DYNAMIC COMPENSATION OF LINEAR VARIABLE DIFFERENTIAL TRANSFORMER BY DEPLOYING MULTIFARIOUS SOFTCOMPUTING TECHNIQUE A COMPARITIVE ANALYSIS

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Abstract: ***In this manuscript probes about design of different Artificial Neural network based dynamic compensator for Linear variable differential transformer different Artificial network encompasses ADALIN, MLP , RBFNN and hybrid soft computing technique Adaptive Neuro Fuzzy inference system all those techniques accuracy and robustness are evaluated as a dynamic compensator, in comparative analysis ANFIS exhibits low Mean square error which evidently shows superior robustness and accuracy of ANFIS equipped dynamic compensator for LVDT.***

Keywords: LVDT, ADALIN, MLP, RBFNN, Hybrid soft computing, ANFIS etc…

I. Introduction:

In much practical control system Linear Variable Differential Transducer LVDT is used as sensing element to sense the displacement. Even it is clear that the performance of control system depends upon the performance of the sensing elements [1]. Diverse investigation has been carried out in last ten years for design LVDT with high linearity [2]. In its sophisticated and precise winding machines are used to accomplish that. Complication arises at the point of trying to fabricate LVDT equally linear. LVDT has diverse nonlinearity present in a control system malfunctions at times because of the differences in sensor characteristics[4].

II.Linear Variable Differential Transducer

Movement in one direction along single axis is termed as linear displacement. To measure the distance of an object traveled from a reference point Position sensor or Displacement sensor is used as in shown in Fig 1, typical linear displacement measurement measured in Millimeters (mm) or in inches (in) in association with positive or negative directions.

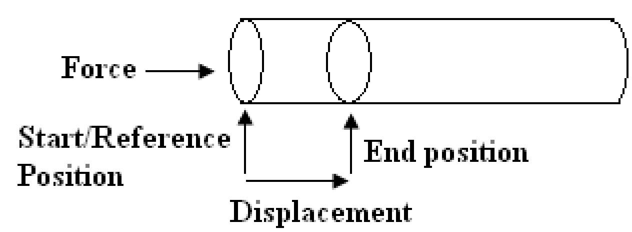


Fig 1. Measurement of Linear Displacement.

Linear Variable Differential Transformer makes use of principle of transformer to measure linear Displacement, core and coil assembly vitally constitutes LVDT core is held over the object whose position is being to measure while coil assembly mounted on stationary frame. Hallow form wounded by wire wound by three coils constitutes coil assembly. Primary is contributed by Permeable core material that slides freely along the center of inner coil energized by an AC source and an AC voltage in every coil.

