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Demand Forecasting Using Fuzzy Methods Approach in Supply Chain Management

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Abstract: **Modern businesses are confronted with a variety of challenges in a challenging climate. Companies that succeed are more flexible, and they immediately adopt new or revised concepts for corporate governance. As time goes on, they begin to use these techniques in their everyday work. For a company, forecasting is a vital part of its operations. This is regarded as the most basic input in the SCM department and the company. In the context of SCM functions, companies whose chronological development is close to that of the SCM evolution begin to pay attention to the forecast. This research reveals that the firm's organization can use the barriers and few practical solutions for forecasting. However, retail organizations are continuously looking for a forecasting approach that will allow them to keep their purchasing and sales in balance.**

Keywords: Supply Chain Management, Forecast, Machine Learning.

I. Introduction

Demand planning is a supply chain management process that involves forecasting the demand for products to ensure they can be delivered and satisfy customers. The goal is to find a balance between having enough inventory to meet customer needs without having a franchise. Demand forecasting uses historical data and other information to make estimates of future customer demand over a defined period of time. The process of producing an estimate of forecasted demand of customer by using the historical data of sales is called Demand forecasting. The technique gives an estimation of services and goods that will be purchased by the customers in the near future.

Forecasting demand is an essential part of the supply chain process. It is the basis of almost all supply chain decisions. Demand forecasting is undoubtedly important, but it is also one of the most difficult aspects of supply chain planning. The question is often volatile, so the question involves both an art and a science.

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All operational and strategic plans are dependent on the demand forecasting. forecasts are an important part in management of supply chain from reduction of cost to satisfaction of consumer. It Help to companies in completing orders on time, avoiding the unnecessary costs of inventory and planning for price fluctuations.

The forecasts should include an analysis of their potential errors. In general, the longer the forecast horizon, the less accurate the forecast is. Converting an expected amount to a known amount can often be beneficial. Information systems play a key role, especially in operational planning and administration. Almost all companies need to start and run their own business without having relevant information from Enterprise Resource Planning (ERP) systems.

There are multiple techniques of predicting the demand. On the used model of forecast may categories the forecast technique. Using several demand forecasts is preferred as the best for practice and gives a enhanced idea for your sales of future. The contrast between different forecast can also be described by using the several models of forecast.

The simplest variety of forecasting is Passive demand forecasting. The data of sales done in past is used in the future sales prediction. The Active demand forecasting is selected as the best technique for just starting and growing businesses. The model of active forecasting takes into account your market research, expansion plans and marketing campaigns. The demand forecast of short-term is only for the next 3 to 12 months and useful in your supply chain management just in time.

II. Literature Review

Rajkumar Sharma, Piyush Singhal (2019) [1] offered in this article to demonstrate how to forecast the demands of commercial lubrication tests. Quality, affordability, and delivery timeframes are all important factors in determining demand for most industrial lubricants, according to the authors. These aspects are investigated and contrasted with those of other competitors that deal with similar products. Quality is represented by three fuzzy parameters, which are as follows: lower, equal, and greater quality. The costs are associated to 3 linguistic terms, namely, high, low, equal, as shown in the table below.

Gunawan et al. (2018) [2] developed a program to estimate the value of sub-criteria using the fuzzy AHP technique, to pick the optimal provider using the fuzzy TOPSIS method, and to assign quotas to each supplier using the fuzzy MOLP technique. The model demonstrates with assurance that the fuzzy AHP methodology could be used to produce the superior product of the variables as the best sub-criterion by generating the superior output of the variables as the best sub-criterion (with a value of 0.221). In order to contact the supplier, the fuzzy TOPSIS methodology can be employed, and the fuzzy MOLP approach can be used in order to determine the quota distribution.

HaixiaSang's et al. (2018)[3] investigated the inventory problem in the rental housing industry. Because the rental unit is a "traffic" product, it presents a more difficult inventory management challenge than most other items do. Using a systematic and flexible approach, this study suggests a process that successfully come equipped with essential decision-making resources to help them evaluate and verify inventories concerns in the distribution network of rental housing. A number of inventory elements, such as the forecasting method used, the time period, the initial inventory, and the supply indication, are taken into consideration by the proposed method. Furthermore, the technique is tested on an actual supply chain of rental housing in order to determine its efficacy and efficiency. Moreover, the suggested technique has proven to be both practical and useful in assisting managers in making on-going choices in their organisations.

