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A DATA DRIVEN REGRESSION LEARNING MODEL FOR SUPPLY CHAIN FORECASTING

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ABSTRACT
Supply chain forecasting has seen a major inclination towards machine learning and to evolutionary algorithms due to their capability to analyze large data sets. Sales forecasting is typically complex due to the volatility of the associated variables. This paper presents a machine learning based approach on the principal component analysis (PCA) and the Scaled Conjugate Gradient (SCG) algorithm for sales forecasting. The performance of the proposed system was evaluated in terms of the mean absolute percentage error (MAPE) and the regression. It was observed that the proposed system outperforms then previously existing system with 95.22% accuracy and MAPE of 4.78% on the benchmark datasets.

KEYWORDS
Supply chain forecasting, Regression Learning, Principal Component Analysis (PCA), Steepest Descent, Scaled Conjugate Gradient (SCG), Mean Absolute Percentage Error, Regression.

I. Introduction

Global Markets have encountered a lot of volatility in the last decade due to -
Trade Wars,
Formulations of cartels,
Outbreaks of new diseases (such as Ebola and Covid – 19)
Global economic slowdown etc.
Some specific products and services account for the Gross Domestic Product (GDP) of countries. There is a large diversity in such products, while china relies heavily on Electronics and industrial manufacturing (Zhang et al. [1]).
Generally, the major export depends on the geographical conditions, manpower and natural resources of the country. Supply chain management plays a pivotal role for such industries in streamlining the processes and deciding the profits. Supply chain management can be defined as the management of the flow of goods and services including all processes which are intertwined with the transformation of raw materials into final products.
Inventory Management,
Warehousing and distribution,
Logistics,
Procurement,
Revenue management and
Information Technology (IT) related to business are different domains which affected by supply chain management.

II. Supply Chain Forecasting:

Supply chain forecasting can be defined as the prediction of demand metrics based on the previous demands and associated variables. It's a critical domain of supply chain management. Thus, apart from increasing profits and streamlining business, supply chain management and forecasting can also have deep impacts on employment, food security, peace and political conditions in a country (Wang et al [2].).
Supply chain forecasting tries to find patterns in previously existing data and forecast future demands. The sales or demands are generally modeled as a function of time and associated variables given by (Sharma et al. [3]):

Demand = function (time, associated variables)
These are the expected associated variables for demand:
Current Economic conditions of the Country with respect to export
Global Economic condition
Political Relations among countries
Supply from other countries etc.
Accurate predictions or estimates need to be made considering a pervasive set of associated parameters.
F**eizabadi et al**. [4] presented many supply chains, firms staged in upstream of the chain suffer from variance amplification emanating from demand information distortion in a multi-stage supply chain and, consequently, their operation inefficiency. Both time series and explanatory factors are feed into the developed method. The method was applied and evaluated in the context of functional product and a steel manufacturer. The statistically significant supply chain performance improvement differences were found across traditional and ML-based demand forecasting methods. The implications for the theory and practice are also presented.
Fildes [5] Analyzed the paper computer-based demand forecasting systems have been widely adopted in supply chain companies. Authors report the findings of a case study of demand forecasting in a pharmaceutical company over a 15-year period. The reasons for the longevity of these practices are examined both from the perspective of the individual forecaster and the organization as a whole.
Goodarzian et al. [6] presented in the pharmaceutical industry, a growing concern with sustainability has become a strict consideration during the COVID-19 pandemic. Three hybrid meta-heuristic algorithms, namely, ant colony optimization, fish swarm algorithm, and firefly algorithm are suggested, hybridized with variable neighborhood search to solve the sustainable medical supply chain network model. Response surface method is used to tune the parameters since meta-heuristic algorithms are sensitive to input parameters.
Amalnick et al.[7] proposed an accurate demand forecasting in pharmaceutical industries has always been one of the main concerns of planning managers because a lot of downstream supply chain activities depend on the amount of final product demand. In the current study, a five-step intelligent algorithm is presented based on data mining and neural network techniques to forecast demand in pharmaceutical industries.
Viegas et al. in [8] concluded that the Pharmaceutical Supply Chain (PSC) is responsible for considerable environmental and product-value impacts. This research proposes a classificatory review in which three categories of reverse flows are identified: donations, Reverse Logistics (RL) and Circular Economy (CE).
Chen et al.[9] considered a pharmaceutical supply chain composed of one pharmaceutical manufacturer and one pharmacy. Authors investigate how price cap regulation affects pharmaceutical firms' pricing decisions. It also evaluates the economic and social performance of the pharmaceutical supply chain and assess the risks associated with price cap regulation. The derived equilibriums under