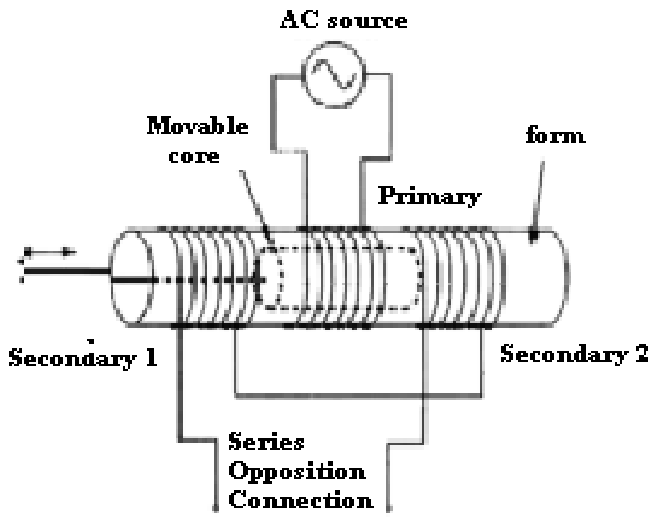


Fig 2 General LVDT Assembly

The focal advantage of LVDT transducer amid existing other type of transducer is aristocratic decree of robustness and preciseness owing to no physical contact along the sensing element that gives rise to no wear and tear in the sensing element. Performance of LVDT relies on the coupling of magnetic flux therefore even diminutive movement can be witnessed by appropriate signal conditioning hardware and the transducers resolution is solely determined by the accuracy and preciseness of the data acquisition system [4].. Measurement of displacement by correlating a exact signal value for any bestowed position of core. The rapport of position to signal value happens through electromagnetic coupling among Exciting AC signal in the primary to the core back to the secondary winding. Core position decides how closely or tightly the signal of the primary coils, two secondary coils is seriously opposed, explicates wound in series but contrary direction, as a virtue of bothsignals 180 degree out of phase in every secondary.Direction, distance and its amplitude are determined by phase of the upshot signal. Cross-sectional view of an LVDT is depicted in Fig 3. Effect of Magnetic field is generated Due to the cause of magnetic field coupling between primary winding and secondary's ,Between the primary and secondary when the core centered and poised as depicted in Fig 3 as given, developed voltage in every secondary is in par and rational in amplitude and 180 deg out of phase. Eventually Voltage output of the LVDT is zero owing to the cancel of equally induced voltages mutually[5].

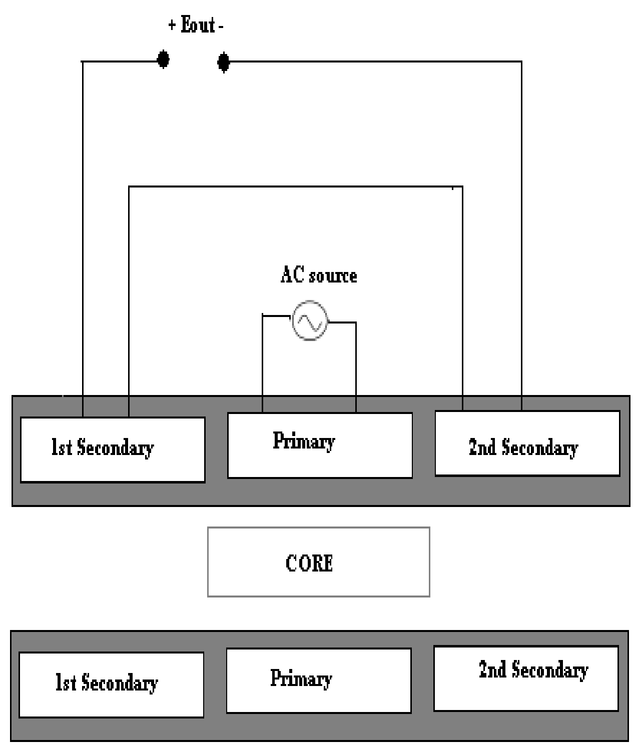


Fig 3 Cross – Sectional views of LVDT core and Winding

To recapitulate LVDT closely traces the properties of an idyllic zeroth – order low frequency structured displacement sensor, and the output is linear to the input[6]. With the crutch of symmetrically wound secondary coil on either side of primary it is coupled through a center core. From the measurement of voltage amplitude and phase it is straight forward to decide the direction of displacement and extent of the core motion

[7]. LVDT has exceptional repeatability, prediction of non-linearity near the limits of the device can be done achieved by table or fitting function of polynomial curve thus extending the range of the device [8].

