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Proposed MAS-SOA-SCM Architecture using Integration Strategy to resolve Supply Chain Management Issues

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Abstract:

This paper provides a MAS-based SCM approach that integrates several forecasting techniques to assist in the prediction of consumer requests, as well as visualization and prediction tools for the Online Product Purchasing System. An agent performs data gathering and cleaning activities in the presented multi-agent system. It can also create demand forecasting models for individual products. Furthermore, the architecture outlines the overall characteristics of all components and the methods for delivering services. It includes an algorithm, flow chart for prediction, and visualization. The goal is to develop a system that can integrate data from different products and apply various forecasting methods to get accurate results. As a result, future research will be able to employ and demonstrate the functioning of my suggested system on a variety of production systems. A research study, a portion on the development process, and the built-in prediction models have been included in this paper. It also provides a summary of the findings and conclusions and a discussion of the domain's issues and future research opportunities.

Keywords —*Artificial Neural Networks (ANNs), Deep Learning (DL), Mean Absolute Deviation (MAD), Mean Absolute Percentage Error (MAPE), Multi-Agent System based Service-Oriented Architecture for Supply Chain Management (MAS-SOA-SCM), Online Product Purchasing System (OPPS), Support Vector Machine (SVM), Time-Series Analysis.*

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I. INTRODUCTION

The SCM industries experience a significant proportion of the difficulties. One of the most critical supply chain concerns is demand forecasting. The goal is to optimize inventory, cut expenses, and boost sales, revenue, and customer loyalty. ML techniques, SVM methods, DL models, and time-series analysis have been using to examine historical data to enhance demand forecasting. A proposed intelligent demand forecasting system has been introducing in this paper. The system has based on historical analysis and interpretation of data using various forecasting methodologies such as time-series analysis, support vector regression, and deep learning models.

As a part of the research paper, I have shown the architecture of my proposed work with an algorithm, sequence diagram, and flow chart. On a small data set, I have demonstrated how DL helps industries forecast future results or predictions. Additionally, it helps in the reduction of Mean Absolute Percentage Error (MAPE) to create more precise results or predictions.

II. PROPOSED ARCHITECTURE TO IMPROVE DEMAND FORECASTING FOR A MAS BASED SCM USING SOA

A. Multi-Agent System based Service Oriented Architecture for Supply Chain Management

Manufacturing companies can approach MAS and SOA techniques for SC solutions to boost supply-demand performance through enhanced inventory activities to cope with the entire globe in the dynamic marketing industry.

MAS is designed for real-world applications, whereas SCM demands constant monitoring and responding to changes in the SC environment [1].

A MAS-based SOA approach facilitates rapid design and implementation across the organization [2].

B. Proposed MAS-SOA-SCM to Collect Historical and Relative Data

In day-to-day operations, MAS-SOA-SCM creates a dynamic platform for consumers, producers, and vendors to collaborate. The benefit is to boost company flexibility and allow businesses to react to evolving business requirements more promptly.

Mainly, MAS-SOA-SCM helps improve customer requests on time and minimize the need for a large inventory at the maker, lowering total costs across the manufacturing chain.

In this work, I develop an agent-based framework by integrating ML into an Online Product Purchasing System (OPPS) to forecast customer needs. Aggregator Agent, Sensor Agent, Model Trainer Agent, Predictor Agent, User Interface Agent, and Decision Maker Agent are six agents with diverse tasks in my proposed framework.

They provide an excellent alternative for extracting concerns with pre-existing platforms and connectivity protocols. User-Driven Site Analysis Agents, Rating Agents, Aggregator Agents, Data Persistence Agents, Model Trainer Agents, Predictor Agents, API Agents, Decision Maker Agents, and Demand Predictions Agents are among the agents in the system.

Agents that are isolated software units positioned in an environment and exhibit autonomy, responsiveness, proactiveness, and social ability [3], make up agent-based systems.

When implementing predictive models, a software solution should run the training set on new input regularly.