different price cap regulations, including retailer price cap regulation, manufacturer price cap regulation and linkage price cap regulation, are compared to that without regulation.
Balashirin et al. in [10] presented that researches confirm that the area that has the greatest reimbursement of outlays on economic development is a higher education, and that is the reason why the formation of a financial policy in the area of higher education is of utmost importance. Improving the quality of higher education and promoting its welfare in the economy, the socioeconomic governance indicators will also improve. The authors proposed a neural network model for the estimation of impact of financing policy on socio economic and socio educational system.
Ahmadi et al. in [11] presented sustainable development of a nation greatly depends on the health of individuals. The emergence of the diseases caused by unhealthy lifestyle as well as the growth and aging of the population have faced the pharmaceutical industry with an increasing demand for drugs and the related products over time. Hence, this work aims to identify the prevalent challenges of PSCs at three different decision levels, i.e., long-term (strategic), mid-term (tactical), and short-term (operational) decisions; as well as presenting various ways to deal with such problems.
Sabouhi et al.[12] presented an integrated hybrid approach based on data envelopment analysis (DEA) and mathematical programming method to design a resilient supply chain. First, the efficiency of potential suppliers is evaluated by a fuzzy DEA model. Afterwards, using the obtained efficiency, a two-stage possibilistic-stochastic programming model is developed for integrated supplier selection and supply chain design under disruption and operational risks.
Settanni et al.[13] evaluated the reconfiguration opportunities in Pharmaceutical Supply Chains (PSC) resulting from technology interventions in manufacturing, and new, more patient-centric delivery models. A critical synthesis of the academic and practice literature is used to identify, conceptualise, analyse and categorise PSC models. From a theoretical perspective, a systems view of operations research is adopted to provide insights on a broader range of OR activities, from conceptual to mathematical modelling and model solving, up to implementation.

III. Machine Learning for Supply Chain Forecasting

Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex and cannot be noticed by either humans or other computer techniques. Other advantages include (Castro et al.[14]):
Adaptive learning: An ability to learn how to do tasks based on the data given for training or initial experience.
Self – Organization: An ANN can create its own organization or representation of the information it receives during learning time.
Real Time Operation: ANN computations may be carried out in parallel, and special hardware devices are being designed and manufactured which take advantage of this capability.
An artificial neural network is shown in fig.1 with different inputs and arbitrary weights

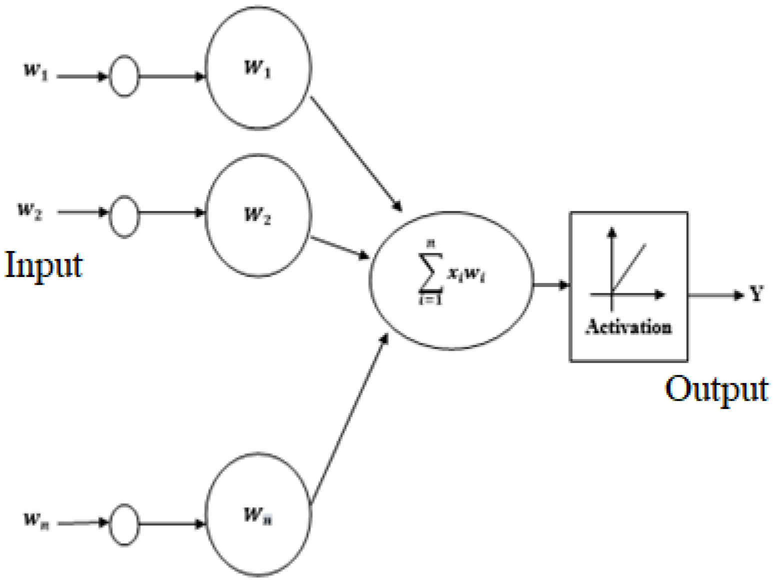

Fig. 1 Mathematical Model of Neural Network

The output of the neural network is given by:

$$y = f(\sum_{i=1}^{n} XiWi \ + \ \Theta) \qquad (1)$$

Where,

X_i = signals arriving through various paths,

W_i = the weight corresponding to the various paths and

θ = bias.

y = output of the neural network.

