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A Constraint in Neuro Fuzzy Approach on Prediction of Dielectric Constant of Doped and Undoped $TbMnO_3$

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Abstract – Artificial Neural Networks are well known for their prediction capability that can simulate human expertise efficiently. Generally Hybrid Neural networks are popular for their greater performance over other popular neural networks. On the other hand each and every Neural Networks has high dependency on the behavior of prediction dataset. This research tries to find out the constraint application of Neuro-Fuzzy Networks. A Comparative analysis is made to envision, the prediction capability of Artificial Neural Networks on dielectric properties of $TbMnO_3$ ceramics doped with Bi and Fe ions in Dielectric Constant prediction where feed forward back propagation networks outperforms the capability of Neuro-Fuzzy Networks.

Keywords - *Adaptive Neuro Fuzzy Systems, Dielectric Constant, Doping, Tolerance, Transfer Functions, Semiconductor*

1. Introduction

This research at the initial stage emphasizes the prediction capability of Feed Forward Back Propagation Network(FFBPN) with respect to alteration of different transfer functions such as TANSIG and LOGSIG. In the Formal Research [10,11] Neuro Fuzzy gained enormous popularity in the field of prediction[13,14]. Hence the letter stage of this research tries to implement Neuro Fuzzy inference system by using it's two popular mechanism such as back propagation and hybrid, to achieve greater prediction accuracy in comparison with feed forward back propagation networks in dielectric constant prediction for doped and undoped Terbium Manganite. The research at the end tries to depict the behavioral changes in prediction mechanism while experimenting with specific dataset. As a whole this research highlights high dependencies between structure of the dataset and the neural networks capabilities. Finally it is found Feed-Forward Backpropagation Network (FFBPN)[22,23,24] outperforms than Artificial Neuro Fuzzy Inference System(ANFIS).

2. Background Study

Terbium is a rare earth metal which has enormous applicability in the field of solid-state devices; but Terbium applicability is visible when it is doped with Calcium Fluoride, Calcium Tungstate, and Strontium Molybdate. Instead of using pure Terbium, here $TbMnO_3$ doped with Bi and Fe ion is used ion's dielectric constant parameter is used. In recent years there are lots of research is going on in the field of semiconductor doping [5] parameters prediction. The concept of doping has some specific benefits over semiconductor field such as sometimes reducing lattice parameters in alloy, and doping weakened the stability of alloy and hydride [3]. Since predicting doping parameters have enormous impact in modern engineering field. The concept of doping is used in

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testing device performances along with the application in organic thin-film [4], also applicable in substantial electric field [5]. Different types of complex experimental methods such as high uniaxial strain [6].

The reason behind selecting doped $TbMnO_3$ dataset is its steadiness with respect to dopant substitution [9]. The dopant substitution property is used to modify the Mn-O-Mn bond angles which results in strengthen ferromagnetic component of magnetic moment. Since magnetic ordering of $TbMnO_3$ is applicable in the class of Magnetoelectric multiferroic which has in general low magnetic moment due to the predominantly antiferromagnetic order[7]; In recent experiment it is proved that phenomenological coupling mechanism is important in order to create new materials with improved magneto-electric effect at high temperature. [8] ANFIS in recent days has several applications [10,11,14,20,21] in the diversified domain which motivates this research to extent the applicability of this Hybrid model in Predicting Doping Parameter.

Prediction capability and implementation power of Artificial Neural Network is beyond human limit. Hence Artificial Neural Network is more successful over manual computation. In general image processing pattern recognition, character recognition and forecasting can be implemented by using feed forward back propagation network. The prime concept behind artificial neural network is subtracting the training output from the desired output and error signal is to obtain the error signal. It then goes back to adjust the weights and biases in the input and hidden layers to reduce the error signal in the field of dielectric constant prediction.

3. Graphical Illustration

The overall systematic approach on which the dielectric constant dataset is fed into the neural networks is highlighted through the following observation. ANN and ANNFIS model both uses 70% of the entire dataset is for training and remaining 15% is used for testing and another 15% is used as a validation dataset in order to escape bias and premature termination.