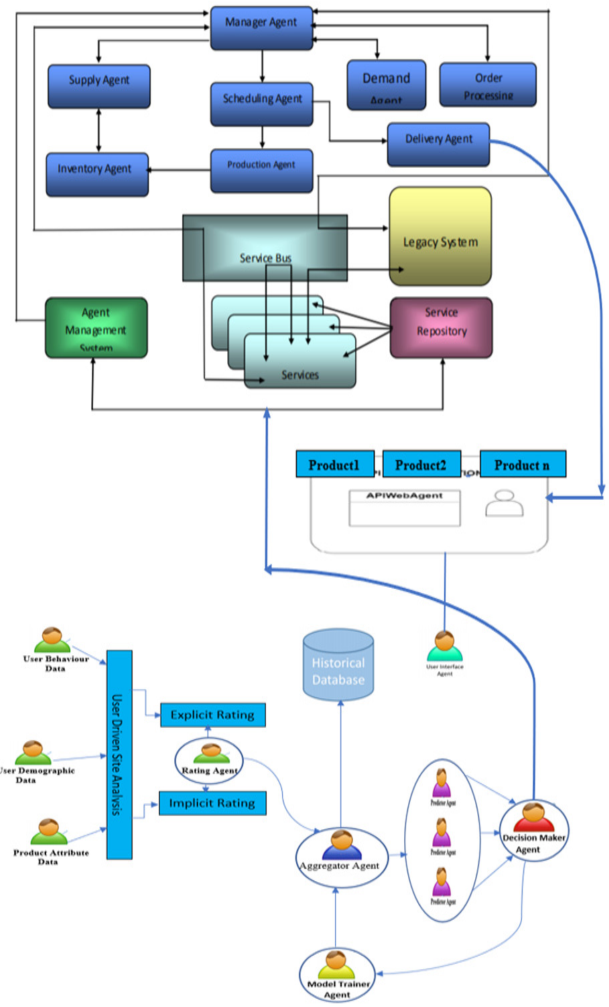

Fig. 1 Proposed Demand Prediction Strategy using MAS SCM

III. CHALLENGES OF SCM INDUSTRIES

A. Various Problems

Some of the biggest challenges faced by SCM industries are:

- Forecasting accuracy as part of Sales and Operations Planning (S&OP).

- Overcoming downstream effects from delays caused by one partner/supplier [4].
- Difficult to keep up the record of consumers and their buying behaviours and order fulfillment.
- Problem associated with delivery and logistics and also to reduce shipment and delivery cost and maximize sales.
- To utilize enormous data collected throughout a supply chain. It is difficult for the company to balance cost and quality.

B. Demand Forecasting

The proper balance between present and future supply-demand is at the core of SC forecasting. At its most basic level, it is the process of merging past purchasing data with consumer purchasing habits to generate a forecast of what selling trends will be like in the future [5].

It's difficult enough to develop an accurate demand prediction within itself.

1) Why the need of Demand Forecasting?

Forecasting is essential to the smooth operation of the entire supply chain.Over- and under-runs in production are also affected by prediction accuracy, reducing time and resource loss.

Demand forecasting improves production timeframes, enhances productivity improvements, saves money, allows for the launch of new products, and has improved customer satisfaction [6].

Demand Forecasting has a variety of applications.

- *Creating a budget:*Demand forecasting assists in the reduction of risks and the making of cost-effective financial decisions that affect resource allocation, profit margins, operating costs, cash flow, expansion potential, inventory accounting, staffing, and overall spend.
- *Production planning and scheduling:*Demand forecasting helps to give the customers the things they need whenever required. Order fulfillment must be in pace with the marketing before the company launch to forecast demand.
- *Inventory storage:*The more inventory company has, the more costly it is to preserve. Demand forecasting can help save money on both stock purchase requisition and warehousing. Having sufficient stock on hand is an essential part of inventory management.
- *Creating a price plan:*Demand forecasting aids in determining product prices depending on demand. Businesses can expand, design competitive pricing, implement the correct marketing techniques, and invest in their development by analysing the market and possibilities.

C. Demand Forecasting Methods

Demand forecasting is the technique of estimating and predicting future demand for a product or service by applying predictive analysis of previous data. It enables businesses to produce better supply decisions that evaluate total profits and profitability for the future [2].

Businesses can use demand forecasting to improve inventory by anticipating future sales based on historical data, allowing them to make better decisions from inventory management and storage requirements to executing flash deals and meeting consumer expectations.

The most challenging part of forecasting demand is deciding on an appropriate technique.

The following are some of the most commonly used techniques:

1)Time Series

A time series is a collection of observations arranged in a time sequence. In other words, it is a collection of data organized according to their occurrence time.

The relationship between two variables has depicted by a time series. One of those factors is time, while the other is any quantitative variable. It could be rising for some and falling for others at different times [7].