It can be seen that various signals traversing different paths have been assigned names X and each path has been assigned a weight W. The signal traversing a particular path gets multiplied by a corresponding weight W and finally the overall summation of the signals multiplied by the corresponding path weights reaches the neuron which reacts to it according to the bias θ. Finally its the bias that decides the activation function that is responsible for the decision taken upon by the neural network. The activation function φ is used to decide the final output. The learning capability of the ANN structure is based on the temporal learning capability governed by the relation (Singhry et al. [15])

$$w(i) = f(i, e) \qquad (2)$$

Here,

W_i represents the instantaneous weights i is the iteration

e is the prediction error

The weight changes dynamically and is given by:

$$W_k \xrightarrow{e,i} W_{k+1} \qquad (3)$$

Here,

W_k = the weight of the current iteration.

W_{k+1} = the weight of the subsequent iteration.

The following are the differnet learning models for prediction of output :

(i) Regression Learning Model

Regression learning has found several applications in supervized learning algorithms where the regression analysis among dependednt and independent variables is needed. Different regression models differ based on the the kind of relationship between dependent and independent variables, they are considering and the number of independent variables being used (Bowersox et al.[16]). Regression performs the task to predict a dependent variable value (y) based on a given independent variable (x). So, this regression technique finds out a relationship between x (input) and y(output). Mathematically,

$$\boldsymbol{y = \theta_1 + \theta_2 x} \qquad \textbf{(4)}$$

Here,
x = state vector of inut variables
y = state vector of output variable or variables.
θ_1 *and* θ_2 = co-efficents which try to fit the regression learning models output vector to the input vector (Mishra et al.[17])
By achieving the best-fit regression line, the model aims to predict y value such that the error difference between predicted value and true value is minimum. So, it is very important to update the θ_1 and θ_2 values, to reach the best value that minimize the error between predicted y value (pred) and true y value (y). The cost function J is mathematically defined as:

$$\boldsymbol{J = \frac{1}{n}\sum_{i=1}^{n}(pred_1 - y_i)^2} \qquad \textbf{(5)}$$

Here,
n = number of samples
y = target
pred = actual output or modelled output.

(ii) Descent in Regression Learning

To update θ_1 and θ_2 values in order to reduce Cost function (minimizing MSE value) and achieving the best fit line the model uses Gradient Descent. The idea is to start with random θ_1 and θ_2 values and then iteratively updating the values, reaching minimum cost. The main aim is to minimize the cost function J (Hazen et al.[18])

IV. The Steepest Descent Algorithm and Principal Component Analysis

The critical aspect about steepest descent is the fact that it repeatedly feeds the errors in every iteration to the network till the errors become constant or the maximum number of allowable iterations is over. This can be shown in figure 2 [Rajesh et al.[19]:

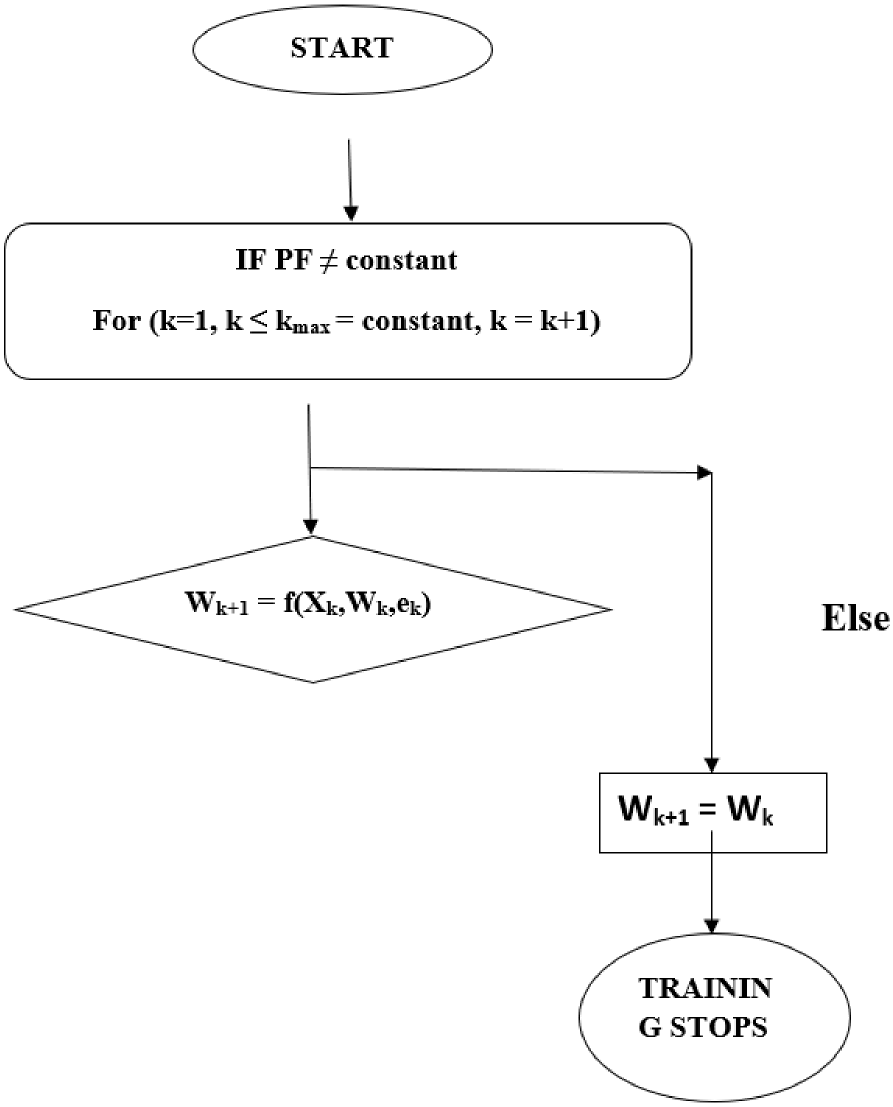

Fig 2 - Block Diagram for training of network.

Here,
X_k = the input to the kth iteration
W_k = the weight to the kth iteration
W_{k+1} = the weight to the (k+1)st iteration
e_k = the error to the kth iteration
k = the iteration number
PF = the performance function deciding the end of training
k_{max} = the maximum number of iterations
Figure 2 depicts the iterative learning process for steepest descent.

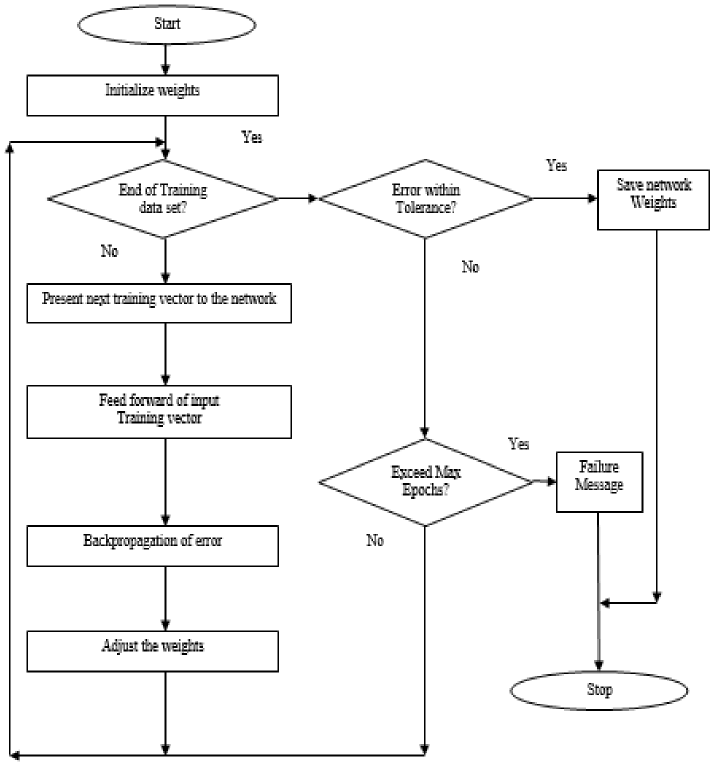

Fig. 3 Block Diagram of Steepest Descent Process

Thus if the error is within tolerance, which is generally not feasible to find beforehand in time series data, the training is stopped if the performance function (which can be the training error) becomes constant for multiple iterations or the maximum number of iterations are over. Now there are various ways in which the error can be minimized. However, the steepest fall of the error with respect to weights is envisaged. It is depicted in the figure 4. Although the error in training keeps plummeting in all the three cases of gradient descent, the gradient 3 or g_3 attains the maximum negative descent resulting in the quickest training among all the approaches and hence the least time complexity. This would be inferred from the number of iterations which are required to stop training. Thus, the number of iterations would be a function of the gradient with which the error falls (Chopra et al. [20]).

