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Prediction of Interest Rate using Generalized Neural Method

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***Abstract*: It is essential to estimate the financial index for the national welfare and people's livelihood. In this paper, we present an artificial neural network method, adaptive neuro fuzzy inference system and generalized neural network method of forecasting financial index. Artificial neural networks can be used for predicting nonlinear, dynamic systems through learning, which can easily accommodate the nonlinearities. Adaptive neuro fuzzy inference system is hybridization of fuzzy and neural network with adaptive nature. Taking advantage of the characteristics of a generalized neuron (GN), that requires much smaller training data. The feasibility of this method is discussed by means of its application to a twenty years financial statistics data.**

Keywords: Fuzzy, Artificial Neural network, ANFIS, Generalized Neural Network, Forecasting, Interest Rate.

I. Introduction

The stabilization of the financial index for the national welfare and people's livelihood has been a challenging problem since the early days of the modern money and capital market. The market has two sides, one is positive, another is negative. The positive role is its financing function which can raise money needed for business and the nationality construction items. The negative one is its latent risk which arise financial crisis frequently in a corporation or spread over an area, even the worldwide. Keeping in view the randomness and complexity of the market, it is difficult to carry forward the positive and control the negative. Therefore, the research for financial forecasting model is needed, which includes the development of models related to national, regional, and local financial system [8, 11, 14, 17-18]. The conventional forecasting methods require large computational effort and also sometimes give unrealistic results. These motivate us to develop the new method for the financial forecasting.

Forecasting is of considerable interest in the financial world. More recently some investigations have been done in signal analysis and forecasting problems using the dynamically and inductive property of the neural networks for solving the problems encountered with the traditional methods. A set of applications has been done in financial forecasting and modeling.

The common neuron model has been modified to obtain a generalized neuron (GN) model to overcome the problems such as large number of neurons and layers required for conventional ANN complex function approximation, which not only affect the training time but also the fault tolerant capabilities of the ANN (see Appendix-B).

Generalized neural network method is an artificial intelligence (AI) approach to mathematical modeling. Neural networks are systems that are loosely patterned on the human brain, that can learn and discern patterns in real-world conditions where data is incomplete or the number of variables is vast. Neural networks can model dynamic, non-linear phenomena that are too complex to be described by analytical methods or empirical rules [9, 16, 19]. Neural networks can be implemented for advanced control, data and sensor validation, pattern recognition, and multivariable quality control applications. The generalized neural network is employed here due to the successful application in many fields of engineering [2-7] and the perfect character of neural network fitted particularly in describing that of the financial system.

II. Factors Affecting Interest Rates

There are following five factors which affect interest rate:

- Previous interest rates (Δ IR)
- Real Gross National Product (Δ GNP)
- Consumer Price Index (Δ CPI)
- M2 national money supply (ΔM2)
- Personal wealth (ΔPW)

Personal wealth is the accumulation of the difference between personal income and personal consumption. The M2 money supply consists of cash in circulation and deposits in savings and checking accounts and represents readily available liquid assets. Consumer price index is a measure of the inflation trend [13].

The Figure 1 shows a block diagram of the model. There are five inputs and one output for financial forecasting model.

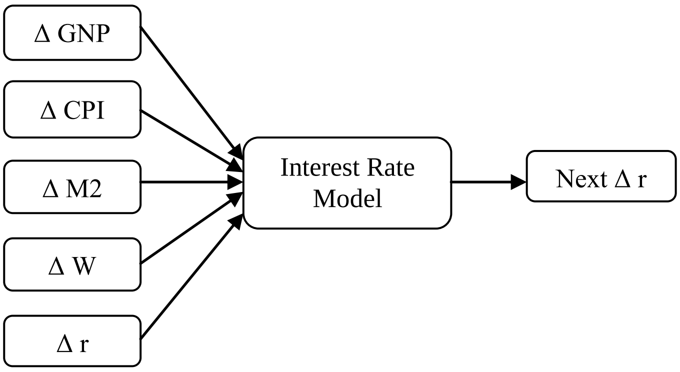


Figure1: Block Diagram of the interest rate forecasting Model

III. Financial Data

Input vector 1 and output vector 1 show input and output of first order model for forecasting. The input vector for first order model consists of five inputs namely real Gross National Product (ΔGNP), Consumer Price Index (ΔCPI), national money supply (ΔM2), Personal wealth (ΔW), Previous interest rates Δr (t) as given in equation (1). The trend of these input variables is shown in Figure 2.