Working of Time Series

Sales projections created using this method by analysing historical data from the previous year's account books. This method forecasts a product's demand using time-series data on sales.

The format of a time series is as follows:

y = f (t) (1)

The value of the variable under analysis at time t denoted by y. If the population is the variable observed at each time interval t, t, t,..., t.

If y is the value of the time series at time t. The trend values, seasonal, cyclic, and random fluctuations at time t represented by T, S, C, and R, respectively.

A time series described using the additive model as follows:

y = T + S + C + R (2)

This model indicates that the time series' four components operate independently of one another.

A time series described using the multiplicative model as follows:

y = T × S × C × R (3)

This model proposes various components of a time series interact proportionally.

TABLE 1
TIME SERIES DATA OF ABC ORGANIZATION

Year	Sales in Hundreds
2010	22
2011	26
2012	24
2013	32
2014	38
2015	30
2016	42
2017	38
2018	44
2019	52

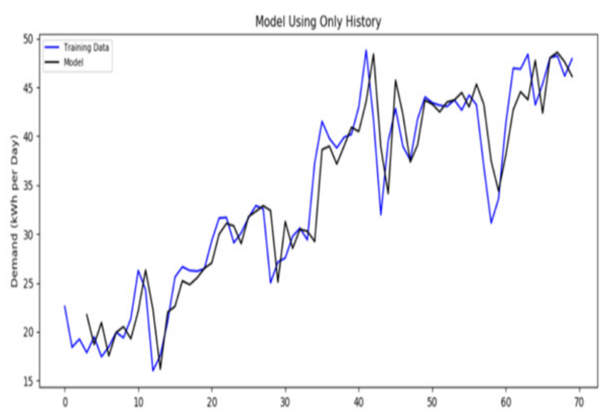

Fig. 2 Time Series Dataset with graphical Representation

2) Support Vector Machine

SVM is a data classification technique for predictive analysis that allocates incoming data items to the previously identified groups. It is a binary classifier in most circumstances, assuming that the information in question has two target values [8].

For classification, regression, and other learning problems, it is a preferred ML method.

SVMs are training machines that use the minimal structural risk inductive principle to achieve strong generalization on a small set of learning trends [3].

It is a linear model used to solve regression and classification problems. It can tackle both linear and nonlinear issues and is for a wide range of applications. SVM's concept is straightforward; the algorithm generates a line or hyperplane that divides the data into classes [1].

The SVM algorithm's purpose is to find the optimum line or decision boundary for categorizing n-dimensional space into categories so that additional data points are in the appropriate category in the future. A hyperplane is a name for the optimal decision boundary.

The maximal vectors/points that assist create the hyperplane chosen via SVM. These ultimate scenarios are support vectors, and the algorithm is a support vector machine.

The diagram below shows how a decision boundary or hyperplane classifies two different groups.

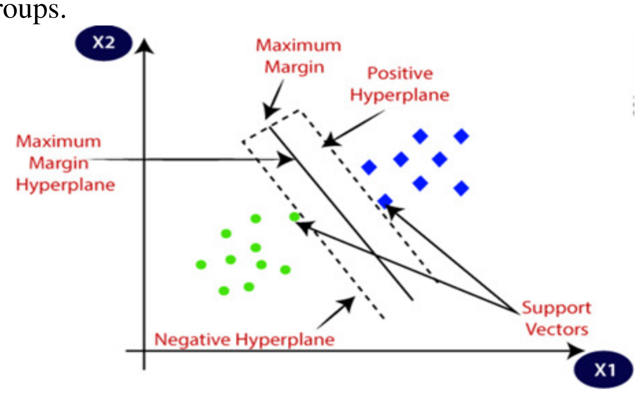

Fig. 3 Decision boundary/hyperplane to classify two different categories

Algorithm

SVM regression for forecasting customer demand [9].

Assign actual values to random variable a_1 to a_n

for i=1 to m do

Perform SVM to find a regression model

end for

for j=1 to n do

Predict values with the regression model up to period n

end for

print results

return c

The data collected determines the parameters. Then, after feeding the data into the model, the SVM training process begins. The algorithm continues to run until it discovers a suitable regression model. This model is used to test all of the values found by the algorithm, and the results are declared.

The model development flow chart illustrates in Figure 1. Data should be collected first, based on previous searches, purchases, and reviews of various products, and then a dataset is prepared.

