An Fully Automated Ai Based Trading System

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Abstract- *Generating reliable and meaningful product demand predictions is an open challenge in the industrial environment.. Demand forecasting is still an active avenue of research since it significantly affects business profitability because of uncertainties related to demand predictability, high product variety, and supply fluctuation. This paper deals with a practical real-life case study of a leading international company. Particularly, we investigate the demand forecasting for the industrial products .The proposed implementation was how the historical demand data could be utilized to forecast future demand and how the automatic buy and selling of the stocks performed and it also able to do portfolio management. The historical demand information was used to develop several autoregressive integrated moving average (ARIMA) models by using Box–Jenkins time series procedure and the adequate model was selected according to four performance criteria: Akaike criterion, Schwarz Bayesian criterion, maximum likelihood, and standard error. The selected model corresponded to the ARIMA (1, 0, 1) and it was validated by another historical demand information under the same conditions. The results obtained prove that the model could be utilized to model and forecast the future demand in this food manufacturing. These results will provide to managers of this manufacturing reliable guidelines in making decisions.*

Keywords- Algorithmic trading, Demand forecasting, Automated buy and sell stocks, Portfolio management.

I. INTRODUCTION

In today's competitive manufacturing environment, and to respond quickly to shifting demand, organizations are moving toward a more effective demand-driven supply chain. The market has evolved into a "pull" environment with customers more demanding and discriminating, dictating to the supplier what products they desire and when they need them delivered.

Demand forecasting is crucial to inventory management. Inventory stock levels depend on demand's forecasts. In fact, inaccurate estimation of demand can cause significant costs to pay, which proves that the process is not improved. Consequently, many systems incur large investments in inventories to avoid "stock outs." A further complicating issue is that some demands can be intermittent demands, which means that there is a time when we have no demand and other time when we have successive demands. Intermittent demands present many difficulties for traditional statistical demand forecasting methods.

For most organizations, managing demand is challenging because of the difficulty in forecasting future consumer needs accurately.1 More than 74 % of the responds in a research survey, shows the poor forecasting accuracy and demand volatility as the increasing major challenges to supply chain flexibility.2 Best performing companies tend to improve supply chain flexibility, agility, and responsiveness through improving forecasting accuracy throughout the long supply chain.2 The managers in these companies must link forecasting to improvement goals and use past performance to avoid past errors and then reach a high level of efficiency.3

Researchers came out with much work in the forecasting domain and suggested many methods among which we find two principal approaches much utilized: time series approaches and artificial neural network (ANN) techniques.

ANN models have been successfully involved in forecasting demand. These models are characterized by intervals with considerable variation of demand. ANN approach is considered as an alternative when it comes to the ability to capture the nonlinearity in data set.

ANN is applied in different fields. Gaafar and Choueiki4 applied a neural network model to a lot-sizing problem as a part of material requirements planning for the case of deterministic time-varying demand.5

To compare ANN and ARIMA method and to assess the performance of the two methods, a study related to electricity demand has been done by Prybutok et al.6 to forecast a time series. ANN seems to be outperformed. Another study was done by Ho et al.7 using simulated failure time of a compressor to determine the more accurate forecasting model. The two methods are used to forecast the failure of the system.8

Aburto and Weber9 combined the two forecasting methods which are ARIMA and neural networks. The efficiency of the hybrid model is compared with traditional forecasting methods.10

This brief review of the literature shows that ANN is a strength tool aiming at the modeling of any time series. Nevertheless, in our article, we will test the ARIMA model at first to prove its ability to make accurate forecasts in the food company as a priori study.

In our article, we are interested the most in the time series approach: autoregressive integrated moving average (ARIMA) models,11–14 multivariate transfer function models,11,15 dynamic models,11 and generalized autoregressive conditional heteroskedasticity (GARCH) models16 have also been proposed. Certainly, ARCH and GARCH models are increasingly utilized and are considered as important tools in the analysis of time series data, especially in the case of financial applications. But, they are specifically dedicated to the analysis and forecasting of volatility which is not our aim in this current article.

In all sectors, demand forecasts are of great importance. Indeed, predicting the demand facilitates the decision on the amount to produce and thus on the supply of the raw material and inventory management. In our case, we will work in a food company—which requires more than in other sectors—forecasts that are very reliable and accurate as long as it will affect the production of perishable goods. Besides, products in a food company having steady predictable demand need efficient supply chains that shorten lead times and support limited inventory.

