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ScienceDirect

Procedia Computer Science 177 (2020) 462–467

Procedia Computer Science

www.elsevier.com/locate/procedia

The 6th International workshop on Big Data and Networks Technologies (BDNT 2020)

November 2-5, 2020, Madeira, Portugal

Prediction models of demand in supply chain

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Abstract

In supply chain management, accurate demand prediction is a crucial issue that can decrease the inventory cost and obtain the desired service level. The purpose of this paper is to highlight some prediction models used on market demand forecasting and Performance measures employed for choosing the optimal model.

Keywords: Demand prediction; the root mean square error; Prediction models; supply chain

1. Introduction

In supply chain management, forecasting changes of market plays a very vital and crucial role not only in bringing the profit but in also maintaining the right quantity of products at the right time. It maintains an inventory level that is just enough to satisfy customer demand. It is one of the key driving factor in planning and decision making for any Supply Chain Management.

The efficiency or accuracy of the demand forecasting is taking as the major account for taking any major decisions such as capacity building, resource allocation, expansion and forward or backward integration etc [12].

During the past few decades, several forecasting methods proposed by the researchers to increase predictive accuracy. For instance, Grey System Model GM is employed to predict the Supply Chain demand of small

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10.1016/j.procs.2020.10.063

enterprises with insufficient related information. The results indicate that the applicability and robustness of grey prediction is acceptable, and more approaches are to be brought in to improve prediction accuracy and test the prediction differentials to actual demand [20].

And for predicting pricing [1] proposed a significant number of researches works pre-diction models for dynamic pricing in airlines. These models try to predict passenger demand for a single flight/route and market share of an individual airline. Most Products in the market are demand-driven. It is dependent on aligning all entities across the supply chain through information flows and it can always adapt to the changing market conditions thereby maintaining or reducing inventory levels and reduce the invasive problem of expedited orders. The common point of these products is that the maturity is short or absent. However, the maturity of some products is long and can not be ignored.

Demand Forecasting is basically a regression problem but time as the primary constraint. the extensive research stream of forecasting models was based on traditional algorithms including time series analysis, regression and grey models, as well as soft computing algorithms including genetic algorithms, fuzzy logic and other machine learning methods [14].

In the time series models the algorithms like ARIMA (Autoregressive Integrated Moving Average,) Moving Average, Weighted Moving Average, Croston Model, etc. and in the regression based models Support Vector Regression, Decision Tree Regression, Random Forest Regression, Linear Regression, Lasso Regression, Artificial Neural Networks, Recurrent Neural Networks etc . All the models tries to minimize the error or deviation from the actuals in the validation set [7].

The widely used time series models for forecasting purpose especially ARIMA model is generally applicable to linear modelling and it hardly captures the non-linearity inherent in time series data. Therefore, artificial neural network (ANN) is preferred as a superior forecasting model because it addresses the limitations of time series models by efficient non-linear mapping between input and output data [34].

Linear methods have dominated the field of time series forecasting for a very long period and found place in real-world applications. Most real-world problems have actually non-linear characteristics, which has drawn attention to non-linear techniques [2].

The popular traditional time series models are useful forecasting model when the data series is stationary in nature and follows linear pattern. These models necessitate the statistical information related to data pattern in order to make prediction [17].Linear regression methods depend on the past historical data and have a poor non-linear fitting capability, whereas ARIMA models do not consider external factors as input and generate results only on the basis of past and current data.

Nomenclature

A	radius of
B	position of
C	further nomenclature continues down the page inside the text box

1.1. Time Series Forecasting Model

Time series forecasting tries to predict the future points by analyzing observed points in the series. However, time series data might show different characteristics and show increasing or decreasing trends. Some time series data have seasonal trends in which variations are specific to a particular time range,. On the other hand, some time series data are not seasonal, such as stock market data. Moreover, time series data might show different level of volatility [7].

- Arima

The classical time series forecasting model is auto-regressive (AR) proposed by British statistician U. Yule. The AR model is a representation of stochastic process, and its output variables are linearly dependent on their previous values and random conditions.

Based on this classical model, other improved AR models, such as the moving average (MA) and the autoregressive moving average (ARMA) are proposed [26].

ARMA is a model that uses the dependency between an observation and a residual error from a moving average model applied to lagged observations. However, the ARMA model is not suitable for non-stationary time series data. In other word, It can't use the difference of raw observations in order to make the time series stationary. Due to this reason, the Autoregressive Integrated Moving Average model (ARIMA) is pro-posed later. ARIMA models demonstrated the potential to predict stock prices satisfactory on short-term basis [3].

The model can also contain seasonal component of time series data analysis multiplicative Seasonal Auto-Regression Integrated Moving Average (SARIMA) [32]. ARIMA give good accuracy in forecasting relatively stationary time series data. However it makes a strong assumption that the future data values are linearly dependent on the current and past data values [7].

The effect of autoregressive and moving average parameter on bullwhip effect BWE is analysed. It has observed that BWE does not always exist within the supply chain. It occurs only when the autoregressive coefficients is higher than the moving average coefficients [17].

- EWMA

Exponentially weighted moving average (EWMA) methods have proved to be useful tools for capturing such time variation in a parsimonious and effective way [20].It is shown that the exponentially weighted moving average (EWMA) provides a better estimate of the arrival rate than the simple moving average (SMA) [15].