Second, the data cleaning process should remove any missing or unnecessary data. It includes formatting the gathered data and declaring parameters.

In the third phase, we'll create a parameter list around which the SVM model will be used to train and test data.

Finally, the SVM training process initiates by providing input to the model. The SVM model works by itself with the help of the algorithm till the fitness value attains. The fitness value is then validated or matched to the criteria. If the fitness value match, start forecasting values based on it.

If it doesn't match, go back to the beginning and improve the SVM training process until you find the required predicting value. This value passes to the SVM model, which uses a few of them to obtain the final forecast values.

A tabular dataset comprising actual and predicted values prepares after acquiring the final result. Traditional methods of evaluating the error percent, such as MAPEand MSE [10], determines the performance level. In addition, the efficacy of the predicting values. Finally, the model brings the process to a close.

3) Deep Learning

Deep learning is a type of ML that aims to train a system about human instincts. A computer algorithm learns to execute classification tasks directly on complicated input such as photos, text, or voice.

It is an AI function that mimics the human brain's processing of data and pattern creation to make decisions. Deep neural learning or deep neural network are other terms for the same.

Working of Deep Learning

Deep learning algorithms use supervised and unsupervised learning algorithms to train outputs based on the inputs provided.

ANN uses the backpropagation algorithm idea, which is widely used in the field of machine learning [11].

All the circles in the following diagram represent linked neurons. Input, Hidden, and Output Layers are three separate hierarchies of layers that the neurons are divided.

- The input layer is the first neuron layer, which receives the data and transfers it to the first hidden layer.
- The computations are done on the received data by the hidden layers. The most challenging part of creating neural networks is deciding on the number of neurons and hidden layers.
- The output layer then generates the required output [12].

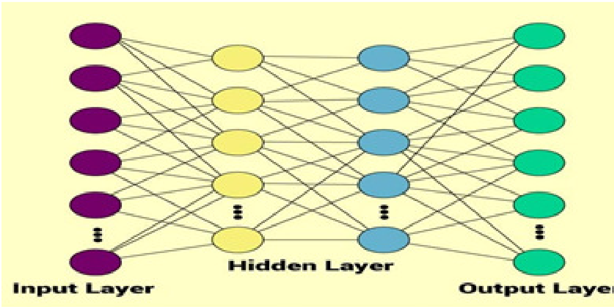

Fig. 4 Different Hierarchies of Neurons

Weights indicate the importance of input values in every link between neurons. An activation function normalizes the outputs.

Two crucial measures are taken into account when training the network. The first is to gather a large amount of data, and the second is to have a lot of computing power. The term "deep learning" refers to the number of hidden layers used by the model to train the data set.

IV. PROPOSED INTEGRATION STRATEGY

The proposed integration strategy produces the result by combining the strengths of several algorithms into a single collaboration method ideology. The goal is to increase the proposed forecasting system's success by merging various algorithms.As we all know, every algorithm has its own set of flaws in different circumstances. Therefore, combining the outcomes of each model produces more effective and efficient decision-making results.

To make accurate classifications based upon individual users, their choices of products, the date when they bought the products, and so on, different time series, support vector regression models, and deep learning algorithms factors.

A. Algorithm: Proposed Integration Strategy

S is the number of online stores.

P is the number of products visited, ordered, and searched.

A_n is the algorithms with index n.

$B_{s,p}$ is the matrix containing the number of best-performing algorithms for each online store and product.

$R_{s,p}$ is the matrix that contains the algorithms for each online store and productthat predicted incorrectly(i.e., under rejection).

$F_{s,p}$ is the matrix that stores the final decision of each forecast.

Step 1:Start tracking or keep records of all users who visited online stores for various products.

Apply algorithm to process the data.

If A_n is in list $B_{s,p}$:

Continue.

Else:

Run all algorithms (A_n).

