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An Adaptive Neuro Fuzzy Inference System (ANFIS) Based Model for Supply Demand Forecasting

Abhishek Solanki[1], Prof. Vaishali Upadhyay[2]

Abstract: **Off late, the demand for pharmaceutical products and drugs has ramped up significantly due to the ongoing COVID-19 scenario. Several instances have been reported where large scarcity of drugs have led to fatalities in patients. Hence, the necessity for a holistic approach for demand forecasting for the pharmaceutical supply chain has become imperative. Recently, soft computing techniques are being used widely for demand forecasting due to relatively higher accuracy compared to conventional statistical techniques. This work proposes a wavelet transform-adaptive neuro fuzzy inference system (DWT-ANFIS) hybrid to forecast pharmaceutical products. The DWT has been used as a data cleaning and optimization tool whereas the ANFIS has been used for forecasting. The evaluation of the proposed work has been done based on the mean absolute percentage error, regression and iterations of the system. It has been shown that the proposed system outperforms the existing system in terms of the MAPE.**

Keywords: Demand Forecasting, Pharmaceutical Supply Chain, Soft Computing, Adaptive Neuro Fuzzy Inference Systems (ANFIS), Discrete Wavelet Transform, Mean Absolute Percentage Error (MAPE).

I. INTRODUCTION

Due to the ongoing COVID-19 scenario, the pharmaceutical industry has witnessed extreme pressure in terms of delivering pharmaceutical products. Several instances have been encountered where life saving drugs and amenities fell short of demand causing -

extreme fatalities. Hence, it became evident that demand forecasting for the pharmaceutical supply chain was mandatory [1]. The pharmaceutical market is an important area of the country's economy, which must be given special attention due to the fact that it is one of the necessary factors for the timely provision of human health. Today, there are a large number of pharmaceutical products (medicines and equipment), which are mass-market goods by terms, the use of which can be divided into durable goods (for example, sanitation, hygiene, medical devices) and short-term use (medicines, medicine plant materials, medical cosmetics) [2]. The management became extremely hard-pressed in times of the pandemics due to the large variations and sudden up-surge in the demand for pharmaceutical products. The demand forecasting can actually be modelled as a time series given by:

$$\boldsymbol{Demand} = \boldsymbol{f}(\boldsymbol{time}, \boldsymbol{assocauted\ attributes}) \quad \textbf{(1)}$$

Here,
f denotes a function of.

The dependence of pharmaceutical demand over time makes it somewhat predictable under similar other conditions of global influencing variables. However, even the slightest of changes can derail the prediction completely.

II. NEED FOR SOFT COMPUTING FOR DEMAND FOREASTING

Primarily, soft computing based techniques are used where the data to be analyzed is extremely large and complex to be analyzed by conventional computational or statistical techniques. There are various soft computing based approaches used for time series prediction or fitting applications out of which neural networks and fuzzy logic have gained substantial prominence. With the advent of deep learning, the computational capability of algorithms have also risen allowing us to find trends in highly non-linear and uncorrelated data [3]. The following section briefly explains the fundamentals of neural networks and fuzzy systems and their application to stock market prediction.

2.1 Artificial Neural Networks (ANN)

Artificial Neural Networks try to copy or emulate the thinking process of the human brain to predict data. The fundamental properties are:

1) Parallel data processing capability
2) Learning and Adapting capability
3) Self-Organization

The mathematical model of ANN is shown below:

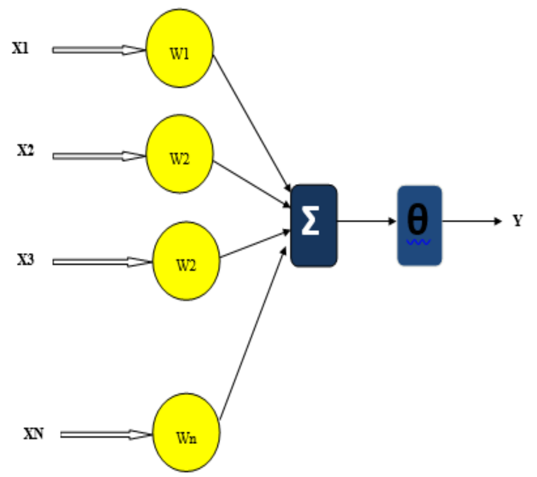

Fig.1 Mathematical Model of Neural Network

The output of the neural network is given by:

$$\sum_{i=1}^{n} XiWi + \Theta \qquad (2)$$

here,

Xi represents the signals arriving through various paths,

Wi represents the weight corresponding to the various paths and

ϴ is the bias.