Input Vector 1=

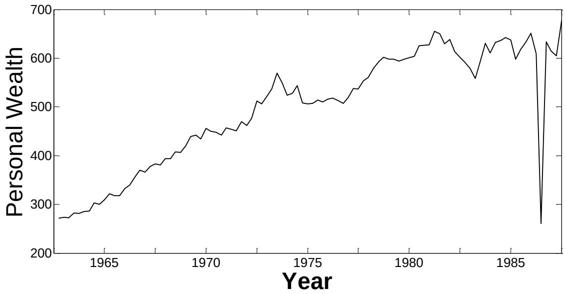
[ΔGNP (t) ΔCPI (t) ΔM2 (t) ΔW (t) Δr (t)] ---- (1)

and the *Output Vector 1= [Δr (t+1)]*

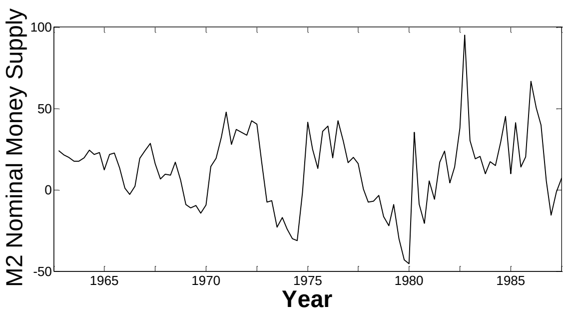
Now for 2nd order models the past two interest rates are considered as mentioned in equation (2).

Input Vector 2 =

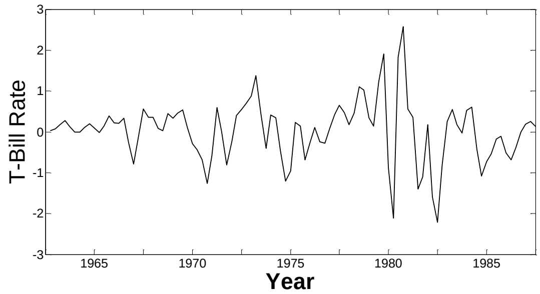
[ΔGNP (t) ΔCPI (t) ΔM2 (t) ΔW (t) Δr (t-1) Δr (t)] ---- (2)



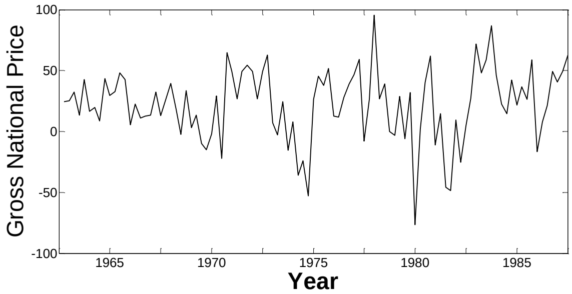
(a) Personal Wealth Data



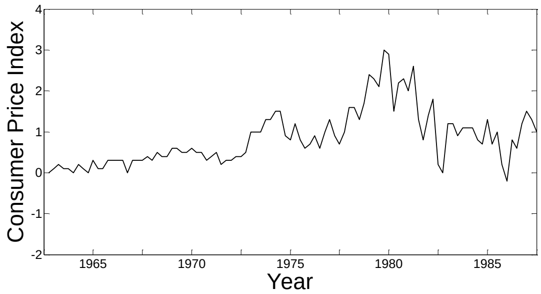
(b) M2 National Money Supply



(c) T-Bill Rate Data



(d) Gross National Price



(e) Consumer Price Index

Figure 2: Trend of five input Variables

Input Vector 3 for 3^{rd} *order model*

[ΔGNP (t) ΔCPI (t) ΔM2 (t) ΔW (t) Δr (t-2) Δr (t-1) Δr (t)]

---- (3)

Similarly for 4^{th} order model, past four values of interest rate, are taken and so on.

IV. Adaptive Neuro Fuzzy Inference System for Modeling of Interest Rate Model

The acronym ANFIS derives its name from Adaptive Neuro-Fuzzy Inference System. Using a given input/output data set, ANFIS constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using either a back-propagation algorithm alone or in combination with a least squares type of method. This adjustment allows fuzzy systems to learn from the data used for modeling. The combination of neural network and fuzzy is used for load forecasting [20, 21]. Its performance is better than artificial neural network.