GokhanMertYagli et al. (2018) [6] used hierarchical models to model the forecast at several geographic and temporal scales. Directly forecasting regional time series or aggregateing individual forecasts for sub-areas can be used to produce global forecasts for regions in a geographical hierarchy. Total inconsistency arises as a result of this, as it is possible that the model's predictions will diverge. Because of this, the practise isn't the best. Consistent predictions are generated through reconciliation, a statistically optimal aggregation.

Lindsay R. Berry et al.(2018) [7] proposed a brand-new Bayesian approach to forecasting consumer spending. We use dynamic counter models to anticipate the transactions of individual customers and introduce novel cascaded dynamic models to predict the quantity of products per transaction in order to focus on multi-step forecasting of daily sales of various supermarket items. Predictors of price, time, action, unpredictability and other sales aspects can be included in these transaction and sales models.

Britta Gammelgaard et al. (2018) [8] aimed for better knowledge of Supply Chain Management (SCM) abilities by categorising them into human and organisational components and assessing their influence on the supply chain performance outcomes in a quantitative manner. The hypothesized relationships are investigated using structural equation models and mediation analyses based on data from 273 CEOs participating in an international survey of this nature. Supply chain management and human resource management are two areas where it makes use of knowledge management theory and literary currents of individual competences.

ChristophFlöthmann et al. (2018) [9] analyzed the careers of 307 supply chain managers (SCEs). Motivated by career theory, our ideas create new insights into the educational background and careers that lead to SCE positions. Based on an optimal matching analysis, we can distinguish six career models for SCEs. They differ in terms of previous work experience, training and time needed to reach a position of leadership. By characterizing the antecedents and career paths of CEMs, we show that Supply Chain Management (SCM) is a truly cross-functional profession.

Rajeev A et al. (2017) [10] concerned about the exponential growth of the subject. This article seeks to understand the evolution of sustainability issues by analyzing trends in different sectors and economies and using different methods. A complete thematic analysis was conducted for 1068 articles filtered from 2000 to 2015 to highlight the evolution and importance of the knowledge stock.

III. Methodology

Having the ability to anticipate the future based on prior data is a crucial tool for assisting individuals and organisations in making decisions. When it comes to complex systems, TSF (Time Series Forecasting) is a technique that focuses solely on historical trends of the same phenomenon in order to anticipate their future behaviour. The forecasting process is an essential component of supply chain management. Traditional forecasting approaches are subject to significant restrictions that have a negative impact on forecasting accuracy. Because of their ability to handle non-linear data, artificial neural network algorithms (ANN) have proven to be effective tools for anticipating demand.

Optimization problems are most typically solved using neural networks, which are the most widely utilised computer technology in this field. This is extremely essential in the context of supply chain management. The usage of neural networks to solve problems such as supply chain management optimization is something we've looked into in the past. Load planning, warehouse management, route selection, and other tasks are all part of the job. Some of these issues are critical to the development of the company's logistics information system. Others are merely inconveniences. Furthermore, when compared to other technologies, the neural network is extremely adaptive and provides for the rapid resolution of new boundaries in real-time processing activities.

The proposed methodology works in different levels as discussed below:

i. The dataset is taken.
ii. Select Parameters for Fuzzy Rule Designing.
iii. Weekly Forecasting Demand for Different Shoe Size with item Code.
iv. Determine the shortfall for future weeks.

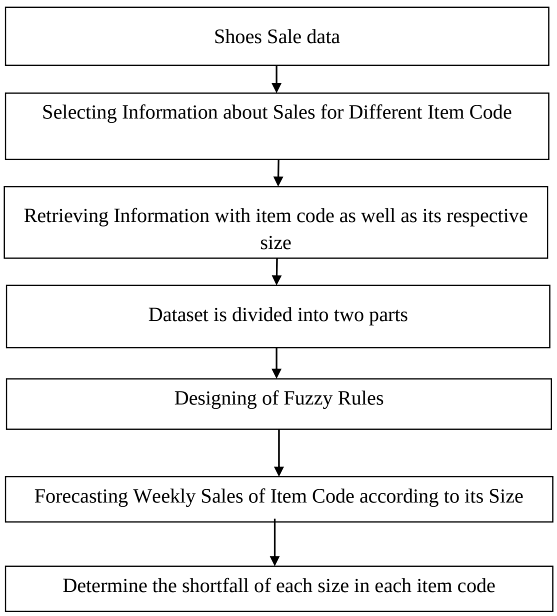


Figure 1: Flow Chart of Work

Based on the adaptive neuro-fuzzy inference system (ANFIS), which has universal approximation capabilities and is therefore widely utilised for function approximation, the methodology is described below. In the ANFIS network, the learning power of neural networks and the knowledge representation of fuzzy logic are combined.