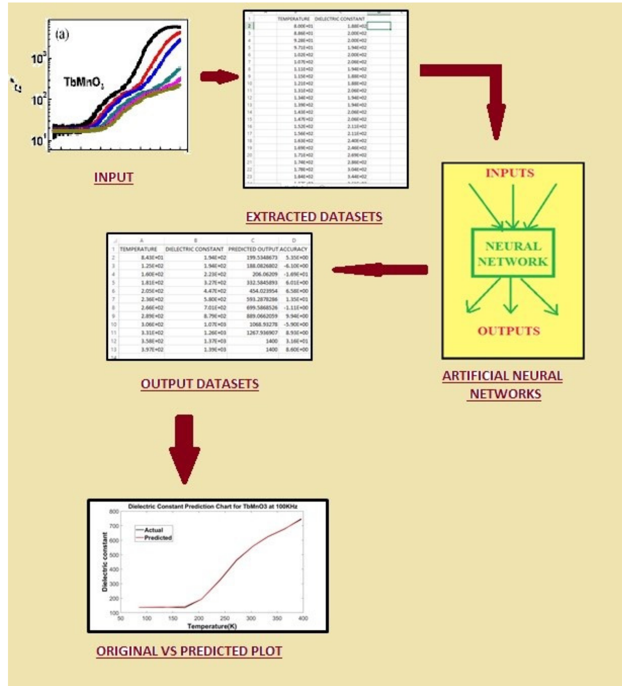

Fig 1: Graphical framework of working principle of prediction on doped and undoped $TbMnO_3$ using FFBN and ANFIS networks.

5. Dataset Description

In this paper doped Terbium Manganite with Bismuth and Fe is used [1]. The specific importance behind this dataset is magnetic ordering in $TbMnO_3$ which causes Ferro electricity which can be considered as valuable step in the domain of magnetically driven Ferroelctricity. $TbMnO_3$ an orthorhombic ally distorted perovskite manganite ($RMnO_3$ where R= Trivalent rare earth material). The dielectric nature of $TbMnO_3$ varies by altering the temperature and frequency. In this research the dielectric constant of several level of doping of $TbMnO_3$ is examined with respect to temperature. Dielectric or electrical insulating materials when doped it changes in the dielectric properties. Henceforth dielectric constant of an insulating material is the ability to store electric energy in an electric field.

In general dielectric constant may vary with temperature, Frequency and dielectric materials. dielectric constants (ε') of $TbMnO_3$, $Tb_{0.95}Bi_{0.05}MnO_3$, $Tb_{0.9}Bi_{0.1}MnO_3$ and $Tb_{0.9}Bi_{0.1}Mn_{0.95}Fe_{0.05}O_3$ ceramic composites have been measured and studied as a function of the temperature from 75 to 400 K and at different frequency like 1kHz,5 kHz,10kHz,50kHz,100kHz, 200kHz. Remarkably, doping Bi makes dielectric constant decrease in the high temperature range. Again dielectric constant becomes larger again in the high temperature range after Fe doping appropriately. Analysis indicates that the perovskite structures gradually vary with the increase of Bi replacing Tb, thus the dielectric properties could be enhanced with the small amount of Mn replacement with Fe.

6. Results

$TbMnO_3$ Transfer function Tansig performs better based on accuracy percentage at different frequencies. In the second graph $Tb_{0.95}Bi_{0.05}MnO_3$ the analyzed result represents the fact in different frequencies the behavior of transfer functions oscillates at frequency 1 kHz, 5 kHz, 10 kHz, 50 kHz, 100, 200kHz where Tansig performs well .Similarly in third graph $Tb_{0.9}Bi_{0.1}MnO_3$ Logsig gives more accurate output at all frequencies. In last graph $Tb_{0.9}Bi_{0.1}Mn_{0.95}Fe_{0.05}O_3$ at frequency 1 kHz, 10 kHz, 50 kHz, 100 kHz, 200 kHz Tansig performs well and Logsig performs well for the frequencies 5 kHz. In all the observation Purelin function gives worst resultant. During this observation it is also found out that Mean Square Error value is better for Tansig and Logsig at different frequencies.