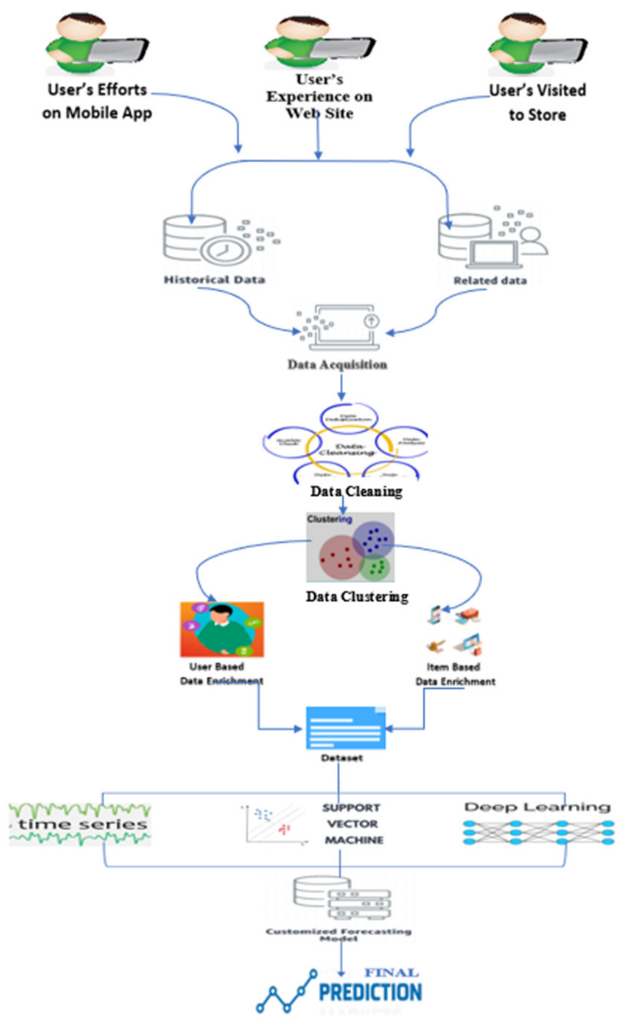

Fig. 5 Proposed Demand Prediction Integration Strategy using MAS SCM

Step 2: If successfully predicted the value:

Calculate algorithm weight then, keep in $B_{s,p}$.

Else:

Keep algorithm in $R_{s,p}$.

Step 3: After multiple iterations on various data sets using different techniques.

We now have a list of the best-performing algorithms ($B_{s,p}$) as well as a rejected list of algorithms ($R_{s,p}$).

Step 4: Apply algorithms one by one from the list ($B_{s,p}$) on proposed integration strategy on every successful result generated by the algorithms, keep the algorithms in ($F_{s,p}$).

For A_n in $B_{s,p}$:

Return $F_{s,p}$.

Else:

Repeat Step 2.

Step 5: End.

V. WORKING OF PROPOSED INTEGRATION STRATEGY

The working of the proposed integration strategy demonstrates by defining multiple approaches on the below dataset.

A. Data Set

Field Name	Description
Vendor_Id	Online Vendor Number
Vendor_Name	Online Vendor Name
Product_Id	Product Identification Number
Product_Name	Product Description
Product_Qty	Total Number of Individual Products
Sales_Qty	Total Number of Product Sale
Stock_Qty	Number of Products Available in Stock
Return_Qty	Number of Return Product Items
Order_Id	Order Identification Number
Return_Date	Date of Return
Reason_For_Return	Description About the Reason to Return the Product
Product_Sales_Count_Weekwise	Total Number of Product Sales on Weekly Basis
Product_Sales_Count_Monthwise	Total Number of Product Sales on Monthly Basis
Discount_Amount	Product Wise Discount Amount
Purchased_Date	Date of Purchase
Returned_Date	Date of Return
Visited_Customer_Count	Number of Customers Visited Online to See the Product
Customers_Purchased_Product_Count	Number of Customers PurchasedProduct Online

B.Different Approaches Followed during Forecasting of Customer's Demands

Approach 1: The task is to predict demands. Each forecasting algorithm uses a method to predict the product demand based on user searches, purchases, and visits to the online store from the past weeks, running weeks, and the following weeks.

Approach 2: It uses the Back Propagation Network and Feed Forward Network to choose the best forecasting algorithms. It depends on the prediction outcomes and enhances the weight of each algorithm.

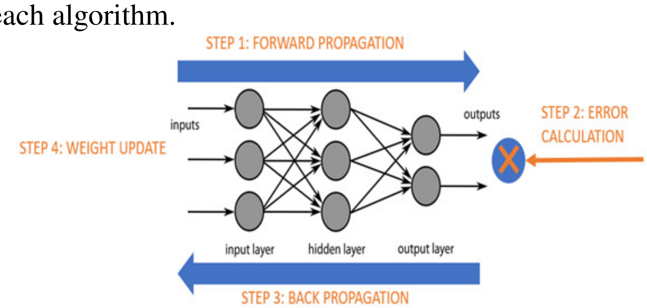

Fig. 6 Back propagation Network and Feed Forward Network

Approach 3: The algorithms that do not perform well in the prediction process will be in the blacklist algorithms category and will no longer be in the prediction process for that demand prediction cycle.