It has been applied to neuro-fuzzy systems in order to reduce their computational complexity using the ELM idea. EL-ANFIS makes use of the Takagi–Sugeno–Kang (TSK) fuzzy inference system, which produces accurate models of the environment.

Extreme learning ANFIS (ELANFIS) has demonstrated promising results in the analysis of regression situations.

In total, there are five layers: the firing strength computational layer, the firing strength normalization layer, the consequent parameter layer, the output and the input layer.

Input layer

Nodes of this layer represent an input variable.

Fuzzification layer

This layer is made up of L clusters, which correspond to the number of fuzzy rules in the layer. Each cluster contains n nodes, each of which represents a fuzzy membership function for a set of n inputs. When constructing this network's membership functions, two-sided Gaussian functions are employed. In mathematics, two-sided Gaussian functions are denoted by the following mathematical expression:

$$g(x_j, c_{ijL}, \sigma_{ijL}, c_{ijR}, \sigma_{ijR}) = \begin{cases} e^{\frac{-(x_j - c_{ijL})^2}{2\sigma_{ijL}^2}}, & x_j < c_L \\ 1, & c_L \le x_j \le c_R \\ e^{\frac{-(x_j - c_{ijR})^2}{2\sigma_{ijR}^2}}, & x_j > c_R \end{cases}$$

where c_{ijL}, σ_{ijL}, c_{ijR}, and σ_{ijR} are the premise parameters.

cijL and cijR are the left and right centers, respectively

σijL and σijR are the standard deviation on the left side and right side, respectively, of the membership function for the jth input variable in ith rule.

The variables of the hypothesis are chosen at random from among the cluster centres that have been discovered. The membership function for the input x_j is calculated by solving the equation above for the input x_j.

The firing intensity of the regulations can be computed using the formula below.

$$w_i(x) = \mu_{1ci}(x_1) \otimes \mu_{2ci}(x_2) \otimes \cdots \otimes \mu_{nci}(x_n)$$

where ⊗ indicates 'and' operator of the fuzzy logic.

Firing strength normalization layer

The firing strength obtained in the previous layer is normalized using equation

$$\bar{w}_i(x) = \frac{w_i(x)}{\sum_{k=1}^{L} w_k(x)}$$

The consequent part of the fuzzy rule is obtained by a neural network with p_{ij} as the weight parameters.

Consequent parameter layer

This layer is comprised of a neural network with the weight assigned to it based on the consequences of fuzzy rules. The extreme learning algorithm is used to determine the parameters that result from this. The output of the layer is calculated using the equation shown below.

$$\beta_i = p_{i0} + p_{i1}x_1 + p_{i2}x_2 + \cdots + p_{in}x_n$$

where p_{ij} (j=0, 1, 2, …, n) are the consequent parameters.