A robust supply chain management system requires the presence of managers who are aware of the necessity of collaboration between different functions: planning, procurement, manufacturing, and logistics. Let's take the example of the collaboration of planning function with suppliers. Over time, we feed our database to build a history that will be used to make our forecasts. After developing our model, which is the purpose of our article, we will easily have the planned application transmitted to the planning function. The latter carries out its production plan related to suppliers

The aim is therefore to devise an optimal production plan based on accurate forecasts to minimize the total production cost composed by the procurement, processing, storage, and distribution costs. Expected benefits from these forecasts are reduced inventories, lower supply chain costs, increased return on assets, greater customer satisfaction, and reduced lead times. However, this optimal production plan should meet different company constraints among others: production capacity, minimum production lots, and so on.

We will be interested in the evolution by making forecasts of the demand in a Moroccan food company. To achieve its objectives, the company must rely on precise forecasts. In this context, our article aims mainly to study the demand to provide precise forecasts and to respect the permissible error margin. The main idea is that forecasting accuracy drives the performance of inventory management.

The aim of the present study is the modeling and forecasting of demand by using Box–Jenkins time series approach, especially the ARIMA. To achieve this goal, we used large and consistent historical demand data: from January 2010 until December 2015. Several ARIMA models were developed and evaluated by four performance criteria: Akaike criterion (AIC), Schwarz Bayesian criterion (SBC), maximum likelihood, and standard error. The adequate model was validated by new historical demand data under the same conditions. In this article, the second section presents a literature review about demand forecasting studies. The third section is consecrated to the results and discussions of our case study. Finally, the article concludes with a summary and the future work.

EXISTING WORK

In terms of overall profitability, annualized volatility, and risk-adjusted performance, the ARIMA-SVM model outperforms the other two hybrid models and different independent models.

Instead of minimizing the training error, SVM minimizes an upper bound on the generalisation error.

The ARIMA-SVM hybrid model could probably be not use by policy in forecasting financial and economic data, apart from traders.

EXISTING METHODS

The goal of this study was to predict stock market movement using machine learning and deep learning algorithms. Four groups of stocks from Tehran's stock exchange, namely diversified financials, petroleum, non-metallic minerals and basic metals were chosen. The dataset was based on ten years' worth of historical data with technical features. 9 machine learning models(Decision Tree, Random Forest, Adaboost, XGBoost and SVC) plus two deep-learning networks(KNN and Logistic Regression) have been implemented in our program.

SUPPORT VECTOR MACHINE

Support vector machines are a class of advanced statistical learning algorithms originally developed for the purpose of classification and regression in pattern recognition problems. They are very successful at solving small-sample high-dimensional problems that occur in vision, speech, text analysis and machine learning.Machine learning is quickly becoming the mainstream technology of face recognition. In this implementation, we use features extracted from faces and the Support Vector Machine (SVM) to distinguish between different people on our database by finding a hyperplane in its two-dimensional space. Due to the limited number of training data, SVM may classify samples outside the training set more correctly than those included in it..Therefore, we choose the line that is farthest away from any of our data points—the support vector. This method has the strongest ability to predict new entries. The above method can be applied to three-dimensional or even higher dimensional space, but the boundary that is found becomes a plane in those cases.

DISADVANTAGES

- Slow data processing
- Lot of paperwork
- Time consuming
- Less accurate.
- Poorer performance for long term forecasts.
- Cannot be used for seasonal time series.
- Less explainable than exponential smoothing

II. PROPOSED SYSTEM

This project addresses different problems in the management of direct sales and purchases. In this system we have classified individual aspects that affect both areas of management.Proper stock management is important for retail businesses, which often handle transactions relating to consumer goods. Without proper stock control in such a business, it may run out of an important item—and lose potential sales as a result.A good stock management system will alert the wholesaler when it is time to record. Automated Stock Management System also help minimize errors while recording large shipments.

PROPOSED SYSTEM IMPLEMENTATION

The aim of the present study is to model and forecast demand by applying a time series methodology, especially Autoregressive Integrated Moving Average (ARIMA) models.In order to meet this goal, we used large and consistent historical demand data: from January 2010 until December 2015. We developed several ARIMA models using four performance criteria—the Akaike criterion (AIC), Schwarz Bayesian criterion (SBC), In this article, the first section presents a review of previous research on demand forecasting methods. The second section describes our study and its results—we found that maximum likelihood estimation and standard error are appropriate for this problem because they better fit the historical data when compared to other possible models (e.g., exponential smoothing). We then applied these tools to new data collected under the same conditions in order validate their adequacy.The third portion of the article presents our findings and our conclusions.