The essence of neural networks lies in the fact that neural networks can find a relation among variables which may seem highly uncorrelated. Moreover, as the data keeps changing, the neural network structure keeps adapting in terms of the weights so as to optimize the model and reduce the errors in the output [4]. Fundamentally, the learning is sub categorized as under:

1) Computational Intelligence
2) Artificial Intelligence
3) Machine Learning
4) Deep Learning

A set theoretic relationship among the above can be seen to be depicted by figure 2

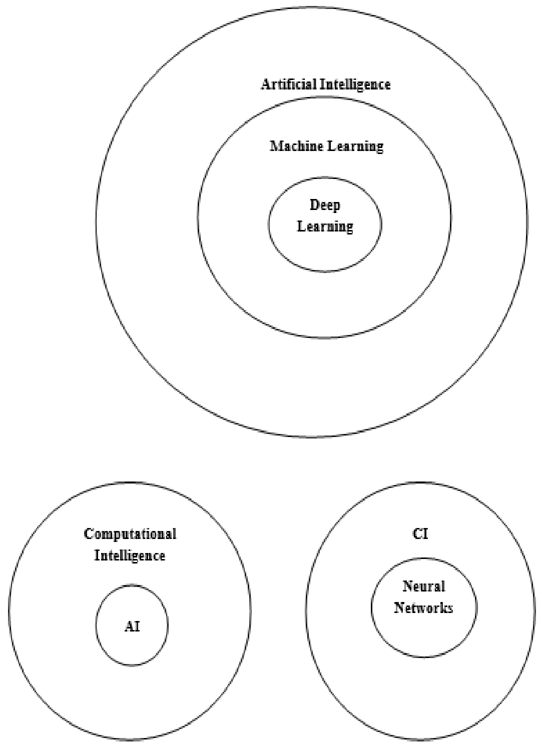

Fig.2 Relationship between machine learning paradigms

Moreover, neural network architectures are also categorized as:

Feedforward Networks: Feed forward networks consist of only the feed forward path for data to travel from input layer towards output layer

Recurrent Networks: Recurrent networks have at least one closed data path loop.

Back Propagation: Back Propagation feeds back the error at the output as an input

The diagrammatic representations are given below:

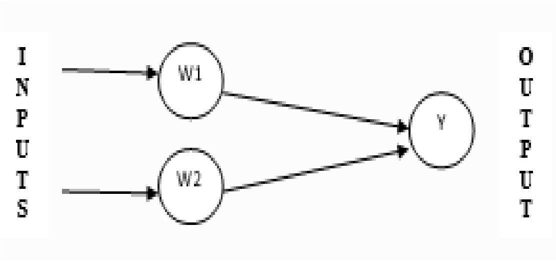

Fig.3 Single Layer Feed Forward Network

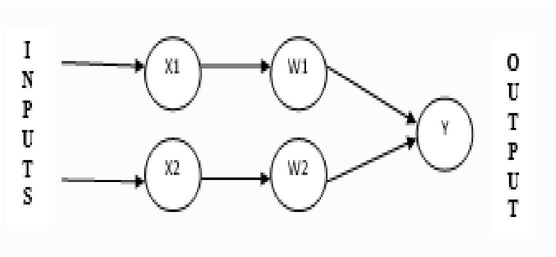

Fig.4 Multi-Layer Feed Forward Network

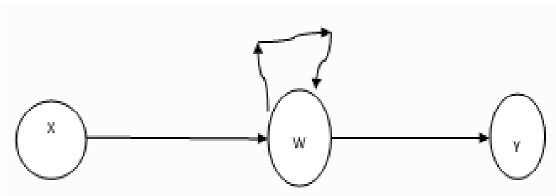

Fig.5 Recurrent Network

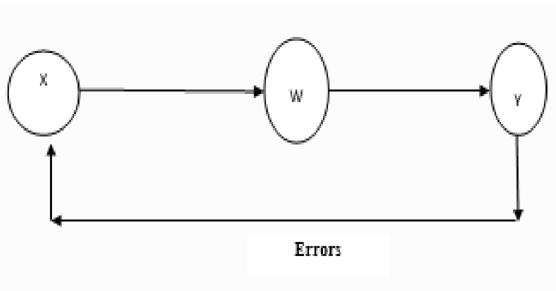

Fig.6 Network with back propagation

Out of the empirical neural network architectures, back propagation has gained significance due to its accuracy in prediction of time series applications. However the performance for different training algorithms vary considerably in terms of errors and number of iterations [5]

2.2 Fuzzy Logic

Another tool that proves to be effective in several prediction problems is fuzzy logic. It is often termed as expert view systems. It is useful for systems where there is no clear boundary among multiple variable groups. The relationship among the inputs and outputs are often expressed as membership functions expressed as [6]:

A membership function for a fuzzy set A on the universe of discourse (Input) X is defined as:

$$\mu A: X \rightarrow [0, 1] \qquad (3)$$

Here,

each element of X is mapped to a value between 0 and 1. It quantifies the degree of membership of the element in X to the fuzzy set A.

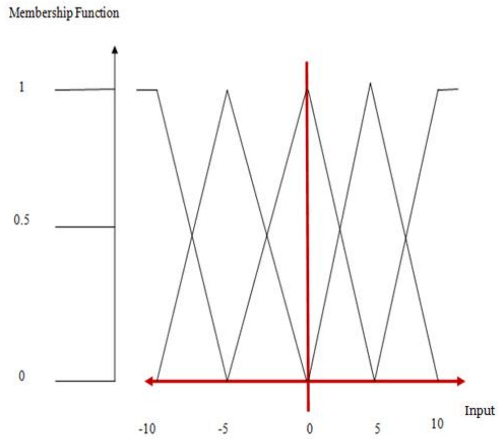

Fig.7 Graphical Representation of Membership Functions

Here,

x axis represents the universe of discourse (Input).

y axis represents the degrees of membership in the [0, 1] interval.

The final category is neuro fuzzy expert systems which governs the defining range of the membership functions.

2.3 Adaptive Neuro Fuzzy Inference Systems (ANFIS)

The ANFIS can be thought of as a combination of neural networks and fuzzy logic. In this mechanism, the neural network module decides the membership functions of the fuzzy module. The ANFIS structure is depicted in figure 8.

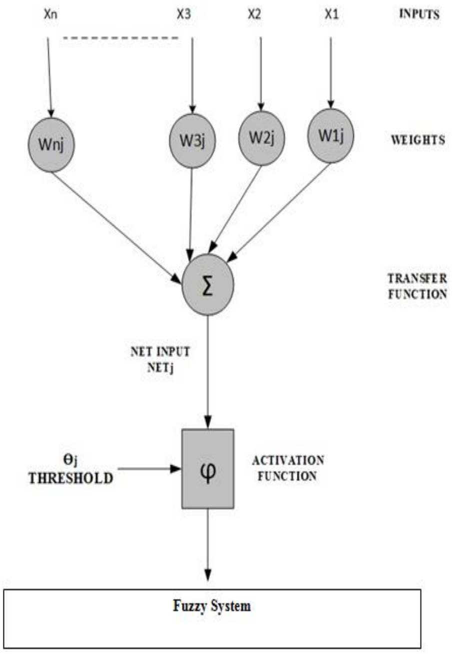

Fig.8 Block Diagram of Neuro-Fuzzy Expert Systems

III. DATA CLEANING

One of the most complex tasks related to demand forecasting is the analysis of extremely random and volatile data. Thus the proposed approach employs data cleaning techniques such as the wavelet transform.
The mathematical formulation for the wavelet transform is given by the scaling and shifting approach of the wavelet function [7].
The scaling, shifting dependence can be defined as:

$$W\varphi(Sc, Sh) = ₩[x, t] \quad \textbf{(4)}$$

Here,
x is the space variable
t is the time variable
₩ is the transform
sc is the scaling factor
sh is the shifting factor