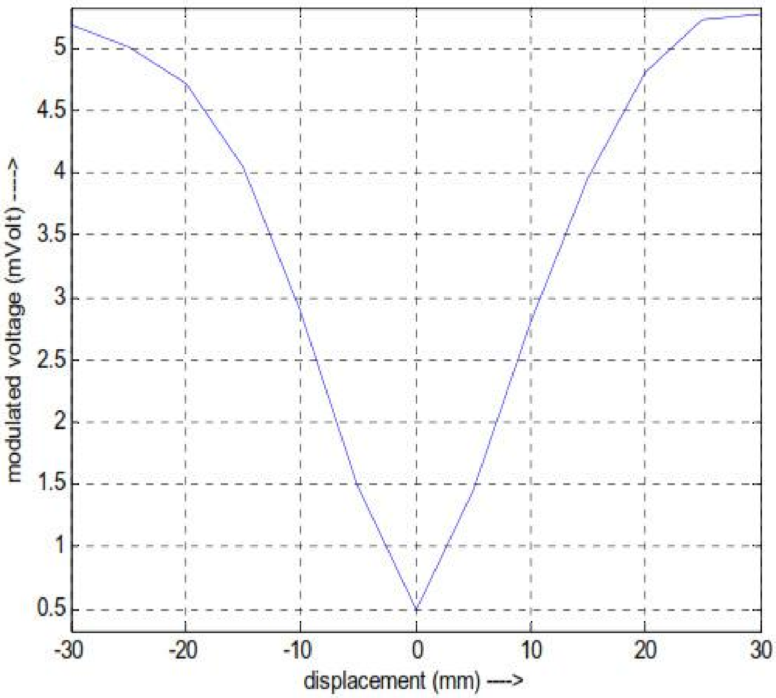


Fig 4 Appropriate linear response of LVDT to Displacement of Core

III. Proposed Dynamic compensation of LVDT's

Dynamic compensation scheme proposed is depicted in Figure 5. In the proposed scheme LVDT can be controlled by a displacement actuator. The central controller delivers an actuating signal and it is picked up by the displacement actuator, which displaces the core of the LVDT. Dynamic compensators differential voltage can be fortified by using different Artificial intelligence technique like ADALIN, MLP, RBF-NN and ANFIS. Upshot of eh ANN based dynamic compensator is compared with the desired signal to produce an error signal with this error signal, the weigh vectors of the ANN model are rationalized. Process will continue till minimized least mean square error (MSE) is accomplished.

After the completion of training phase together with ANN model LVDT acts like Dynamic range enhanced linear LVDT.

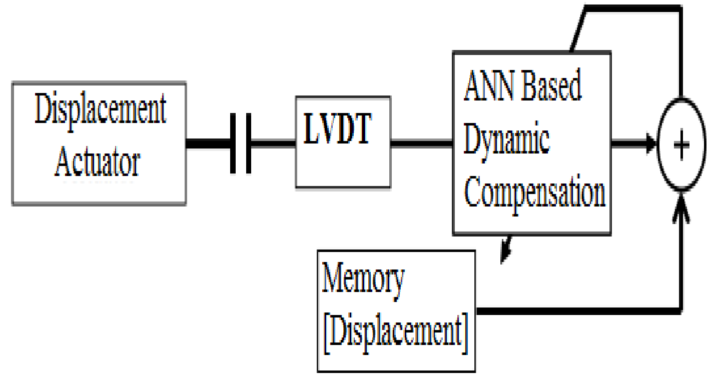


Fig 5. Proposed scheme of Dynamic compensation of LVDT

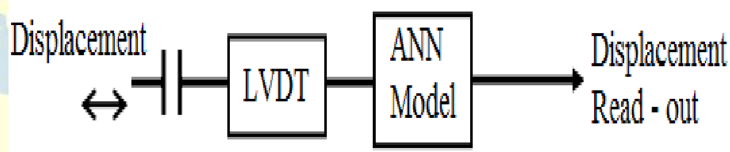


Fig 6 Practical setup of LVDT after learning course.

Fig 6. Depicts the learning process of LVDT concatenated with ANN based dynamic compensator after training.

IV. Simulation results and Discussion

Simulation studies are carried out on a typical LVDT based on the data's acquiesced from experiment feed as input to the ANN to examine its effectualness in dynamic compensation.

SL. NO	Displacement in (mm)	Demodulated Voltage output (e in m Volt)	Differential output voltage (Erms in mVolt)
1	-30	5.185	4.085
2	-25	5.017	3.856
3	-20	4.717	3.731

4	-15	4.039	3.221
5	-10	2.896	2.359
6	-5	1.494	1.273
7	Null Position (0)	0.001	0.204
8	5	1.462	1.153
9	10	1.810	2.226
10	15	3.962	3.118
11	20	4.799	3.748
12	25	5.225	4.050
13	30	5.276	4.085

Table 1 Experimental measured data

ADALIN based Dynamic compensation

Normalizing differential or demodulated output voltage e of LVDT by dividing each value with the maximum value. Normalized voltage output e is subjected to functional expansion and than depending upon dynamic compensator input is fed to the solitary perception. The upshot of the neuron contains activation function of type tanh(.), Dynamic compensation based ADALIN is evaluated and compared with the standardized input displacement of the LVDT. In both of widrow-hoff algorithm learning rate is selected as 0.07 which is used to adapt weights of the neuron, deploying diverse input patterns, the ANN weights are updated using the widrow – hoff algorithm. to make the learning process more précis 1000 iterations are made. Then the weights are used in the ADALIN model as shown in fig 5.it depicts the dynamic compensation of LVDT by ADALIN . In this model MSE is obtained to be 0.34%.