6.1 Tables

6.1.1 Tabular Results of Undoped $TbMnO_3$

Table 1: Analysis of Dielectric Constant Prediction using TANSIG versus LOGSIG Transfer Function of Feed Forward Backpropagation Networks at Different Frequency on Undoped TbMnO3

Dataset	Number of Neurons in Hidden Layer	Epoch	Tolerance	Accuracy (%)	
				TANSIG	LOGSIG
$TbMnO_3$ at Frequency 1 KHz	12	1000	6.0 8.0	83% 91%	50% 50%
$TbMnO_3$ at Frequency 5 KHz	10	1000	6.0 8.0	72% 81%	54% 63%
$TbMnO_3$ at Frequency1 0 KHz	10	1000	6.0 8.0	58% 75%	75% 91%
$TbMnO_3$ at Frequency 50 KHz	10	1000	6.0 8.0	83% 91%	75% 75%
$TbMnO_3$ at Frequency 100 KHz	10	1000	6.0 8.0	90% 100%	80% 90%
$TbMnO_3$ at Frequency2 00 KHz	14	1300	6.0 8.0	60% 80%	60% 70%

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Table 2: Analysis Report on the basis of Accuracy % of Feed Forward Backpropagation Network (FFBN) vs. Neuro-Fuzzy Networks with Backpropagation and Hybrid Approach on Undoped TbMnO3 (Tolerance 8.0)

Frequency	Tolerance	Algorithms' Accuracy(%)		
		ANN FFBN	Neuro Fuzzy	
			Back Propagation	Hybrid
1 KHz	8.0	91	33.33	58.33
200 KHz	8.0	80	70	80

Table 3: Comparative Analysis Report on the basis of Accuracy % with Tolerance 8.0, Neuro-Fuzzy Networks with Backpropagation and Hybrid Approach on Undoped TbMnO3

Dataset	Epoch	Tolerance	Accuracy (%)	
			Back Propagation	Hybrid
$TbMnO_3$ at Frequency 1 kHz	20000	8.0	33.33	58.33
$TbMnO_3$ at Frequency 200 kHz	20000	8.0	70	80

6.1.2 Tabular Results of Doped $TbMnO_3$

Table 4: Analysis of Dielectric Constant Prediction using TANSIG versus LOGSIG Transfer Function of Feed Forward Backpropagation Networks at Different Frequency on Doped Tb0.9Bi0.1Mn0.95Fe0.05O3

Dataset	Number of Neurons in Hidden Layer	Epoch	Tolerance	Accuracy (%)	
				TANSIG	LOGSIG
$Tb_{0.9}Bi_{0.1}Mn_{0.95}$ $Fe0._{05}O_3$ at Frequency 1 KHz	10	1000	6.0 8.0	88% 100%	88% 88%
$Tb_{0.9}Bi_{0.1}Mn_{0.95}$ $Fe0._{05}O_3$ at Frequency 5 KHz	10	1000	12 15	88% 100	100% 100%
$Tb_{0.9}Bi_{0.1}Mn_{0.95}$ $Fe0._{05}O_3$ at Frequency10 KHz	10	1000	8.0 10	90% 90%	70% 80%
$Tb_{0.9}Bi_{0.1}Mn_{0.95}$ $Fe0._{05}O_3$ at Frequency 50 KHz	10	1000	6.0 8.0	80% 100%	80% 90%
$Tb_{0.9}Bi_{0.1}Mn_{0.95}$ $Fe0._{05}O_3$ at Frequency 100 KHz	8	1000	6.0 8.0	90% 90%	80% 90%
$Tb_{0.9}Bi_{0.1}Mn_{0.95}$ $Fe0._{05}O_3$ at Frequency200 KHz	10	1000	8.0 10	77% 100%	77% 88%

Table 5: Analysis Report on the basis of Accuracy % of Feed Forward Back Propagation Network (FFBN) vs. Neuro-Fuzzy Networks with Backpropagation and Hybrid Approach on Doped Tb0.9Bi0.1Mn0.95Fe0.05O3 (Tolerance 8.0)

Frequency	Tolerance	Algorithms' Accuracy (%)		
		ANN FFBF	Neuro-Fuzzy	
			Back Propagation	Hybrid
1 KHz	8.0	100	77	88
200 KHz	8.0	77	77	77

Table 6: Comparative Analysis Report on the basis of Accuracy % with Tolerance 8.0, Neuro-Fuzzy Networks with Backpropagation and Hybrid Approach on Doped Tb0.9Bi0.1Mn0.95Fe0.05O3