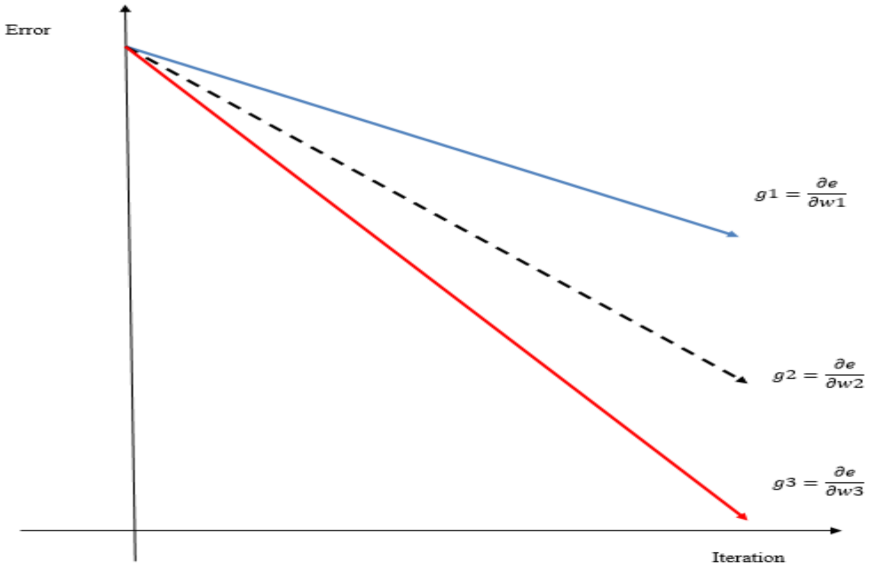

Fig.4 The concept of Steepest Descent

This is mathematically given by:

$$\boldsymbol{k_n = f(g = \frac{\partial e}{\partial w})} \qquad \textbf{(6)}$$

Here,
k_n = the number of iterations to stop training.
g = the gradient
w = the weight
e = the error

The proposed methodology uses two key components one of which is the training algorithm and the other is the training optimization algorithm. Both are explained in this section.

(a) The Scaled Conjugate Gradient (SCG) Algorithm

There are several ways to implement the back propagation technique in the neural networks. One consideration however always remains that of the least time and space complexity so as to reduce the amount of computational cost that is associated with the training algorithm. The essence of the scaled conjugate gradient algorithm is the fact that it has very low space and time complexity making it ideally suited to large data sets to be analyzed in real time applications where the time is a constraint. The training rule for the algorithm is given by (Jaipuria et al. [21]):

$$\boldsymbol{A_0 = -g_0} \qquad \textbf{(7)}$$

A is the initial search vector for steepest gradient search
g is the actual gradient
weight of next iteration is presented in eq^n (8)

$$\boldsymbol{w_{k+1} = w_k + \mu_k g_k} \qquad \textbf{(8)}$$

Here,
w_{k+1} = the weight of the next iteration
w_k = the weight of the present iteration
μ_k = the combination co-efficient

(b) The Principal Component Analysis (PCA)

The principal component analysis (PCA) is basically a dimensional reduction tool which helps to clear out the redundancies in the training data vector in such a way that the training is optimized for lesser number of variables and mean absolute percentage error hits the least values in the lest number of

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iterations possible. The parameters in the estimation are the various temporal parameters affecting demand are: Unit Cost, Time, and previous Unit Sales.
The training is stopped based on the mean square error or MSE shown in eq^n (9) -

$$\boldsymbol{MSE = \frac{\sum_{i=1}^{n} e_i^2}{n}} \quad \textbf{(9)}$$

The final computation of the performance metric is the mean absolute percentage error MAPE shown in eq^n (10) -

$$\boldsymbol{MAPE \ = \frac{100}{M} \sum_{i=1}^{N} \frac{E - E_i|}{i}} \quad \textbf{(10)}$$