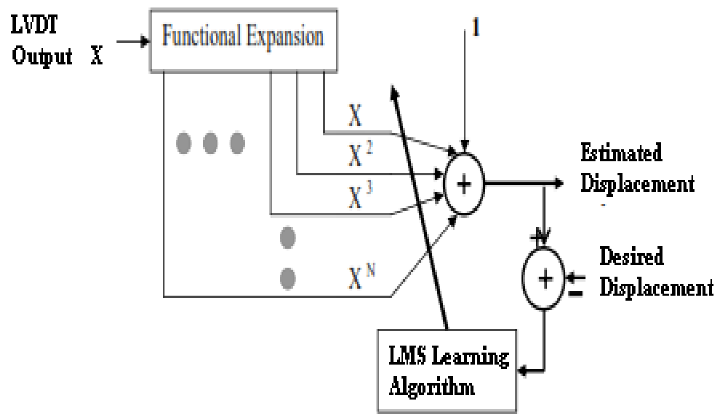


Fig 7. Architecture of ADALIN Network.

MLP based Dynamic Compensation

MLP based dynamic compensator is feed with normalized voltage output e. in that case of the MLP, we use different neurons with diverse layers. Nevertheless the 1 – 30 – 50 – 1 network is observed to perform in a great way hence it is preferred for simulation . all the hidden and output layer contains tanh(.) type instigation function. Upshot of MLP based dynamic compensator is compared with the normalized input displacement of LVDT. Momentum rate and learning rate is chosen as 1 and 0.1 respectively for BP algorithm in which used to adapt the weight of the MLP. Employing diverse input pattern weights of ANN are updated using BPO algorithm and 400 iterations are made to complete the erudition process then the weights of the various layer starting from input layer, hidden layers and output layers of the MLP stored and frozen in the memory in this model MSE is obtained to be 0.0022.

RBFNN Based Dynamic compensation

RBFNN is a single layered network, 1-5-1 structure is chosen for simulation of RBFN, learning rate is chosen as 0.7 in RBFNN. diverse input patterns are applied after making use of all pattern. The MSE is minimized as possible as minimum which is condition to terminate ANN weights and to make the learning thriving, 2,000 iterations are needed. Once the training complete weights of the RBFNN is retained by the different layers in their memory. Here the centers of RBFNN were selected by hit and trail in order to get lowest mean square error.

ANFIS based dynamic compensation

Adaptive neuro fuzzy inference system is two layered network for the simulation 1*8 fuzzy input triangular member function is used as shown in figure 9. ANFIS structure chosen for dynamic compensation is shown in figure 8. after applying diverse input patterns the weight (Wi) are updated using update algorithm. This process is continued till minimum attainment of Mean square error is accomplished, once training process is completed the RBFNN model will work as inverse model of LVDTs. 200 iterations is indeed to make the learning process of ANFIS successful in this model MSE is obtained to be 0.00077.

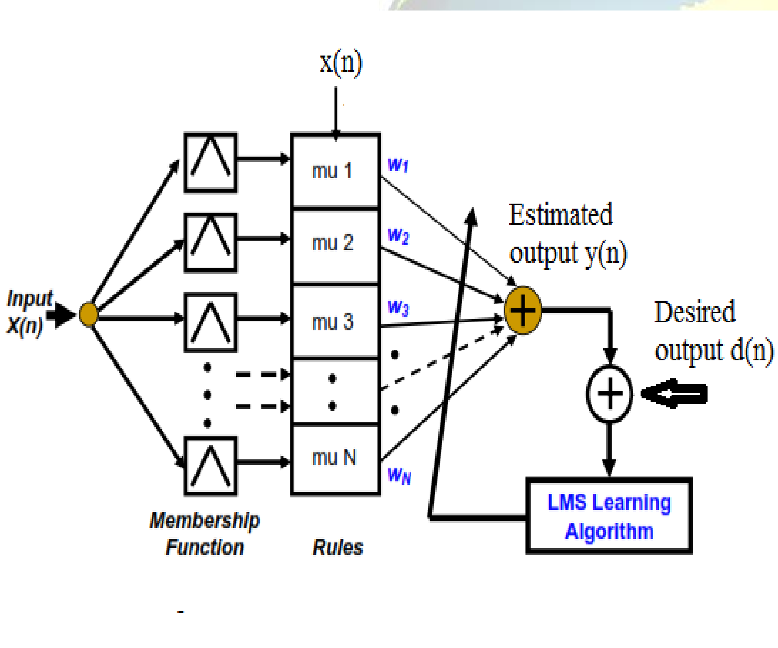


Figure 8.LVDT dynamic compensation model for ANFIS.