Dataset	Epoch	Tolerance	Accuracy (%)	
			Back Propagation	Hybrid
$Tb_{0.9}Bi_{0.1}Mn_{0.9}$ $_5Fe0._{05}O_3$ at Frequency 1 KHz	2000	8.0	77	88
$Tb_{0.9}Bi_{0.1}Mn_{0.9}$ $_5Fe0._{05}O_3$ at Frequency 200 KHz	2000	8.0	77	77

6.2 Graphical Results

6.2.1 Graphical Reports of Undoped $TbMnO_3$

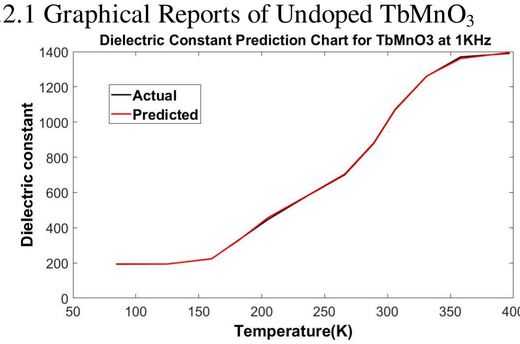

Fig. 2: Dielectric Constant Prediction Chart for Undoped $TbMnO_3$ at Frequency 1 kHz using Feed Forward Backpropagation Network.

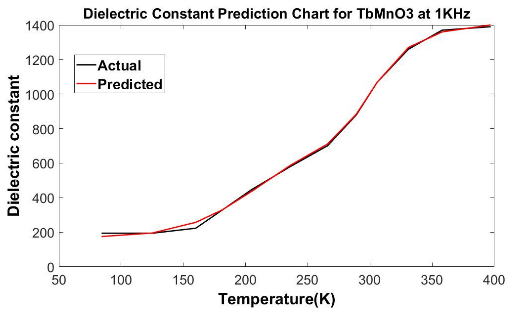

Fig. 3: Dielectric Constant Prediction Chart for Undoped $TbMnO_3$ at Frequency 1 kHz using Neuro-Fuzzy Network with Backpropagation.

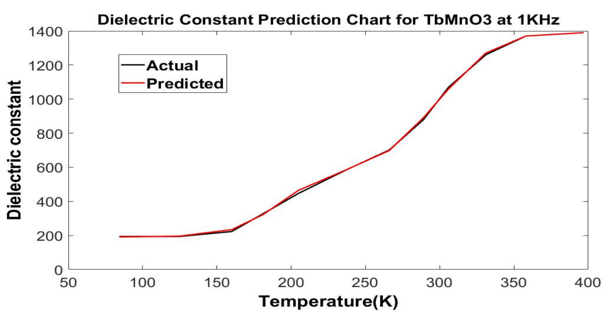

Fig. 4: Dielectric Constant Prediction Chart for Undoped $TbMnO_3$ at Frequency 1 kHz using Neuro-Fuzzy Network with Hybrid approach.

6.2.2 Graphical Reports of Doped $TbMnO_3$

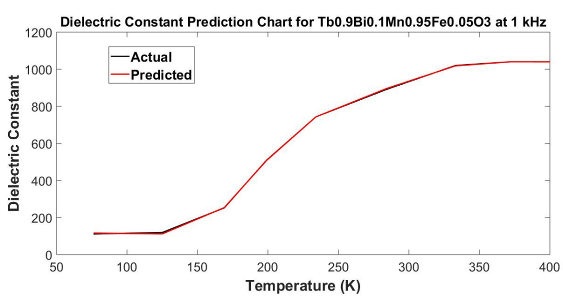

Fig. 5: Dielectric Constant Prediction Chart for doped $TbMnO_3$ at Frequency 1 kHz using Feed Forward Backpropagation Network.