The wavelet transform is an effective tool for removal of local disturbances. Pharmaceutical demands show extremely random behavior and local disturbances. Hence conventional Fourier methods do not render good results for highly fluctuating data sets. The major advantage of the wavelet transform is the fact that it is capable of handling fluctuating natured data and also local disturbances. The DWT can be defined as [8]:

$$\mathbf{W\Phi\ (Jo, k)} = \frac{1}{\sqrt{M}} \sum_n S(n).\Phi(n)_{jo\prime k} \quad \textbf{(5)}$$

IV. PROPOSED APPRAOCH

The proposed approach employs the data claeaning followed by the back propagation based training rule for neural network weight updates.

$$w_{k+1} = w_k - (J_k J_k^T + \mu I)^{-1}(J_k^T e_k) \quad \textbf{(6)}$$

Here,
w_{k+1} is weight of next iteration,
w_k is weight of present iteration
J_k is the Jacobian Matrix
J_k^T is Transpose of Jacobian Matrix
e_k is error of Present Iteration
μ is step size
I is an identity matrix.

The next step is the design of a fuzy system whose membership functions are to be updated using the neural networks output [9]. Some fundamentals of the membership function for the fuzzy model are given below:

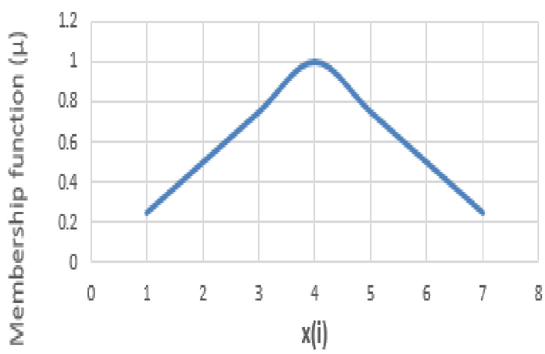

Fig.9 Illustration of a Fuzzy Set

The membership functions for the fuzzy set varies in magnitude based on two major factors:

1) Input variables
2) Type of membership function.

The most commonly used membership function type is the triangular membership function given by:

$$\mu_{traingle} = max\left(min\left(\frac{x-a}{b-a},\frac{c-x}{c-b}\right),0\right) \quad (7)$$

Here,

$\mu_{traingle}$ denotes the trangular membership depicted in figure 10.

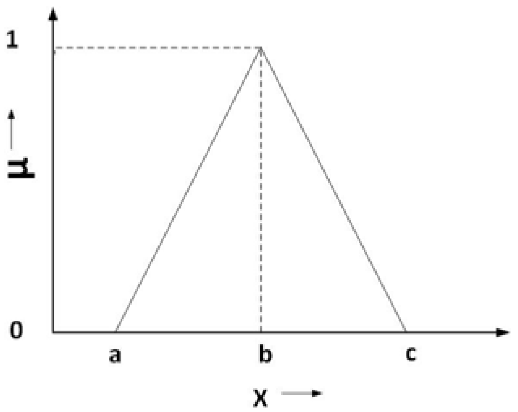

Fig.10 The Triangular Membership Function

Finally, the prediction is done based on the output of the ANFIS and the perfrmance indices computed are [10]:

Mean Square Error:

It is mathematically defined as:

$$mse = \frac{1}{n}\sum_{I=1}^{N}(X - X')^2 \quad (8)$$

Here,

X is the predicted value and

X' is the actual value and

n is the number of samples.

Mean Absolute Percentage Error (MAPE)

It is mathematically defined as:

$$MAPE = \frac{100}{M}\sum_{t=1}^{N}\frac{E-E_t|}{E_t} \quad (8)$$

Here,

E_t and $E_{t}^{\sim}$ stand for the predicted and actual values respectively.

Iterations:

The iterations denote the number of cycles of training needed to reach convergence.

V. EXPERIMENTAL RESULTS

The experimental results obtained in the study are presented in this section. The system has been designed on Matlab. The data set used is extracted from Kaggle [1]. The parameters used are:

1) Date
2) Month
3) Generic Name
4) Brand Name
5) Medical Use
6) Shipped to Country
7) Sold in
8) Delivery Plant
9) External Agent Assigned/Not-Assigned
10) Price
11) Revenue
12) Commission
13) Demand/Sales

The data set parameters are depicted in figure 11.

