared with actual data and then the auto regressive model is fed with data for the following period and retrained again. Figure 2 shows that in almost each case study, the auto regressive model with cross prediction performs better with our dataset.

Figure 2. Comparing RMSE of auto regressive model and auto regressive with cross prediction

4.5 Supply and order management chain application

This section aims to present a supply and order management chain application that can benefit from the proposed model based on the cross prediction feature. This application is supposed to deliver deep customer insight and enable effective management of inventory and order booking. The proposed model can be used to predict the sales for every single product for the following period.

Supply chain analytics

Products forecasting detail list

Home

Order management dashboard

*difference quantity = existing inventory - sales forecasting (period of 2016/06 - 2016/08)

id	thickness	width	length	existing inventory	sales forecasting	differenceQuantity	
58	21	113	4	61.85	6.25	55.60	
25	21	93	4	223.52	122.06	101.46	
19	21	92	4	19.10	59.39	-40.29	
341	63	63	4	102.18	21.89	80.28	
14	21	60	3	0.06	2.77	-2.70	
55	21	110	3	17.26	3.20	14.06	
338	63	63	2	1.48	0.08	1.41	
47	21	95	4	32.18	172.11	-139.93	
77	21	115	4	5.13	90.25	-85.12	
24	21	93	3	29.52	30.40	-0.88	
57	21	113	3	4.90	1.55	3.36	
335	60	60	4	38.42	239.48	-201.06	
389	95	95	4	169.81	7.19	162.62	
255	42	190	4	91.55	77.26	14.28	
56	21	110	4	58.77	19.09	39.67	
307	45	245	4	14.82	2.04	12.77	
240	34	245	4	2.13	8.43	-6.30	
49	21	97	3	26.96	2.24	24.72	
340	63	63	3	18.82	33.47	-14.65	
339	63	63	2.5	2.87	1.22	1.65	
256	42	240	4	38.06	14.85	23.21	
334	60	60	3	141.70	24.47	117.22	

Figure 3. Products forecasting detail list

Figure 3 shows the products list with sales forecasting. Every product has an id and three dimensions (thickness, width and length) and a column for the existing quantity. A “forecasting sales” column is also added to this table. The “difference quantity” column is calculated by subtracting sales forecasting from existing inventory. Negative values indicate a lack of stock and positive values indicate that there is an extra quantity, more items than the expected sales. Figure 3 contains a list of all products but in many cases there is a small difference between values, which is negligible, so an inventory and order management dashboard is created to offer a summarized report. The dashboard filters the table of Figure 3 and displays the most important information for a more interactive report, see **Error! Reference source not found.3**.

Figure 4. Inventory and order management dashboard

Figure 4 includes the “Total sale” graph that aggregates the sales of all products per time. The algorithm can slice the graph into many dimensions (product type, thickness, width and length) by using the filters on the right side. There are two tables on the dashboard that filter the table of Figure 3 and display the most critical items of its content. The first table that is beneath the “Total sale” graph lists the top seven products that have more existing inventory than the necessary quantity predicted by sales

forecasting. The “extra quantity” column is calculated by subtracting sales forecasting from existing quantity. The second table lists the top seven products that have less existing inventory than the necessary quantity predicted by sales forecasting. The “required quantity” column is calculated by subtracting existing quantity from sales forecasting.

5. Findings

The paper aims to propose an inventory management application that can have a satisfactory performance even in the case of training data shortage. The dataset of a timber export company is used as case study. The company relies on wholesale export, so the monthly sales graph looks fluctuating as the order was prepared through a long period before it was finalized. Auto regressive model required stable data input for training. As a solution, the sales were aggregated bimonthly (60 days) as it is seen on the total sales graph of figure 3. The training data set consists of five hundred different products, so a time series is created for every product.

As it is seen on Figure 2, the performance of the model that used auto regressive with cross prediction is better than the performance of the simple auto regressive model. The possible reasons can be summarized as follows:

- Lack of enough training data for every single product; the absence of sufficient training data increases the level of fluctuations.
- The fact that cross prediction handles an extra assumption that takes into consideration the overall sale trend of all products.

6. Discussions

An inventory management application was implemented using time series and cross prediction. The model was trained using historical data. SQL server platform is used for implementing the model at server side. Microsoft Excel is used for implementing the graphical user interface of the inventory management application.

The training data includes transactions of five hundred different products during a continuous period of four years. The type of sale transactions is wholesale, so the number of sales transactions is small but their size is large. As a solution, the data were aggregated in two month (60 days) data sets in order to decrease the fluctuations of the sale transactions.

We observe that even with low fluctuations level, the results remain in favour of time series with cross prediction.

We can point out that using time series can limit the performance as it cannot handle extra assumptions that help to increase the performance of the model. Also a further evaluation is needed in order to determine the degree to which the company can benefit from this proposed solution.

7. Conclusions

It is important to identify all potentials in order to lower the warehouse cost and optimize the stock management. The purpose of the paper is to model a supply chain application that is based on data mining algorithms. An algorithm that has ability to adapt better to the existing data set can help to increase the performance of the proposed application giving more reliable results. It can also save the time and decision costs, so managers can focus on other skills rather than trying to estimate the future demand.

At our case study of timber Export Company, the type of sale transactions is wholesale, so the number of sales transaction is small but their size is large. This characteristic makes the sales graph too fluctuating. It was expected that the problem of value fluctuation and lack of training data can decrease the efficiency of the mining model, so a generic model that can apply to every single product was implemented using the cross prediction feature of Microsoft time series algorithm to fill the gap of data shortage. Two months' data sets were aggregated in order to decrease the fluctuations of data but the validation step in the "algorithms validation modelling" section shows that the performance of the cross prediction exceeds that of a simple auto regressive model. One reason is that cross prediction can handle extra assumptions that help to increase the performance of the model more than time series.

8. Acknowledgments

Part of this work is done under the auspices of the doctoral studies within the Doctoral School of Economic Informatics, Bucharest University of Economic Studies.

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