Approach 4: The contribution of all algorithms that perform well in that prediction system determines the final decision in our decision integration technique. Our method takes into account forecasting algorithm decisions, which perform better when a few previous weeks of the last year are considered, as well as the present week of the last year and the current year. While algorithms improve their forecasting abilities over time, their contribution weights increase in synch, or vice versa, if the following processes are taken into consideration:

Step 1: We do not evaluate the contributions of all algorithms democratically in the initial decision integration approach; we look at contributions of the best algorithms of the associated week.

Step 2: In other words, for each store and product, the final decision is retained by combining the best decisions (chosen based on their previous decisions). The best algorithms of the week, on the other hand, can vary depending on each store and product pair, as each algorithm behaves differently for different products and online vendors, as well as at different times.

VI. RESULTS

A. Figures and Tables

The following steps are used to calculate the MAPE, MAD value, standardization - normalizing of weights, and forecast outcome in this phase.

1) Calculate MAPE and MAD and its average:

The weighted average of Mean Absolute Percentage Error (MAPE) [13] and Mean Absolute Deviation (MAD) [14] used in the second decision integration technique.

These are two commonly used metrics for evaluating the performance of forecasting models. The following are the equations for calculating these forecast accuracy measures.

MAPE (Mean Absolute Percentage Error)

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\frac{|F_t - A_t|}{A_t}$$

MAD (Mean Absolute Deviation)

$$\text{MAD} = \frac{1}{n}\sum_{t=1}^{n}|F_t - A_t|$$

where,

F_t is the expected or estimated value for period t.

A_t is the actual value for period t.

n denotes the number of periods.

Average of MAPE= Sum (MAPE of 1st Week+ MAPE of 2nd Week+ MAPE of 3rd Week+….)

2) Selection of Best Algorithms and Normalization and Standardization of Weights

We choose the best algorithms from all of them based on their MAPE value for the week of each online store and product.

Next, for each algorithm, we observe the results on several datasets and adjust the weights accordingly.

Assume there are five best algorithms, with weights of W_1= 25%, W_2= 20%, W_3= 13%, W_4= 12%, and W_5= 10%, respectively. Here we adopt the values of the numeric data to a common scale without changing the range. Standardization shrinks or stretches the data to fit within a given range.

We must do it by calculating new weights for each of the algorithms.

$$\text{New Weights}=\frac{\text{Individual weight of each algorithm}}{\text{sum of the weights of all algorithms}}$$

1^{st} Algorithm's new weight$=\frac{25}{80}=0.3125$

2^{nd} Algorithm's new weight$=\frac{20}{80}=0.25$

3^{rd} Algorithm's new weight$=\frac{13}{80}=0.1625$

4^{th} Algorithm's new weight$=\frac{12}{80}=0.15$

5^{th} Algorithm's new weight$=\frac{10}{80}=0.125$

3) Calculate the Final Forecasting Result

We can now calculate each algorithm's forecast result by:

Forecast Result= Forecast value of each algorithm* Weight of each algorithm

Assume forecast value of algorithms 1,2,3,4,5 is 25, 20,15,10,5. Then,

Average of Forecasting Result =
(Weight of 1^{st} * Forecast value of 1st algorithm) +
(Weight of 2^{nd} * Forecast value of 2nd algorithm) +
(Weight of 3^{rd} * Forecast value of 3rd algorithm) +
(Weight of 4^{th} * Forecast value of 4th algorithm) +
(Weight of 5^{th} * Forecast value of 5th algorithm)
Now, for the values listed above.

Final Forecast Result
= 25*.31+20*.25+15*.16+10*.15+5*.12
= 7.75+ 5 + 2.4 + 1.5 + 0.6
= 17.25
= 17(Round off)

VII. CONCLUSIONS

As a result, I conclude the study by stating that the success of the support vector model not only improves the prediction but also improves the accuracy of the forecast. However, it significantly reduces percentage error when anticipating consumer requests on a given data set by roughly 4-5 percent at the average MAPE results range. With the help of model trained Agents, the proposed implementation of MAS SCM employing the SVM model presents the final decision to consider for accurate prediction and improvise the model on every result set.

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