Disease Medical Use	Company code	ship to country	Sold-to party Country Full Name	Delivery Plant	External Agent	Sales quantity	Price TC /Kg	Revenue	External commissions	Months
Psychosis; depression	5704	Mexico	Mexico	8370	lot assigne	450	$ 204.0	$ 91,800.0	$ -	Nov
Pain	5704	Thailand	Thailand	8370	lot assigne	374	$ 472.0	$1,76,528.0	$ -	Jun
Pain	5704	Vietnam	Japan	8370	Assigned	138	$ 472.0	$ 65,136.0	$ 4,186.0	Dec
Pain	5704	Australia	Australia	8370	lot assigne	227	$ 472.0	$1,07,144.0	$ -	May
Pain	5704	Singapore	Singapore	8370	lot assigne	394	$ 472.0	$1,85,968.0	$ -	Jul
Pain	5704	Singapore	Singapore	8370	lot assigne	261	$ 472.0	$1,23,192.0	$ -	Feb
Pain	5704	Thailand	Thailand	8370	Assigned	129	$ 472.0	$ 60,888.0	$ 817.0	Apr
Pain	5704	Thailand	Thailand	8370	Assigned	310	$ 472.0	$1,46,320.0	$ 5,063.3	Mar
Pain	5704	Thailand	Thailand	8370	Assigned	111	$ 472.0	$ 52,392.0	$ 1,184.0	Feb
Pain	5704	Egypt	Egypt	8370	lot assigne	109	$ 472.0	$ 51,448.0	$ -	Apr
Neuropathic pain	5887	India	India	8095	lot assigne	46	$ 500.0	$ 23,000.0	$ -	Nov
Neuropathic pain	5887	India	India	8095	lot assigne	376	$ 500.0	$1,88,000.0	$ -	Sep
Neuropathic pain	5887	India	India	8095	lot assigne	135	$ 500.0	$ 67,500.0	$ -	Jul
Neuropathic pain	5887	India	India	8095	lot assigne	379	$ 500.0	$1,89,500.0	$ -	Jul
Neuropathic pain	5887	India	India	8095	lot assigne	104	$ 500.0	$ 52,000.0	$ -	Oct
Neuropathic pain	5887	India	India	8095	Assigned	468	$ 500.0	$2,34,000.0	$ 10,296.0	Feb
Neuropathic pain	5887	Thailand	Thailand	8095	lot assigne	365	$ 500.0	$1,82,500.0	$ -	May
Neuropathic pain	5887	Thailand	Thailand	8095	lot assigne	119	$ 500.0	$ 59,500.0	$ -	Jun
Neuropathic pain	5887	Thailand	Thailand	8095	lot assigne	127	$ 500.0	$ 63,500.0	$ -	May
Neuropathic pain	5887	India	India	8095	lot assigne	254	$ 500.0	$1,27,000.0	$ -	Jul
Neuropathic pain	5887	India	India	8095	lot assigne	171	$ 500.0	$ 85,500.0	$ -	Dec
Neuropathic pain	5887	outh Afric	outh Afric	8095	Assigned	250	$ 500.0	$1,25,000.0	$ 7,833.3	Feb
Neuropathic pain	5887	India	India	8095	lot assigne	240	$ 500.0	$1,20,000.0	$ -	Jul

Fig.11 Used Data Set Parameters

The next step becomes importing the data to the MATLAB workspace so that the training and target data can be split. The split ratio used in this work has bene chosen as 70:30 as a standard thumb rule.

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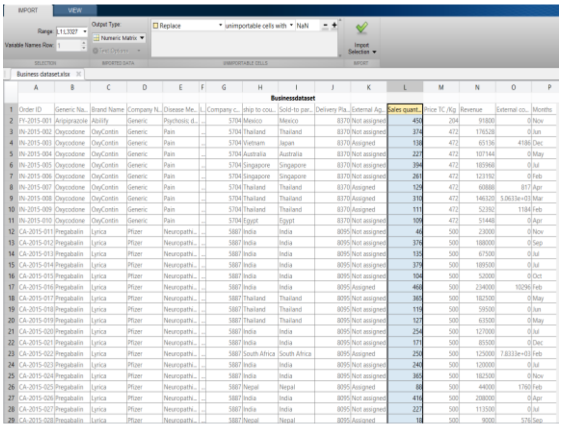

Fig.12 Data Imported to Workspace

The continuous wavelt 1-D using the symlet has been used.