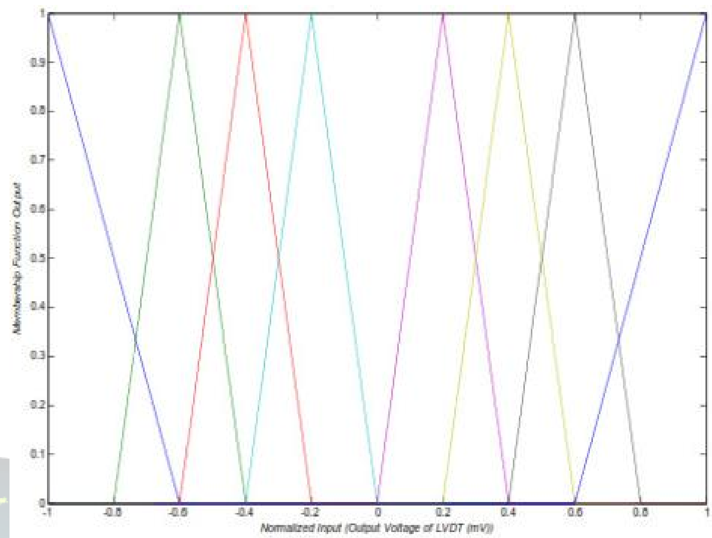
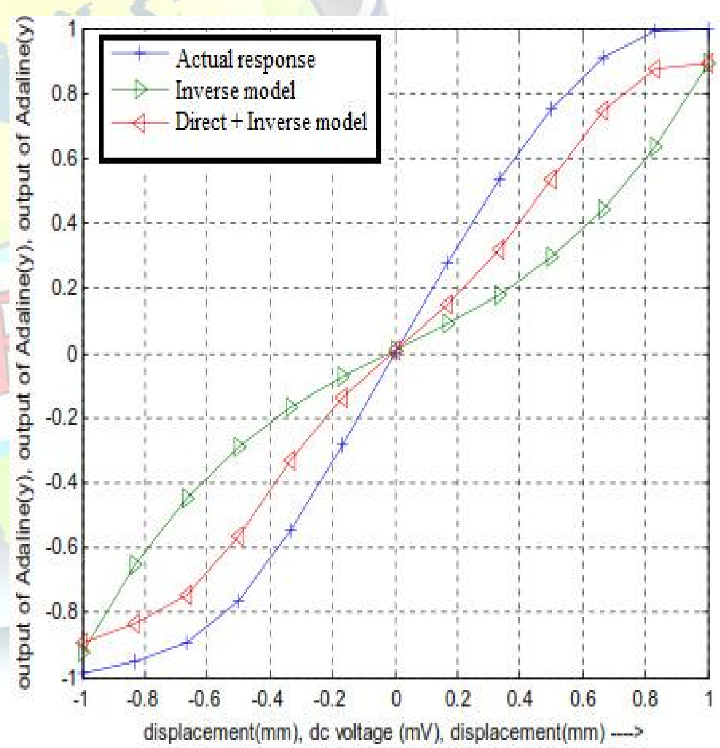
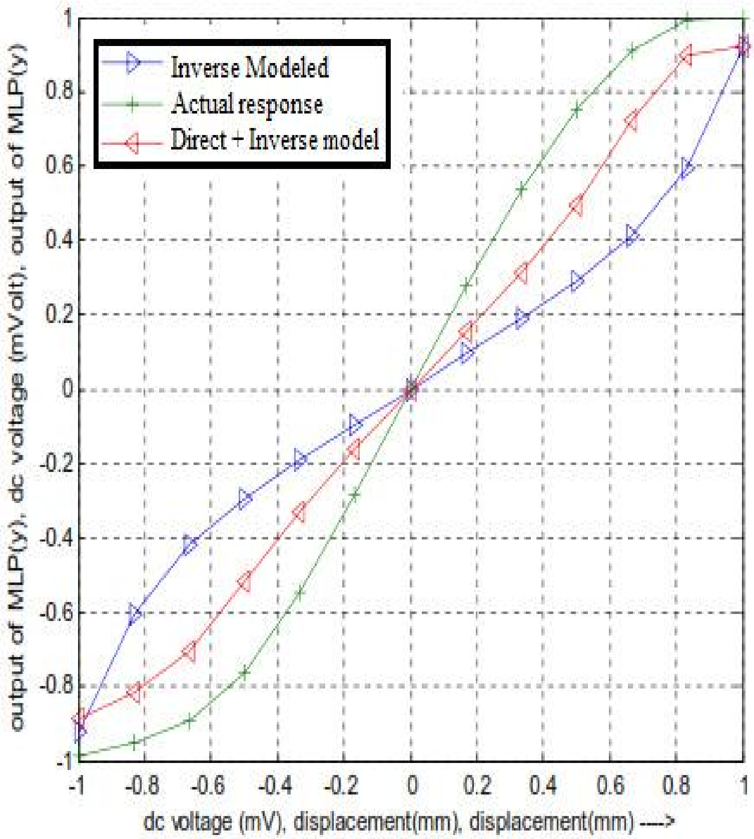