ADVANTAGES

- Arima model It is widely used in demand forecasting, such as in determining future demand in food manufacturing. That is because the model provides managers with reliable guidelines in making decisions related to supply chains.
- ARIMA models can also be used to predict the future price of your stocks based on the past prices.
- Expected benefits from these forecasts are reduced inventories, lower supply chain costs, increased return on assets, greater customer satisfaction
- Inventory management software can also be used to calculate costs.
- Accounting systems always have an accurate assessment of the value of the goods.
- Inventory management Organizations from small to large businesses can make use of inventory management to track their flow of goods.

ALGORITHM

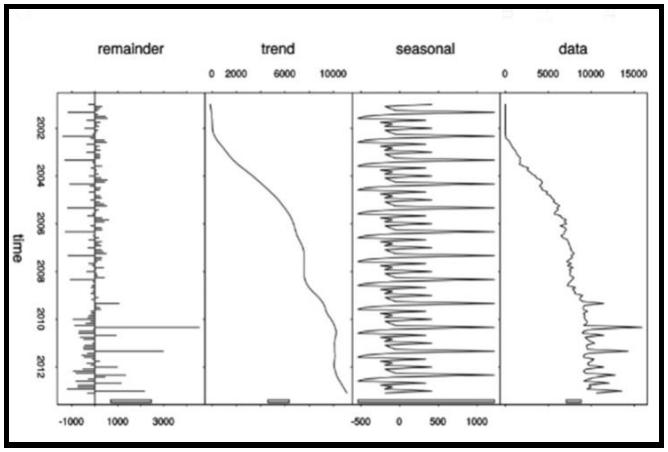
An autoregressive integrated moving average (ARIMA) is a statistical model that uses time series data to forecast future trends.

ARIMA Model Python Example-Time Series Forecasting

The ability to make predictions based upon historical observations can create a competitive advantage. For example, if an organization has the capacity to better forecast sales quantities of a product, it will be in a more favourable position than its competitors and thus likely reap greater rewards for having made such accurate decisions about inventory levels.. This can lead to a more liquid pool of cash, decreased working capital and happy customers by clearing out the back log.In the field of machine learning, there's a set of methods and techniques particularly well-suited to predicting dependent variables. In this article we'll cover Autoregressive Integrated

Moving Average (ARIMA).A time series is a set of data points indexed in order by date (or other category).

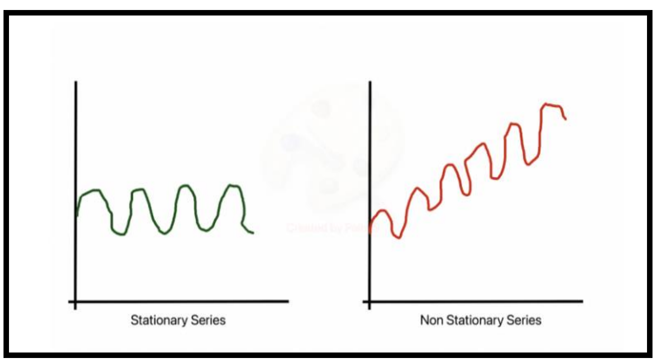
- **Trend:** Upward & downward movement of the data with time over a large period of time (i.e. house appreciation)
- **Seasonality:** Seasonal variance (i.e. an increase in demand for ice cream during summer)
- **Noise:** Spikes & troughs at random intervals



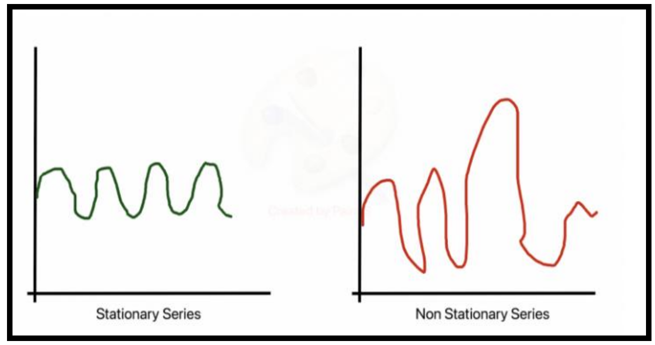
Before applying any statistical model on a time series, we want to ensure it's stationary.

What does it mean for data to be stationary

The meaning of the series should not be a function of time. The red graph below is not stationary because the mean increases over time.