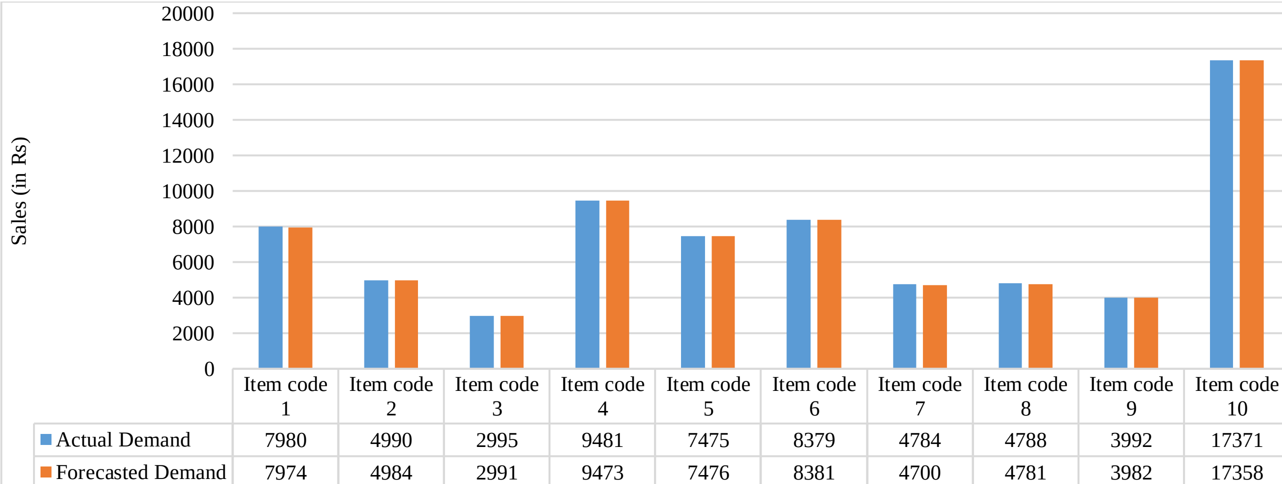
Output layer

The defuzzified output of the overall network is obtained by equation below.

$$y = \sum_{i=1}^{L} \beta_i \bar{w}_i(x)$$

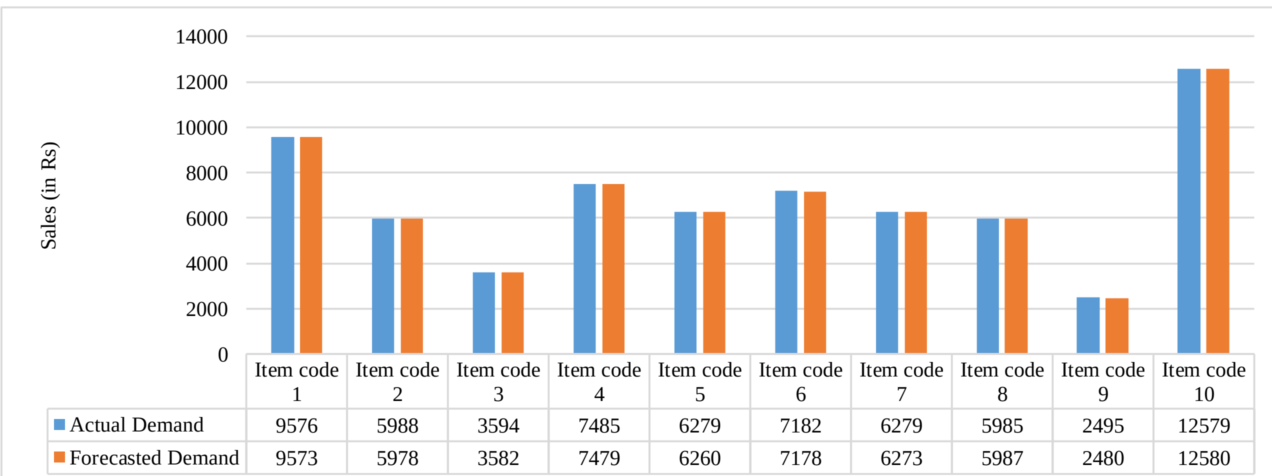
IV. Result Analysis

Input for the demand forecasting model are previous shoe sale (2016-2019) and the output of the model corresponds to the expected demand for the monthly sale. M-file programs are designed to predict demand with EL-ANFIS. The proposed methodology is analyzed monthly.