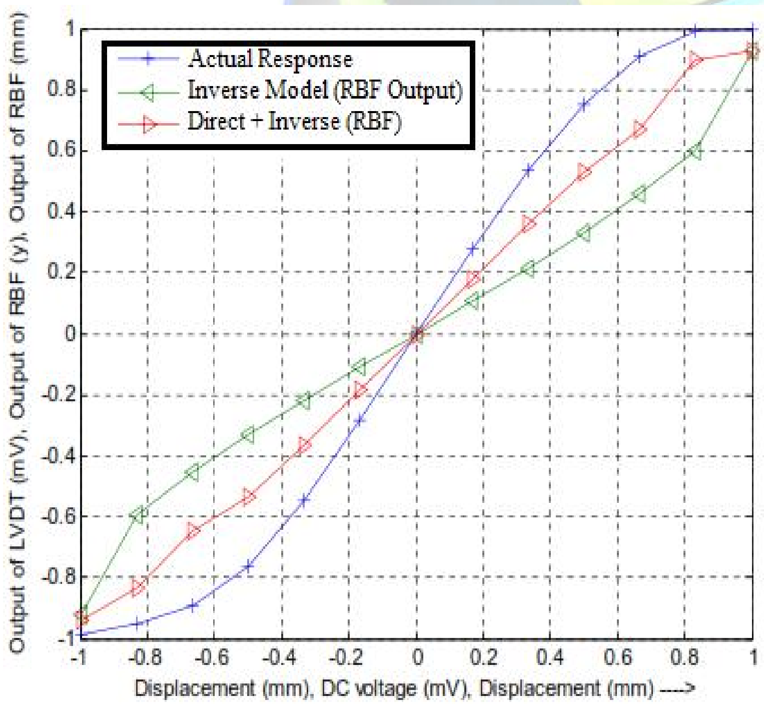
Figure 9.ANFIS's input member ship function structure for dynamic compensation of LVDT.



(a)

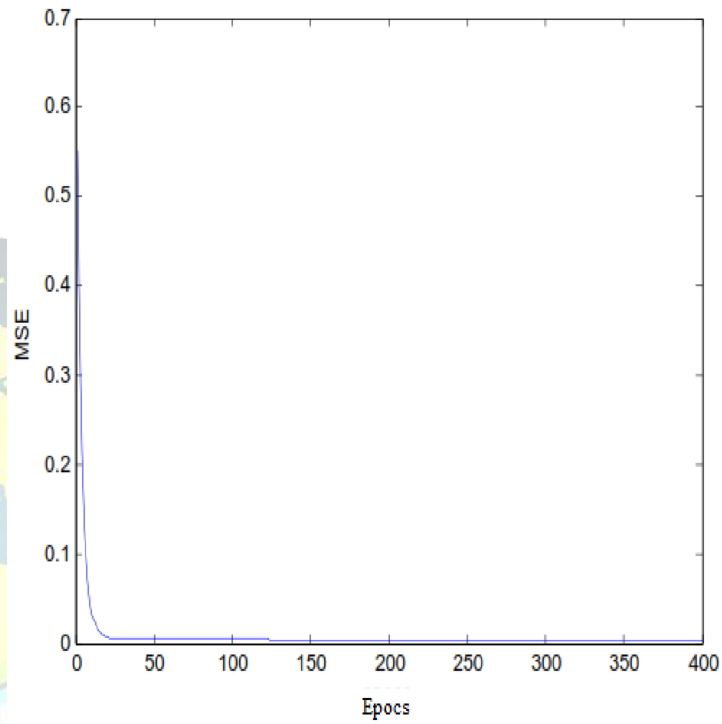


(b)