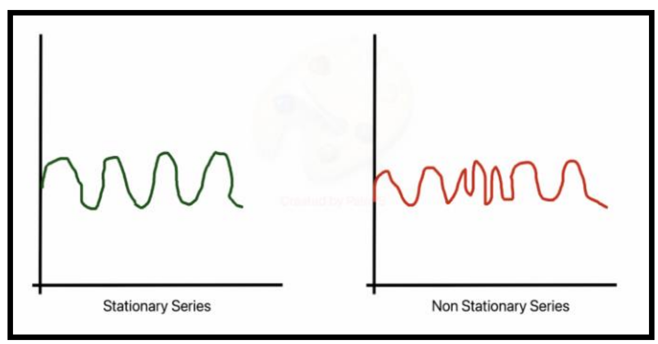
The variance of the series should not be a function of time. This property is known as homoscedasticity. Notice in the red graph the varying spread of data over time.



Finally, the covariance of the ith term of the (i+m)th term should not be a function of time. In the following graph, you will notice the spread becomes closer as the time inceases. Hence, the covariance is not constant with time for the red series.If a time series is stationary and has a particular behaviour over a given time interval, then it is safe to assume that it will have same behaviour at some later point in time. Most statistical modelling methods assume or require the time series to be stationary.

III. SYSTEM TESTING

Testing is a process of discovery. The purpose of testing is to find errors, not create them. Testing provides a way to check the functionality, Software testing is used to check whether the program meets its requirements and won't fail in an unacceptable way.. There are many different types of tests, each one designed to check a specific feature or aspect.



TYPES OF TESTS

Unit testing

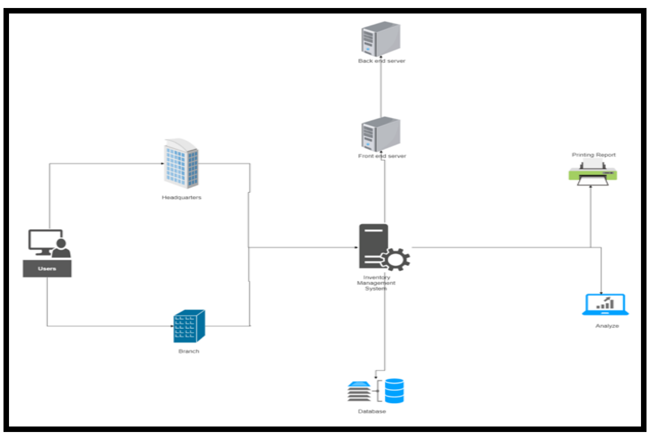
Unit testing validates that the internal program logic is functioning properly, and that inputs produce valid outputs. All decision branches and code flows should be validated to ensure proper functioning of all software units in an application Unit tests are performed after completion of individual functions, before integration. Structural testing relies on knowledge of its construction and is invasive; it checks the system as a whole during each build/release cycle. Basic unit tests test specific business processes—one at a time.Unit tests can be used to ensure that each unique path of a business process performs accurately, and contains clearly defined inputs and expected results.

Integration testing

Integration tests can be used to confirm that integrated software components work together as expected. These tests are event-driven and focus on the fundamental functions of an application or operating system, rather than its user interface elements.Integration tests prove that the combination of individually tested components works as expected.Integration testing is specifically aimed at exposing the problems that arise from the combination of components.

IV. SYSTEM DESIGN

ARCHITECTURE DIAGRAM



This is an illustration of a Network Architecture for Inventory management system. Network architecture may help with security, which is becoming more critical as more consumer devices connect to the network. The network's design and protocols must facilitate rapid and efficient user detection and authorisation. The Open Systems Interconnection Model, or OSI, is used in the majority of network topologies. This conceptual paradigm divides network jobs into seven logical levels, from the most basic to the most complex. The Physical layer, for example, is responsible for the network's wire and cable connections. The uppermost tier, the Application layer, has APIs for application-specific tasks such as chat and file sharing. Download this free EdrawMax template to easily create your own network architecture!

V. CONCLUSION

Forecasting demand is an important part of supply chain management. As a result of its integration with other business functions, it is among the most important planning processes that a company can use in the future. Using a Box-Jenkins time series approach, we developed an ARIMA model to model demand forecasting of the finished product in a food manufacturing industry. Data from historical demand were used to develop several models, and the best one was selected on the basis of four performance criteria: SBC, AIC, standard error, and An interval of confidence based on maximum likelihood. The model that we selected and which minimizes the four previous criteria is ARIMA (1, 0, 1). The results obtained proves that this model can be used for modeling and forecasting the future demand in this food manufacturing; these results will provide to managers of this manufacturing reliable guidelines in making decisions.

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