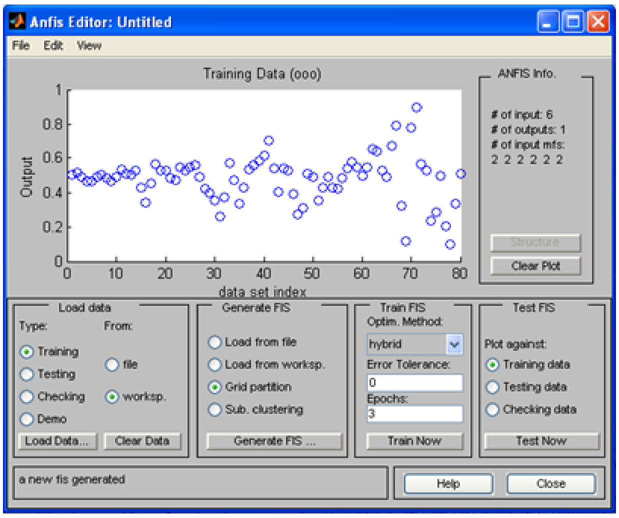


Figure 3: ANFIS Editor window

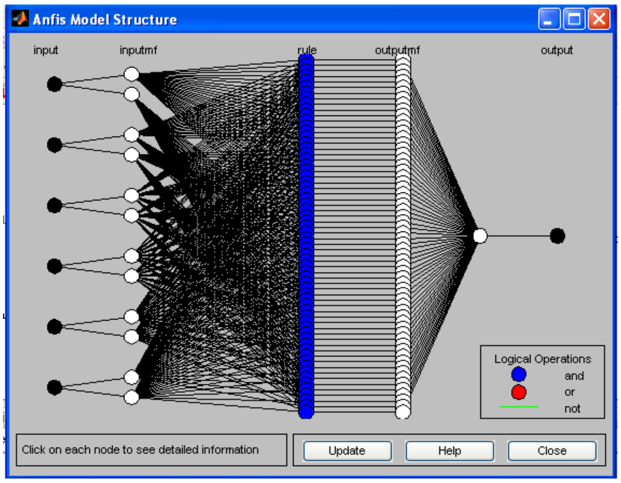


Figure 4: ANFIS Model structure

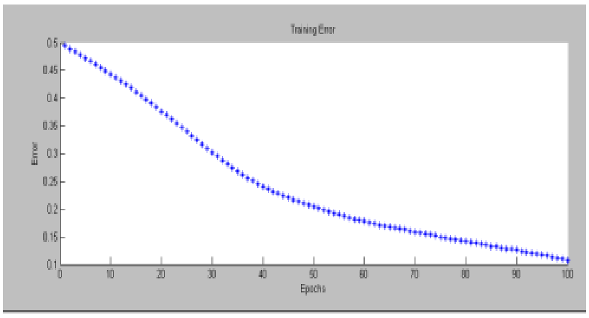


Figure 5: ANFIS Training error

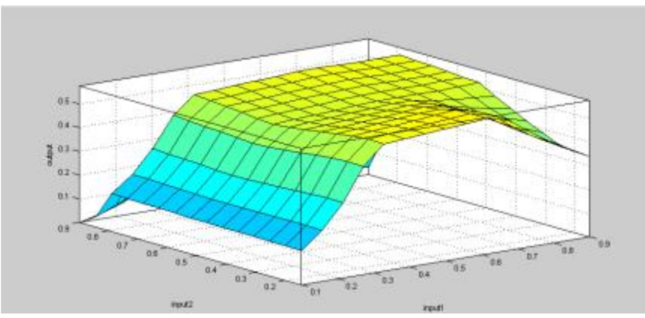


Figure 6: Surface Viewer of ANFIS model

The 3rd order back propagation ANFIS model is developed consisting of two layers of structure (6-1). ANFIS model consists of 729 fuzzy rules. The ANFIS editor window and ANFIS model structure are shown in Figure 3 and Figure 4 respectively. The ANFIS training error for interest rate model is shown in Figure 5 and surface viewer of the same model is shown in Figure 6.

V. The Generalized Neural Model for Interest Rate Modeling

The sigmoidal thresholding function and an ordinary summation or product as aggregation functions in the existing neuron models [1, 10] fail to cope with the nonlinearities involved in real life problems. To deal with these, the proposed model has both sigmoidal and Gaussian functions with weight sharing. The GN model has flexibility at both the aggregation and threshold function level to cope with the nonlinearity involved in the type of applications dealt with, as shown in Figure 7.