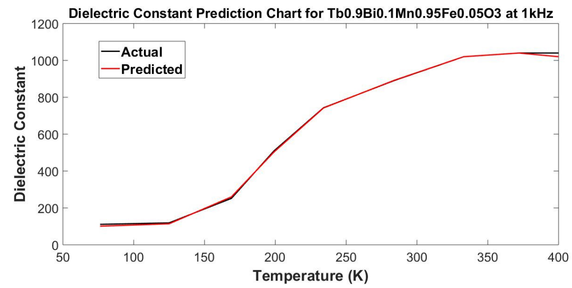

Fig. 6: Dielectric Constant Prediction Chart for doped $TbMnO_3$ at Frequency 1 kHz using Neuro Backpropagation Network.

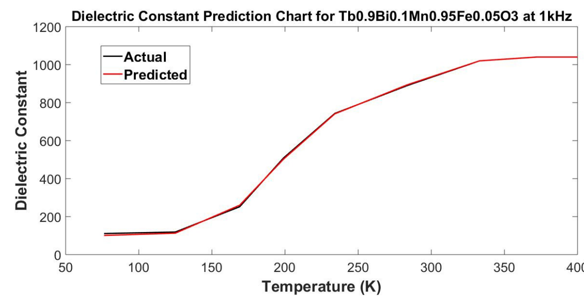

Fig. 7: Dielectric Constant Prediction Chart for doped $TbMnO_3$ at Frequency 1 kHz using Neuro-Fuzzy Network with Hybrid approach.

6.3 Neuro-Fuzzy Training Plots

To improve the Accuracy Percentage in the prediction of Dielectric constant of doped and undoped $TbMnO_3$. The ANFIS model is used to achieve better solution as this hybrid model has the capability of greater reasoning and learning. But the analytical report depicts lesser performance of ANFIS with respect to FFBPN.

6.3.1: Neuro-Fuzzy Training plot for Undoped $TbMnO_3$

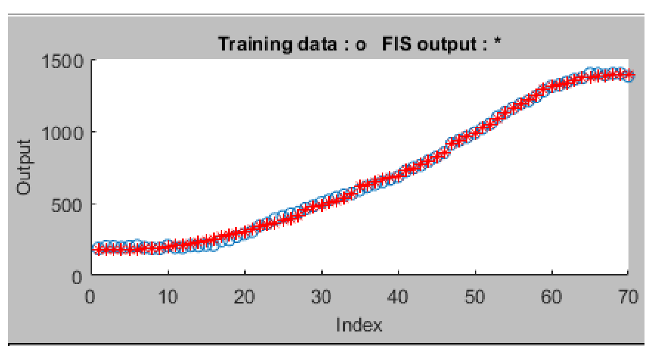

Fig. 8: Neuro-Fuzzy Prediction for Undoped $TbMnO_3$ at Frequency 1 kHz using Backpropagation Mechanism.

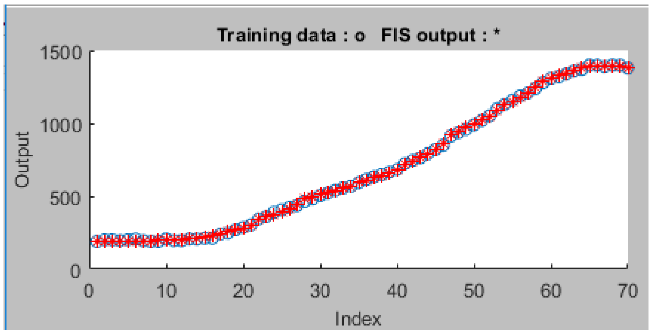

Fig. 9: Neuro-Fuzzy Prediction for Undoped $TbMnO_3$ at Frequency 1 kHz using Hybrid Mechanism.

6.3.2. Neuro Fuzzy Training plot for doped $TbMnO_3$

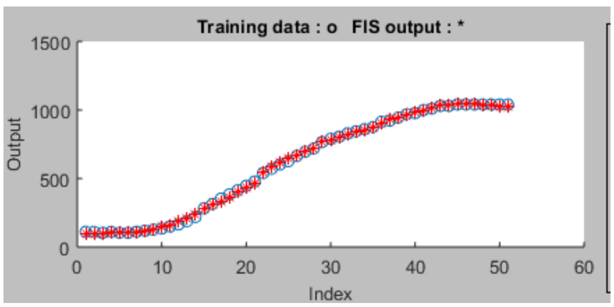

Fig. 10: Neuro-Fuzzy Prediction for doped $TbMnO_3$ at Frequency 1 kHz using Backpropagation Mechanism.