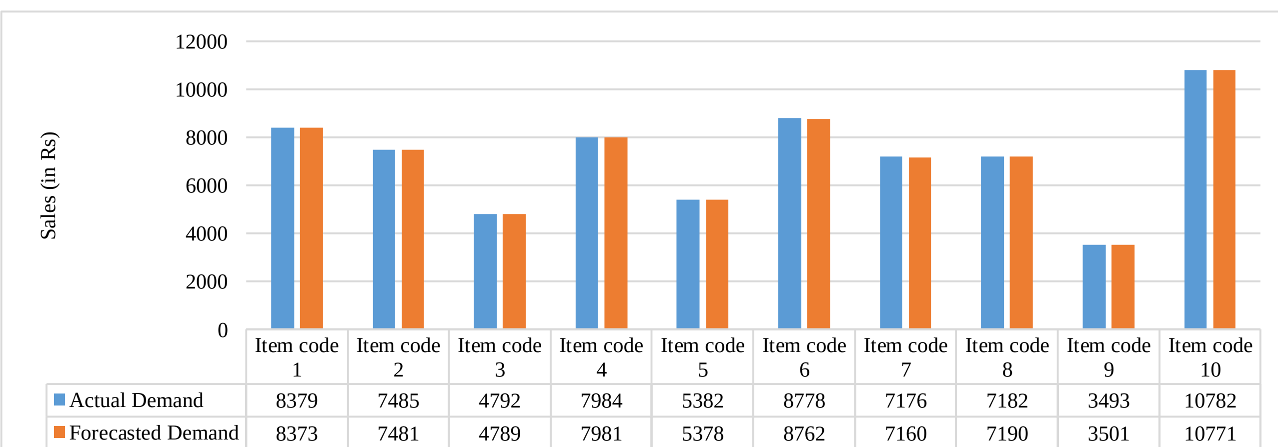
	Item code 1	Item code 2	Item code 3	Item code 4	Item code 5	Item code 6	Item code 7	Item code 8	Item code 9	Item code 10
Actual Demand	7980	4990	2995	9481	7475	8379	4784	4788	3992	17371
Forecasted Demand	7974	4984	2991	9473	7476	8381	4700	4781	3982	17358

Figure 2: Item Sales Forecasting for June 2018



	Item code 1	Item code 2	Item code 3	Item code 4	Item code 5	Item code 6	Item code 7	Item code 8	Item code 9	Item code 10
Actual Demand	9576	5988	3594	7485	6279	7182	6279	5985	2495	12579
Forecasted Demand	9573	5978	3582	7479	6260	7178	6273	5987	2480	12580

Figure 3: Item Sales Forecasting for May 2018



	Item code 1	Item code 2	Item code 3	Item code 4	Item code 5	Item code 6	Item code 7	Item code 8	Item code 9	Item code 10
Actual Demand	8379	7485	4792	7984	5382	8778	7176	7182	3493	10782
Forecasted Demand	8373	7481	4789	7981	5378	8762	7160	7190	3501	10771