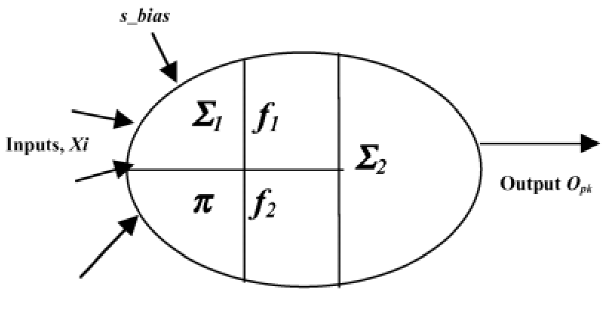


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Figure 7: Generalized Neuron Model

The neuron has both$\sum$ and Π aggregation functions. The Σ_1 aggregation function has been used with the sigmoidal characteristic function (f_1) while the Π aggregation function has been used with the Gaussian function (f_2) as a characteristic function (see Appendix-A).

The main advantage of Generalized neural over ANN is given below:

1. **Less number of unknown weights**. The number of weights in the case of a GN is equal to the twice the number of inputs plus one, which is very low in comparison to a multi-layer feed-forward ANN.
2. **Less training time.** The weights are determined through training. Hence, by reducing the number of unknown weights, training time can be reduced.
3. **Less number of training Pattern.** The number of training patterns required for GN training is dependent on the number of unknown weights.
4. **Size of hidden layer.** There is no hidden layer required in case of GN and single neuron is capable to solve most of the problems.
5. **Complexity of GN.** GN model is less complex as compared to multi-layered ANN model.
6. **Structural level flexibility.** GN models are more flexible at structural level. The aggregation and activations functions could be chosen depending on the problem in hand.

Table 1: Training and Testing performance of different models for 3rd model order			
	ANN Model	**ANFIS Model**	**GN Model**
Root Mean Square of error during Training	0.1078	0.1050	0.0955
Root Mean Square of error during Testing	0.1797	0.1202	0.1170

The neuron model described above is known as the summation type compensatory neuron model, since the outputs of the sigmoidal and Gaussian functions are summed up. Similarly, the product type compensatory neuron models may also be developed. It is found that in most of the applications, the summation-type compensatory neuron model works well [12] and is the one used for the estimation of machine parameters. Here summation and product are used at the aggregation level for simplification, but one can take other fuzzy aggregation operators such as max, min, or compensatory operators, too. Similarly, the thresholding functions are only sigmoidal and Gaussian function for the proposed GN, but other functions like straight line, sine, cosine, etc. can also be used. The weighting factor may be associated with each aggregation function and thresholding function. During training, these weights change and decide the best functions for the GN. The learning algorithm of GN model is given in [3-7]. The response of different model order for financial rate model is done in [22].

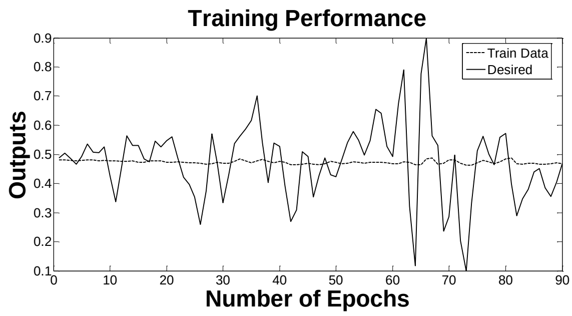
Table 2: Comparison of GN Model for different model order		
GNN Model Order	**Root Mean Square of error during training**	**Root Mean Square of error during testing**
First order	0.1127	0.1381
Second order	0.0985	0.1207
Third order	**0.0955**	**0.1170**
Fourth order	0.0962	0.1178
Fifth order	0.0937	0.1148
Sixth order	0.0936	0.1147
Seventh order	0.1269	0.1555

VI. Results and Discussions

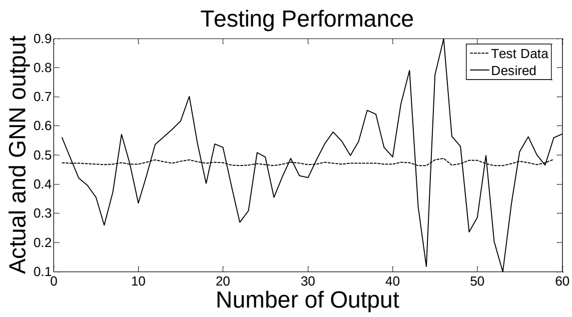
The Table 2shows the training and testing performance of GNN model with different GN model. The GN models are trained up to 1000 epochs and results are compared. The result of 3rd order model of GNN is quite good in comparison with others GNN models with different orders.