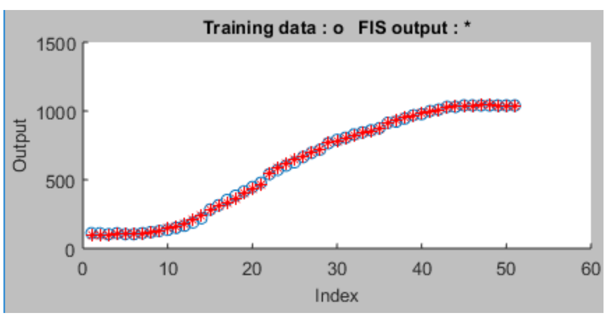

Fig. 11: Neuro-Fuzzy Prediction for doped $TbMnO_3$ at Frequency 1 kHz using Hybrid Mechanism.

7. Statistical Analysis

7.1. Mean Square Error Calculation of $TbMnO_3$

7.1.1. Undoped $TbMnO_3$

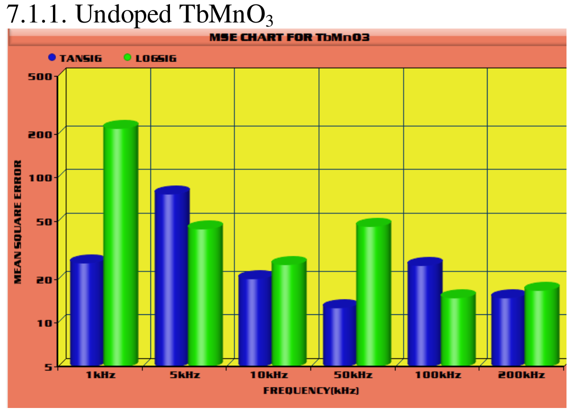

Fig 12: Mean Square Error Calculation for TANSIG and LOGSIG transfer function at difference Frequency using FFBPN for Undoped $TbMnO_3$

7.1.2. Doped $TbMnO_3$

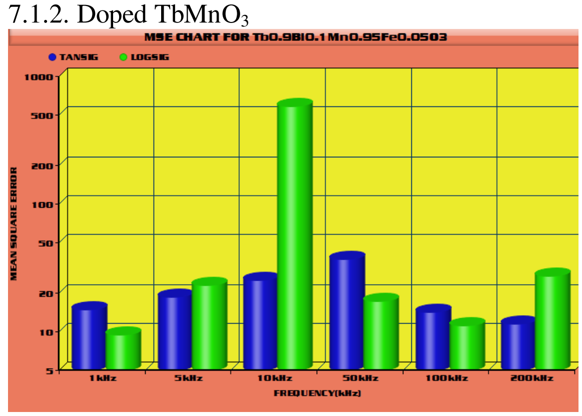

Fig 13: Mean Square Error Calculation for TANSIG and LOGSIG transfer function at difference Frequency using FFBPN

7.2. Accuracy level Calculation of $TbMnO_3$

7.2.1. Undoped $TbMnO_3$

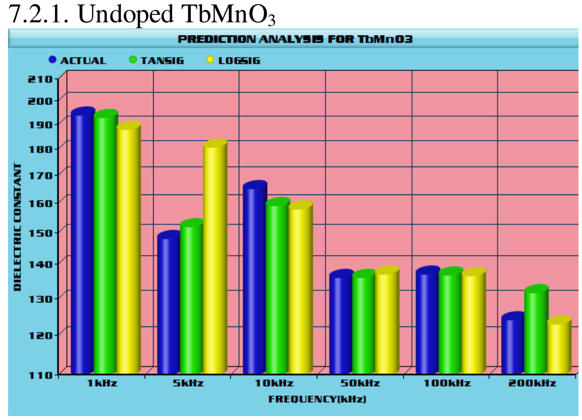

Fig 14: Accuracy level Calculation for Actual datasets, TANSIG and LOGSIG transfer function at difference Frequency using FFBPN for Doped
$TbMnO_3$