Figure 4: Item Sales Forecasting for April 2018

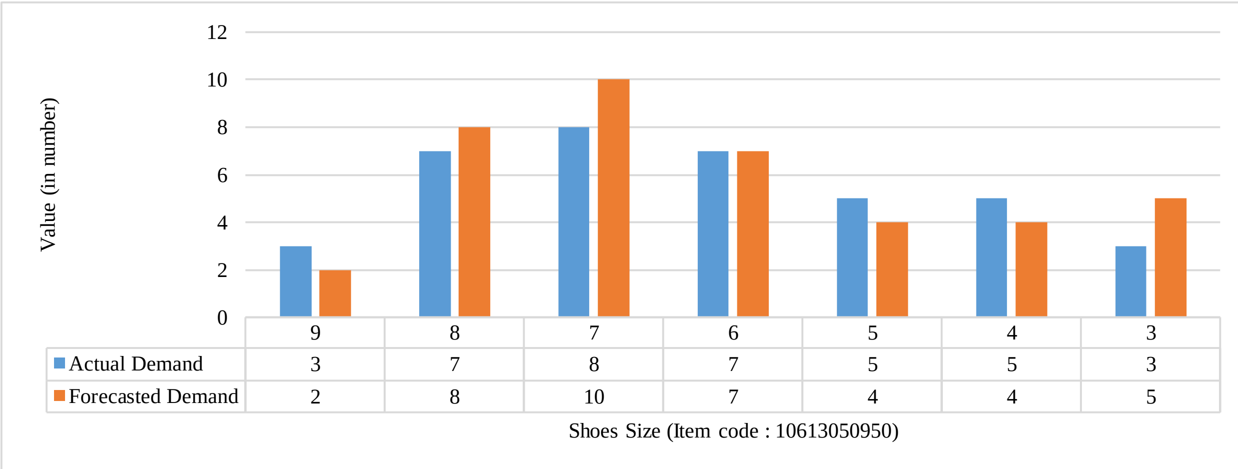


Figure 5 : Demand forecasting Item wise

Season-wise Result Analysis

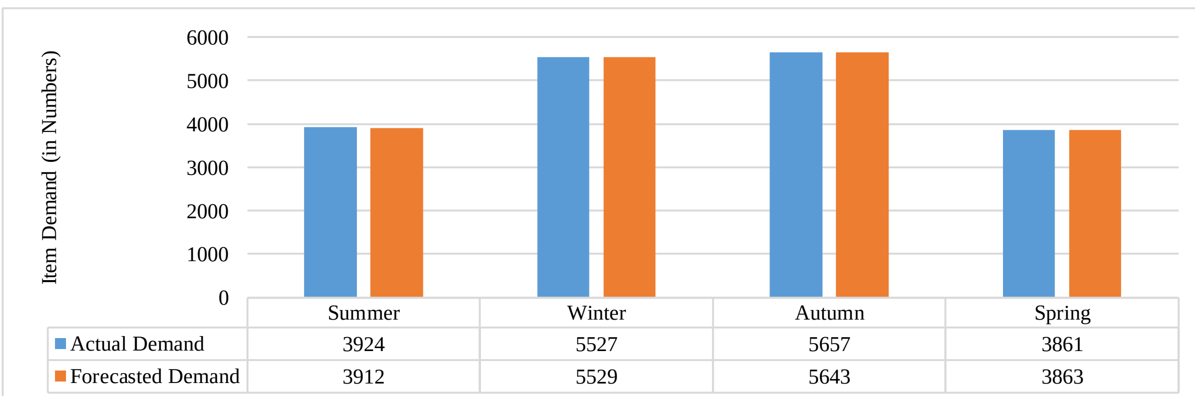


Figure 6: Demand forecasting Season wise

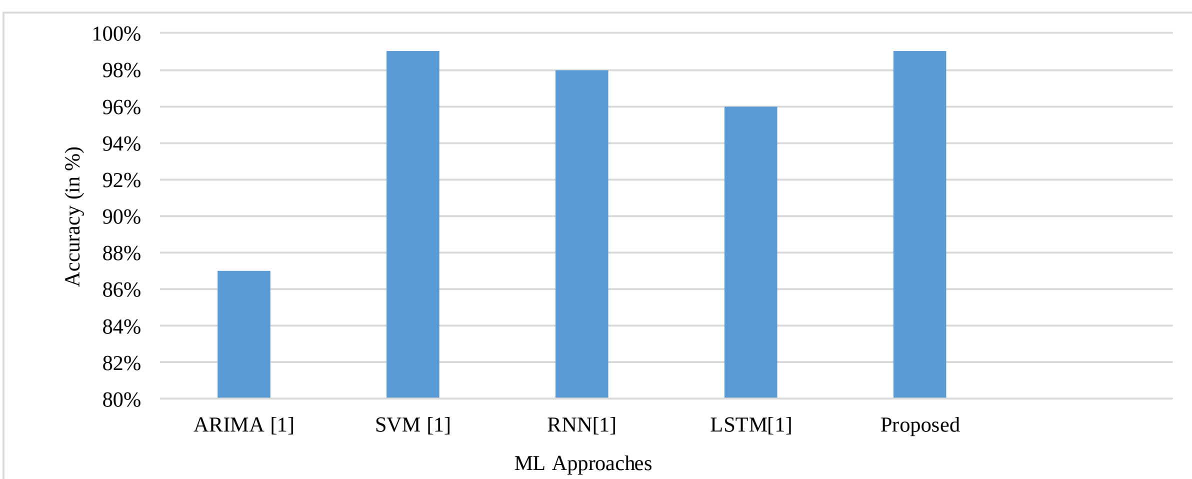


Figure 7 : Comparative Accuracy Analysis

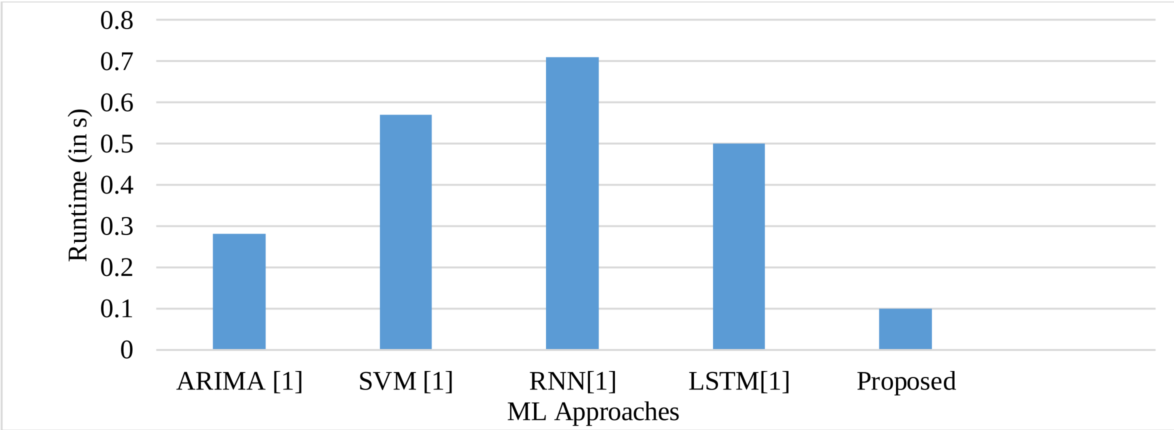


Figure 8: Comparative Runtime Analysis

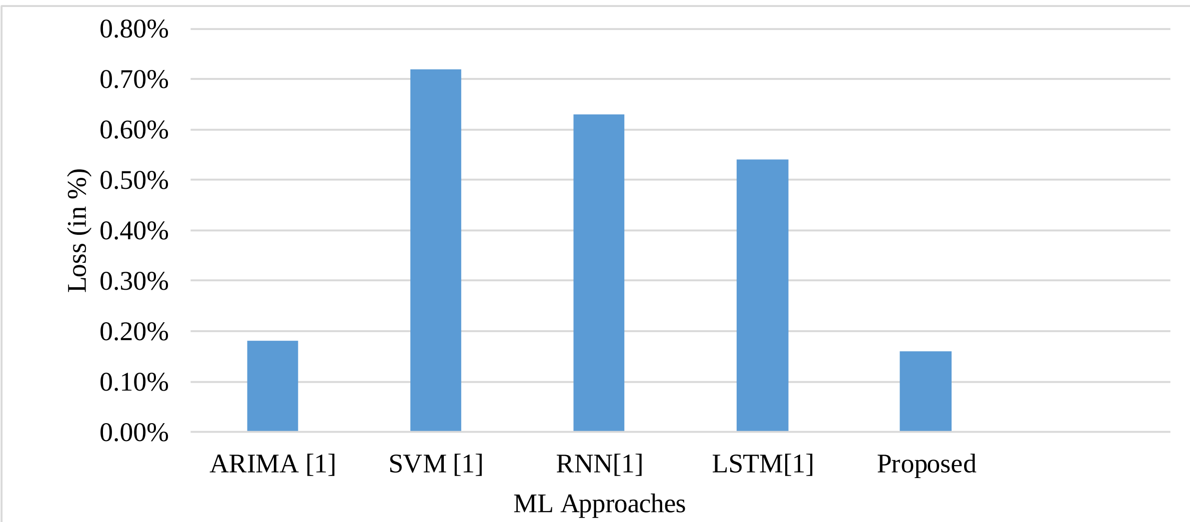


Figure 9: Comparative Loss Analysis

V. Conclusion

Accurate forecasts are crucial for successful manufacturing and can lead to considerable savings when implemented efficiently. Forecasting literature contains a large variety of techniques from simple regression to complex met heuristics such as genetic algorithms. Fuzzy set theory is also another useful tool to increase forecast efficiency and effectiveness.

- The ELM concept has been applied to neuro-fuzzy systems to reduce computational complexity which gives accurate models. As Extreme learning Fuzzy Inference System (ELMFIS) has good results for regression problems.
- Following conclusions are derived from proposed work:
- The analysis was performed month-wise. The month wise analysis shows 1.18% error rate.
- Then analysis was performed item wise monthly demand and shows 0.18% error rate.
- Then analysis was performed according to size of shoes in each item code and shows 25% error rate.
- In last season wise analysis was performed and achieved error rate of about 0.16%.

The proposed work, shows improvement with existing works with respect to running time, cost and accuracy.

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