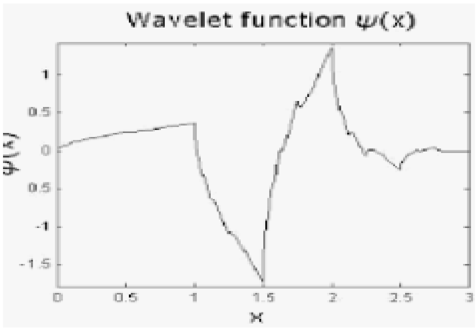

Fig.12 Symlet Wavelet Function

The decomposition has been shown in figure 13.

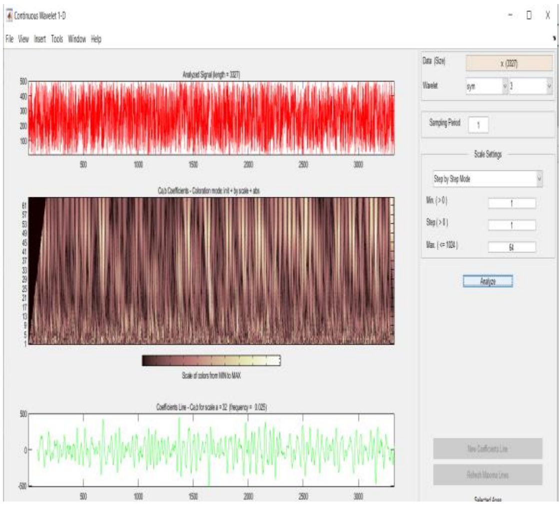

Fig.13 Symlet Decomposition of Data

The decomposition cleans the data which is then applied to the ANFIS.

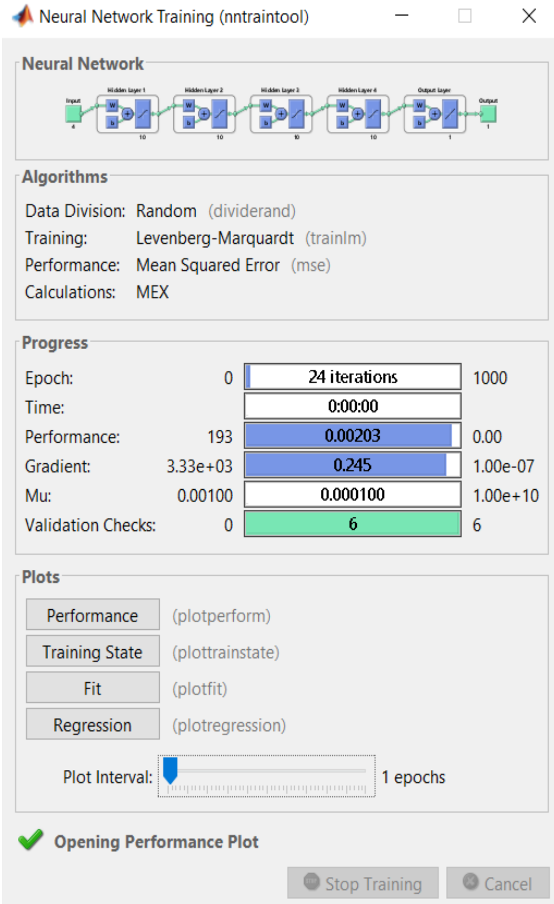

Fig.14 Designed Neural Network

The properties of the neural network have been shown in figure 14

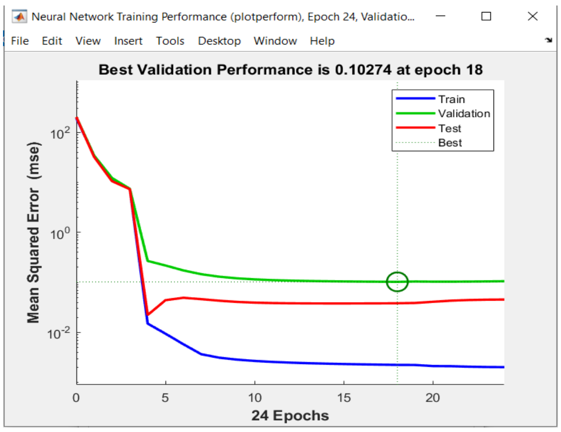

Fig.15 Iterations for convergence of Neural Network

The training epochs to convergence is depicted in figure 15.