Here,
n = the number of errors
i = the iteration number
E = the actual value
E_i = the predicted value
On the basis of algorithm used, the flowchart of the proposed system is presented in figure 4

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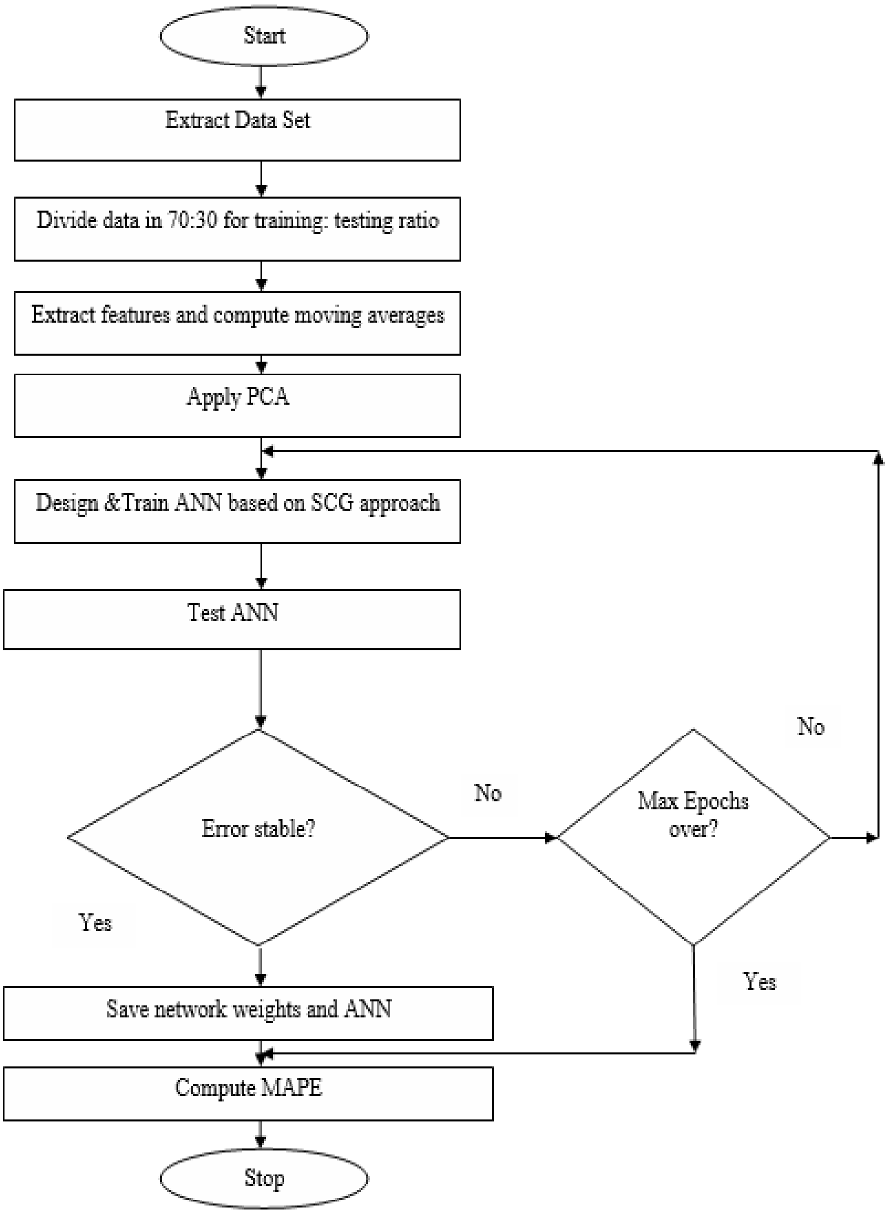

Fig.5 Flowchart of Proposed System

I. RESULTS AND DISCUSSIONS

The data set used for modeling in the proposed work is the global sales, [Web 1] and

The training algorithm used is the steepest descent based scaled conjugate gradient algorithm. The accuracy of temporal prediction is computed as:

$$Ac = 100 - \frac{100}{M}\sum_{i=1}^{N}\frac{E-E_i|}{i}\ \% \qquad \textbf{(11)}$$

Here,

Ac is the accuracy computed in %

Basically a 10 hidden layer deep neural network is design based on the scaled conjugate gradient approach. The need for a deep neural network is seen as a necessity since the cloud data in terms of workload is substantially complex and exhaustive.