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7.2.2. Doped $TbMnO_3$

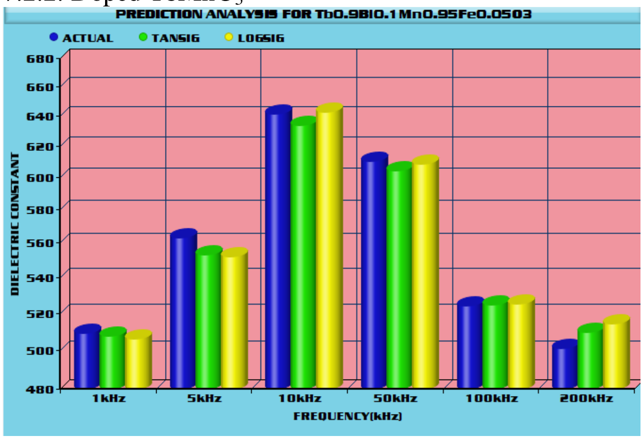

Fig 15: Accuracy level Calculation for Actual datasets, TANSIG and LOGSIG transfer function at difference Frequency using FFBPN

7.3. Analysis of Accuracy percentage of $TbMnO_3$ using three different networks

7.3.1. Undoped $TbMnO_3$

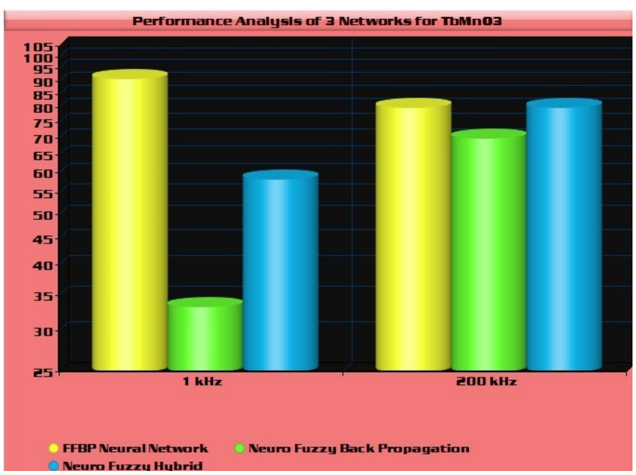

Fig 16: Analysis for Accuracy % of Undoped $TbMnO_3$ at Tolerance 8.0 Using Three Different Networks.

7.3.2. Doped $TbMnO_3$

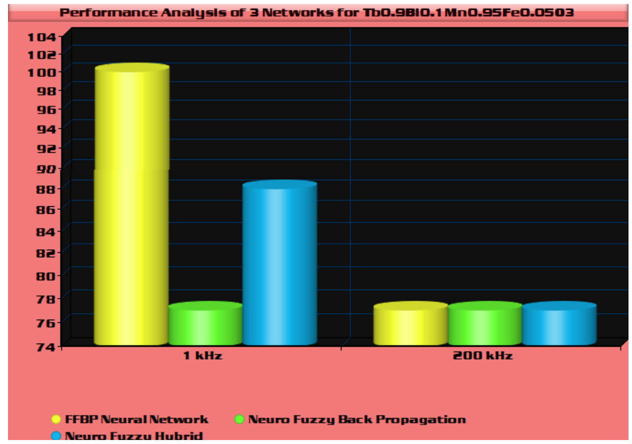

Fig 17: Analysis for Accuracy % of Doped $TbMnO_3$ at Tolerance 8.0 Using Three Different Networks.

8. Conclusion

This research finally concludes on the basis of statistical analysis that there exist no such particular neural networks that can be highlighted as universal best predictor. The ANFIS model with its superior reasoning capability is best suited for dealing with uncertain or imprecise data. In predicting Dielectric constant FFBPN proves to be a most suitable predictor. The analytical survey finds that each and every neural network and their performance on prediction is truly dependent on the nature, type, domain of the datasets. The dielectric constant of Terbium Manganite is one of the crucial dataset in which Neuro-Fuzzy neural networks performs less accurately than feed forward back propagation.

Concept of ferroelectrics and dielectrics are rapidly emerging in the field of MEMS Technology. MEMS application has enormous impact in accelerometers for air bag deployment in cars, micro-motors and pumps, micro heart valves, which have reached the commercial level of exploitation in compact medical, automotive, and space applications. The study of dielectric constant can be applied in all these application domains.

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