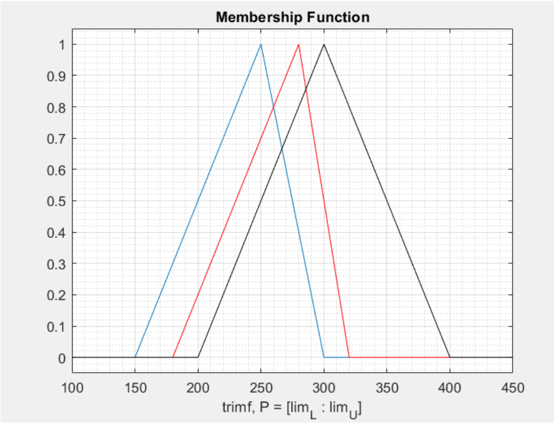

Fig.16 Membership Functions of Fuzzy System

The membership functions for the Fuzzy System are depicted in figure 16. A three tier membership is used which are:

1) Low
2) Moderate
3) 3 High

The range is chosen based on the variation in the parameter values of the demand.

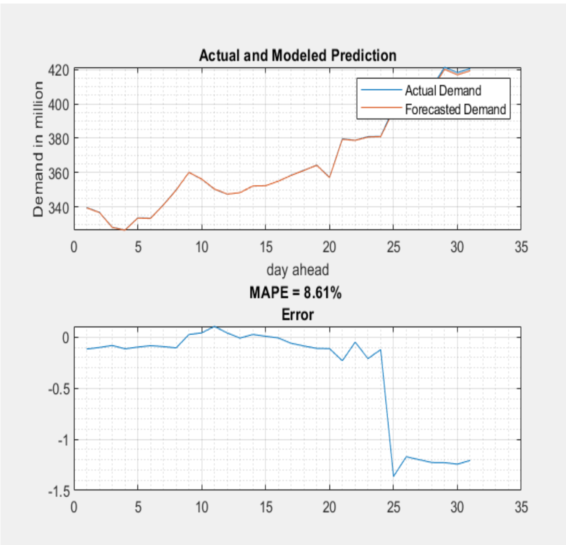

Fig.17 Modelled and Actual Prediction: MAPE Value

The MAPE obtained in the proposed work is 8.61%. Thus the accuracy can be computed as:

$$Accuracy = 100 - MAPE\ \%$$

The accuracy is thus 91.39%

Summary of Results

A summary of results of the proposed system based on the values obtained is tabulated in table 1.

Table 1. Parameter Values

S.No.	Parameter	Value
1.	Dataset	Kaggle
2.	Splitting Ratio	70:30
3.	Pre-Processing	DWT
4.	DWT Family	Symlet
5.	ANFIS Hidden Layers	4
6.	Membership Function	Triangular
7.	Levels	Low, Moderate, High
8.	Iterations	24
9.	MAPE (Proposed)	8.61%
10.	MAPE (Previous)	14%
11.	Accuracy (Previous)	86%
12.	Accuracy (Proposed)	91.39%

CONCLUSION

The proposed work puts forth an ANFIS based technique for demand forecasting of pharmaceutical data. The technique used is a combination of the wavelet transform and adaptive neuro fuzzy inference system (DWT-ANFIS) hybrid to forecast pharmaceutical products. The DWT has been used as a data cleaning and optimization tool whereas the ANFIS has been used for forecasting. The evaluation of the proposed work has been done based on the mean absolute percentage error, regression and iterations of the system. The proposed system attains a MAPE of 8.61% compared to 14% of previous work. The training iterations needed are 24. Thus the proposed system is an improvement over the existing work in terms of accuracy of forecasting.

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