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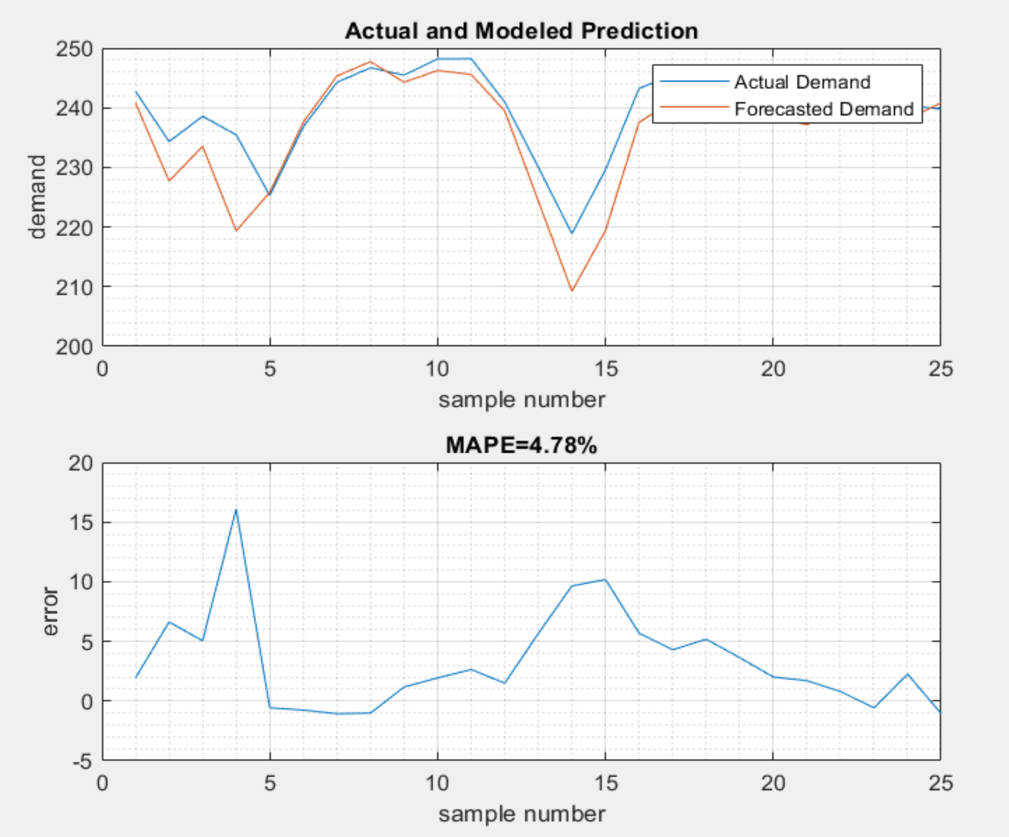

Fig.6 Actual and Modeled values

The figure 6 depicted the actual and the modeled prediction values in which the red curve is the values corresponding to forecasted values and the blue curve corresponds to the actual values. A difference between them yields the error. A close agreement found between target value and modeled value.