The Table 1 shows the training and testing performance of GN, ANN and ANFIS models have been compared for predicting the national financial indices. The 3rd order feed forward back propagation ANN model is developed consisting of three layers of structure (5-3-1).

The training and testing results of GN model for different model order are shown in Figure 8 to Figure 15. The training and testing results of ANN model and ANFIS model for model order 3 are shown in Figure 16 and in Figure 17 respectively. The training and testing result of GN model is shown in Figures 12 and compared with actual data. The results show that the training and testing performance in terms of RMS error of GN model is better than ANN and ANFIS model for same inputs. Sum squared error during training of 3rd order GN model is given in Figure 13.

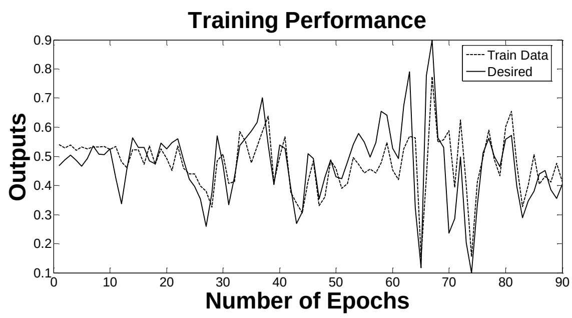


(a) Training Performance of 7th order GN model

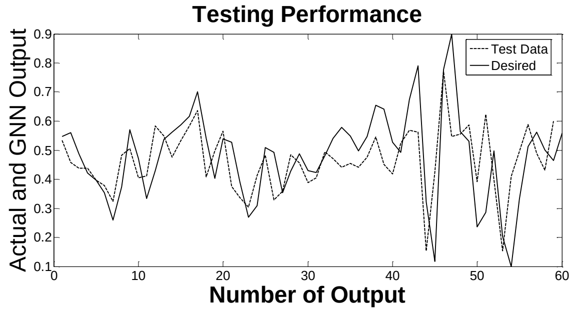


(b) Testing Performance of 7th order GN model

Figure 8: Training and Testing Performance of 7th order GN model