- Croston's method

Croston's method, which applies the exponential smoothing separately to the intervals between non zero demands and their sizes [9].

In fact, it is based on exponential smoothing. In particular, it involves separate simple exponential smoothing of the demand size and the time. It is the most widely used approach that addressed the issues related to intermittent demand forecasting [30].

1.2. Regression

- Neural networks

An artificial neural network is a mathematical tool and it is inspired by the working of biological human brain system where neurons are the basic processing units [22].
These basic units receive information at input nodes, process them internally and generate a response at the output node [13].

In these networks, the individual elements (''neurons'') are organized into layers in such a way that output signals from the neurons of a given layer are passed to all of the neurons of the next layer. Thus, the flow of neural activations goes in one direction only, layer-by-layer. The smallest number of layers is two, namely the input and output layers. More layers, called hidden layers, could be added between the input and the output layer. The function of the hidden layers is to increase the computational power of the neural nets [24].

The superiority of ANN is demonstrated in many fields, such as weather forecasting, bankruptcy forecasting, foreign exchange rate forecasting, stock price forecasting, electric load forecasting, car sales forecasting, etc [30].

A neural network, due to its non linearity and capability of adaptive information processing, is one of the most popular algorithms in current use. The superiority of ANNs is demonstrated in many fields, such electricity forecasting[13].

Neural network can easily learn complex relationships and has strong decision-making capability under uncertain conditions [26].

- The Support Vector Machine (SVM)

The Support Vector Machine (SVM), machine learning algorithm, was invented by Vapnik on 1998. Its robust performance with respect to limited, sparse and noisy data is making it widely used in many applications such face recognition, classification and regression prediction. The SVM model has also been utilized in airport capacity classification pre-diction [8]. Although SVMs were originally proposed to solve linear classification problems, they can be applied to non-linear decision functions by using the so-called kernel function trick [5].

- The decision tree

A decision tree is a data mining algorithm that is widely used for both classification and regression problems [17]. Initially, the decision tree was proposed to solve classification problems, (Quinlan, 1986) . It was then extended to create a regression tree, capable of supporting regression analysis and classification [18].

The decision tree constructs classification models in the form of trees. Each interior node in these trees represents one of the input variables, and it has a number of branches equal to the number of possible values of that input variable. Each leaf node holds a value of the target attribute. The leaf node represents the decision made based on the values of the input variables from the root to the leaf [30]

1.3. Combined methods

In the past, time series forecasting has become an important research area .Several different time series forecasting approaches have been proposed, However, since the time series data, such as financial data, wind data, seismic data, etc., usually are non-linear and non-stationary, these existing approaches can not effectively extract enough sequence data features to achieve accurate time series forecasting results[26]. According to [26]. Artificial neural network (ANN) seems more effective and capable to han-dle the non-linearity and generates an accurate forecast. However, it suffers from over fitting problem thus reducing the accuracy of load forecasts. To overcome this problem, a hybrid methodology is used.

A large number of comparisons between neural networks and traditional time series forecasting techniques have been made in order to determine the potential power of neural networks in time series forecasting. Even if most of these studies have found that neural networks have superiority over traditional techniques [2].
SVM is one of the most robust and accurate methods and is a highly effective model in solving non-linear problems. The SVM can achieve better experimental results than the previous ARIMA model when time series data is very complex [26]. One of the major drawbacks of SVM is higher computational time for the constrained optimization programming [26].

Ref [4] presented an integrated genetic algorithm (GA) and artificial neural network (ANN) to estimate and predict electricity demand using stochastic procedures.
the performance of neural network depends on the sample size and noise level for linear problems [11].They proposes a hybrid model that combines the ARIMA model and neural network. This hybrid model can obtain better forecasting precision on both linear and non-linear data with better performance.

2. Comparing forecasting methods

There are many statistical indices to measure the difference between two time series that are used by scientists and engineers to assess the quality of forecasting methods, including the mean absolute error (MAE), mean squared error (MSE), mean squared error (MSE), and the standard deviation of error (SDE). The most popular is Mean Absolute Error (MAE), Mean Squared Error (MSE) and Mean Absolute Scaled Error (MASE).

The MAE is a measure of difference between two continuous variables. It measures the average magnitude of the error. Mean squared error (MSE) or mean squared deviation (MSD) is a measure of the average of the squares of the errors. The RMSE rep-resents the square root of the second sample moment of the differences between predicted values and observed values or the quadratic mean of these differences.

Historically, the RMSE and MSE have been popular, largely because of their theoretical relevance in statistical modelling. However, they are more sensitive to outliers than MAE [22]

The MAE measures the average magnitude of the errors in a set of forecasts, without considering their direction whereas The RMSE is a quadratic scoring rule which measures the average magnitude of the error. The RMSE is likely to be used for data that has the undesirable large error. And both MAE and RMSE can be used together to diagnose the variation in the errors in a set of forecasts [22].

3. Conclusion

This paper investigated the problem of demand prediction models in supply chain. The traditional forecasting methods can effectively model linear time series, but to accurately forecast non-linear is difficult. Recently, hybrid models have been developed to enhance the forecasting accuracy. In future studies, research efforts will be dedicated to introduce other machine artificial intelligence methods in order to deal with complexity supply chain of the proposed.

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