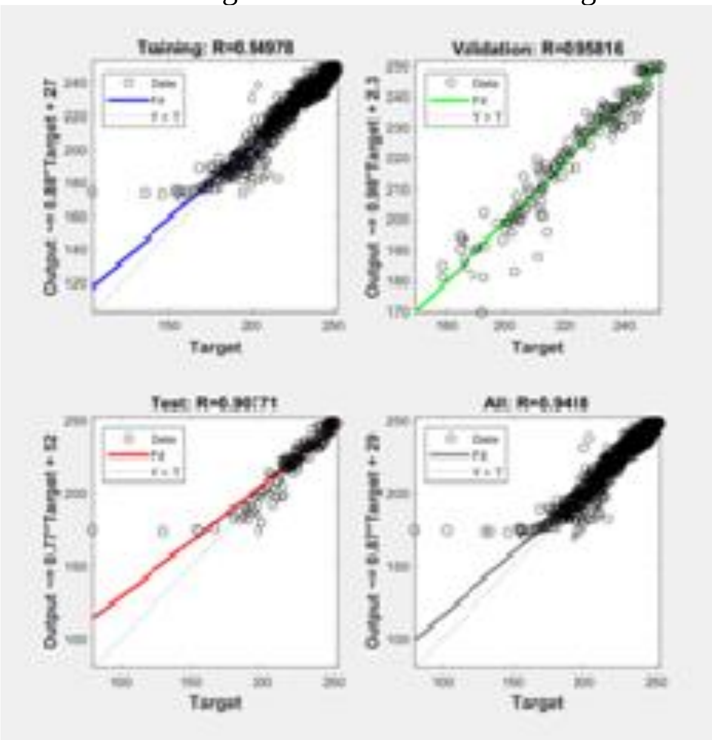

Fig.7 Regression

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The figure 7 shown the regression obtained with training and validation of data in the proposed approach which is a sort of similarity among two random variables. The maximum allowable regression is unity depicting complete similarity.

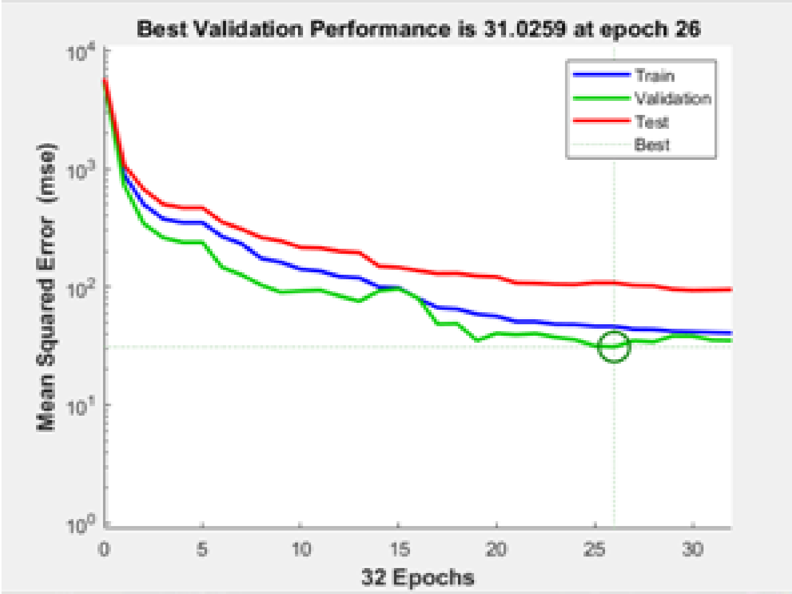

Fig.7 Performance Function

The performance function that decides the culmination of training is the mean squared error in this case given mathematically by the equation (5).
Setting parameter of Artificial Neural Network for training of data are as follow -

Table.1 Obtained Results

S.No	PARAMETER	VALUE
1.	Data Division	Random
2.	Algorithm	SCG
3.	Performance	Mean Squared Error (MSE)
4.	Architecture	Back Propagation
5.	Hidden Layers	10
6.	Iterations	32
7.	MAPE (proposed work)	4.78%
8.	MAPE (previous work)	10.6%
9.	Accuracy (Proposed Work)	95.22%
10.	Accuracy (Previous Work)	89.4%
11.	Regression	0.9418

The performance of the proposed approach is found better compared to previously existing technique [1] which attains a MAPE = 10.6%.

II. CONCLUSION

This research presented a mechanism for supply chain forecasting. The neural network architecture is used to implement machine learning. The architecture of the approach is the use of the back propagation-based approaches to utilize the knowledge about the errors in each iteration to affect the weights of each subsequent iteration. The scaled conjugate gradient (SCG) based steepest descent training rule is utilized in this approach to reduce the number of iterations and also the mean absolute percentage error. The principal component analysis (PCA) is used as a data optimization tool. It is shown that the proposed work performs better in terms of mean absolute percentage error (MAPE) compared to the previously existing technique for the same standard dataset. It can be attributed to the back propagation approach as well as the use of the principal component analysis to fine tune and optimize the training process. The proposed approach attained an accuracy of 95.22% in terms of the accuracy and a MAPE of 4.78%. It is substantially improved compared to previous work [1].

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Web 1
https://data.world/datasets/sales