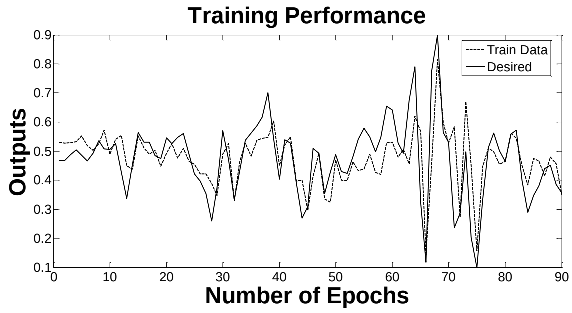


(a) Training Performance of 6th order GN model

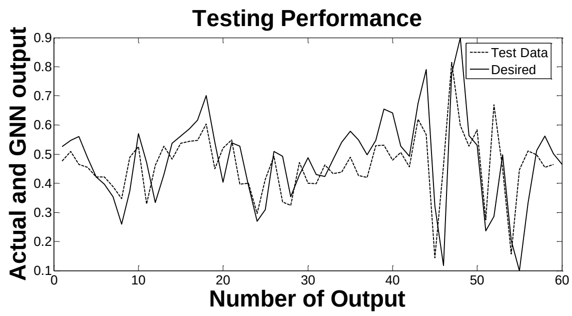


(b) Testing Performance of 6th order GN model

Figure 9: Training and Testing Performance of 6th order GN model

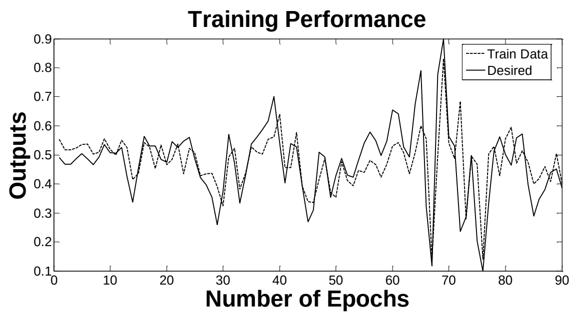


(a) Training Performance of 5th order GN model

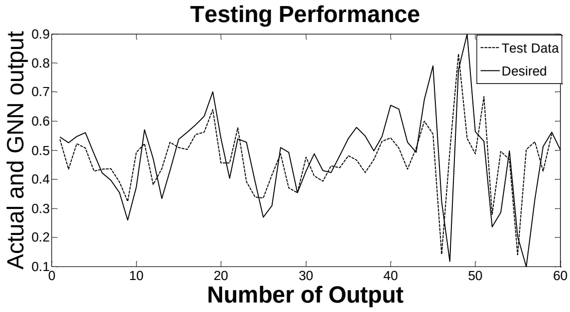


(b) Testing Performance of 5th order GN model

Figure 10: Training and Testing Performance of 5th order GN model

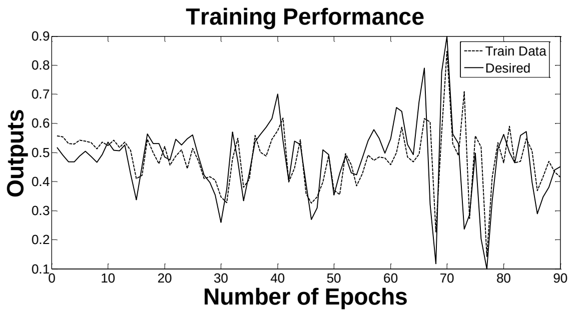


(a) Training Performance of 4th order GN model

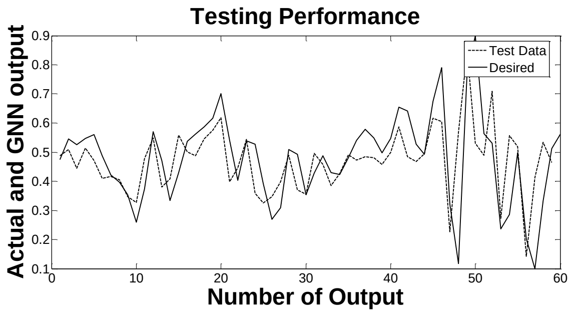


(b) Testing Performance of 4th order GN model

Figure 11: Training and Testing Performance of 4th order GN model



(a) Training Performance of 3rd order GN model



(b) Testing Performance of 3rd order GN model

Figure 12: Training and Testing Performance of 3rd order GN model

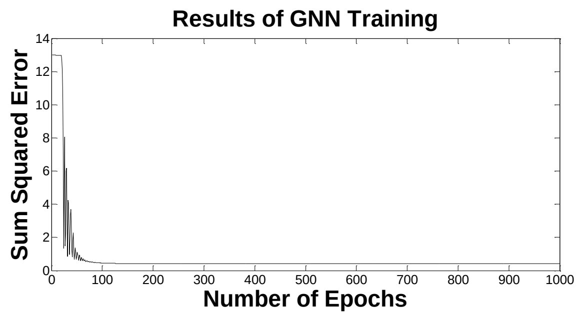
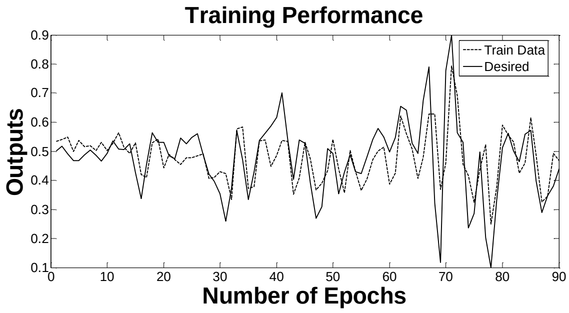
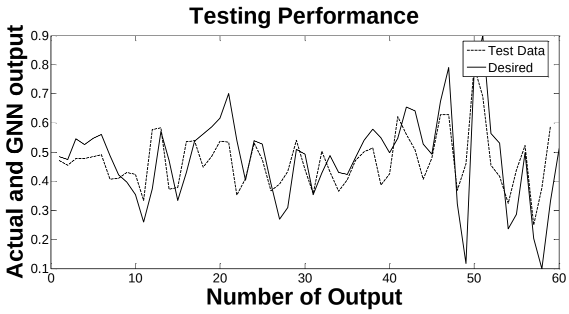


Figure 13: Sum Squared Error during training of 3rd order GN model

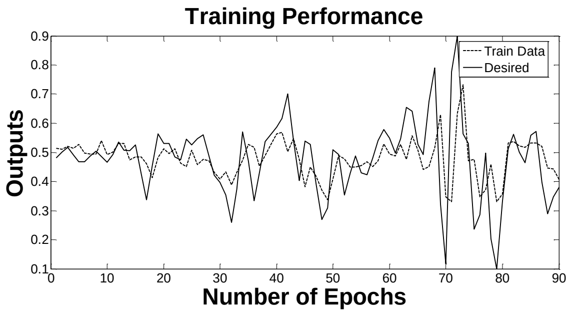


(a) Training Performance of 2nd order GN model

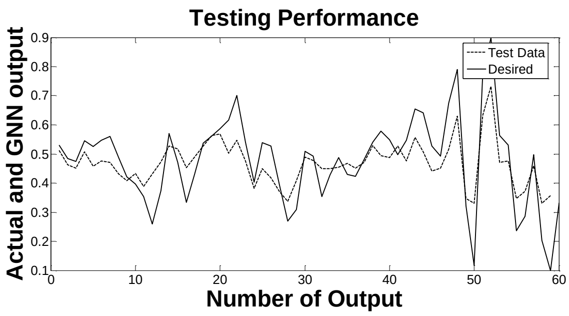


(b) Testing Performance of 2nd order GN model

Figure 14: Training and Testing Performance of 2nd order GN model

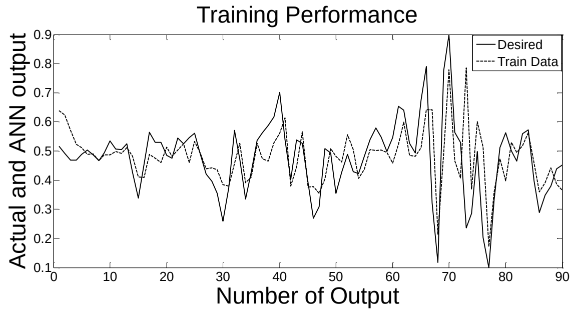


(a) Training Performance of 1st order GN model

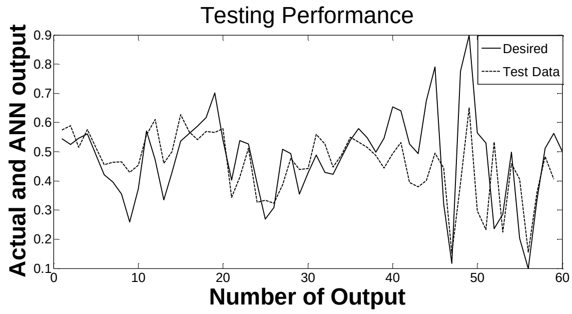


(b) Testing Performance of 1st order GN model

Figure 15: Training and Testing Performance of 1st order GN model

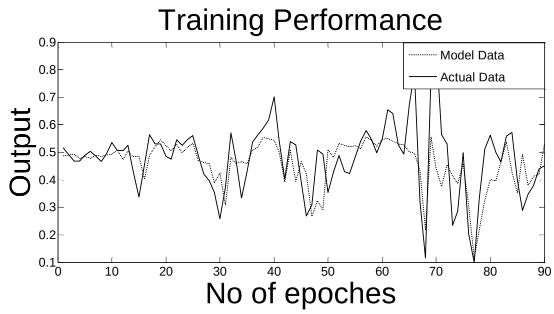


(a) Training Performance of 3rd order ANN Model

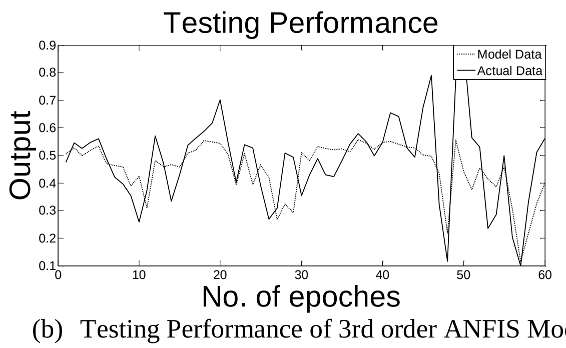


(b) Testing Performance of 3rd order ANN Model

Figure 16: Training and Testing Performance of 3rd order ANN Model



(a) Training Performance of 3rd order ANFIS Model



(b) Testing Performance of 3rd order ANFIS Model

Figure 17: Training and Testing Performance of 3rd order ANFIS Model

VII. Conclusions

In this paper, GN models are developed for forecasting of interest rate and the results are compared with ANN and ANFIS. It is found that GN 3rd order model gives better results as compared to other models. Then ANN 3rd order model and ANFIS 3rd order model are also developed and results are compared with GN model. The GN 3rd order model is even better than ANN and ANFIS models under same training and testing conditions.

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Appendix – A

The output of the Σ_1 part with sigmoidal characteristic function of the GN is

$$0_\Sigma = f_1(s_{net}) = \frac{1}{1+e^{-\lambda_{s*}s_{net}}} \qquad \text{------- (4)}$$

Where $s\_net = \sum W_{\Sigma i} X_i + X_{0\Sigma}$ and λ_s is the gain scale factor for the Σ part.

The output of the Π part with Gaussian characteristic function of the GN is

$$0_\Pi = f_2(pi\_net) = e^{-\lambda_{p*}pi_{net}{}^2} \quad \text{--------- (5)}$$

Where $pi\_net = \prod W_{\Pi i} X_i * X_{0\Pi}$ and λ_p is the gain scale factor of the Π part.

The final output of the neuron is a function of the two outputs O_Σ and O_Π , with the weights W and (1-W), respectively as given by equation 3.

$$O_{pk} = O_\Pi * (1 - W) + O_\Sigma * W \text{ -------- } (6)$$

After calculating the output of the summation type generalized neuron in the forward pass, as in feed-forward neural network, it is compared with the desired output to find the error.

$$\boldsymbol{Error} \quad E_i = Y_i - O_i \quad ----(7)$$

Then, the sum-squred error for convergence of all the pattern is

$$E_p = 0.5\Sigma E_1^2 \; --- \; (8)$$

A multiplication factor of 0.5 has been taken to simplify the calculations.

Appendix – B

Artificial neural networks are biologically inspired but *not necessarily biologically plausible*. The human nervous system, built cells called neurons is of staggering complexity. An estimated 10^{11} interconnections over transmission paths are there that may range for a meter or more. Each neuron shares many characteristics with the other cell in the body, but has unique capabilities to receive, process, and transmit electrochemical signals over neural pathways that comprise the brain's communication system.

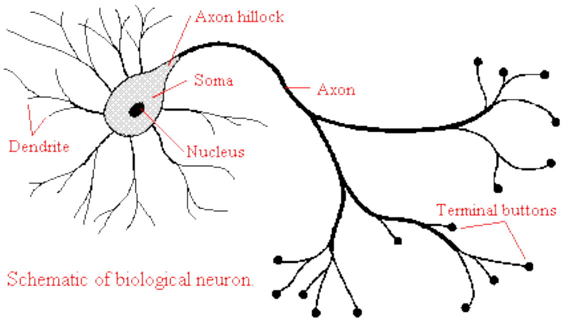

Figure 18: Structure of biological neuron

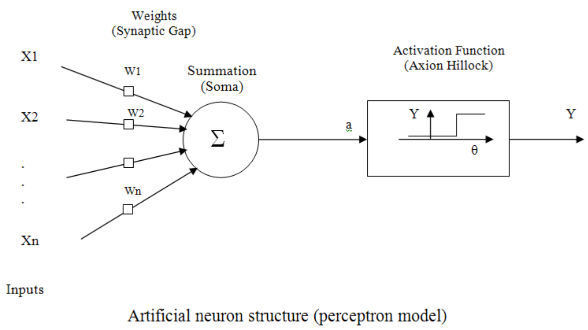

Figure 19: Artificial neuron structure model

The activation a, is given by

$$a = w_1x_1 + w_2x_2 + \cdots . w_nx_n + \theta$$

This may be represented more compactly as

$$a = \sum_{i=1}^{n} X_iW_i + \theta$$

the output y is then given by $y=f(a)$, where f is a activation function.

The properties of artificial neural networks are given below:

1. Neural networks are inherently parallel and implementation can be done on parallel hardware.
2. It has capacity for adaption.
3. ANN has fault tolerant capacity.
4. It has capacity for generalization and easy to construct the ANN model.

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