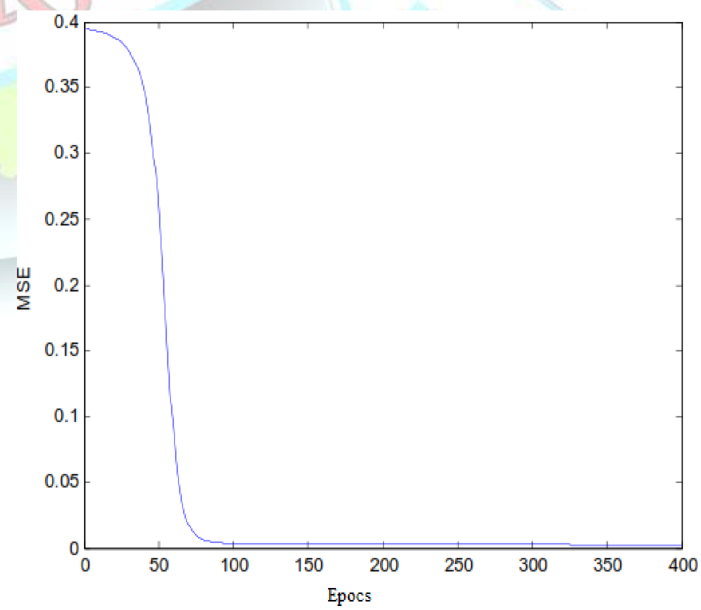


(C)

Fig9. Response of diverse Neural Network for LVDT Dynamic compensation (a) – Response of ADALIN Network ; (b) Response of MLP Network ; (c) Response of RBFNN Network ; (d) Response of ANFIS.



(a)



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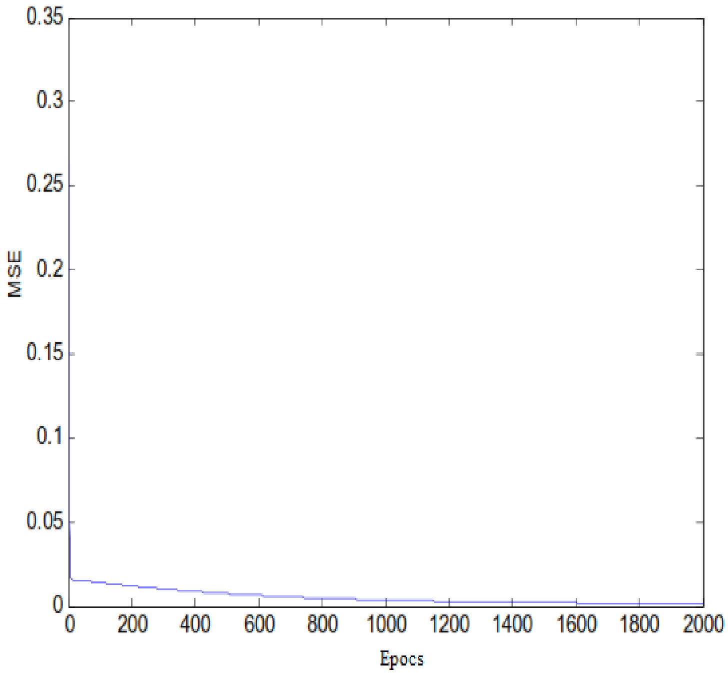

(C)

Fig 9 – MSE plot of diverse ANN for dynamic compensation of LVDT.

(a)– MSE plot of ADALIN; (b) – MSE plot for MLP (c) – MSE for RBFNN.

SL.NO	Actual Displacement in mmd(n)	Output of ANFIS model in mm y(n)	Error
1	-20.001	-19.6380	1.815
2	5.0010	4.9770	0.479
3	15.000	14.9640	0.240

Table 3 – simulation upshots data's of ANFIS model.

Network	MSE
ADALIN	0.00340
MLP	0.00220
RBFNN	0.00140
ANFIS (Sugeno model)	0.00077

Table 4 – MSE Comparative analysis of diverse ANN for Dynamic compensation of LVDT.

Sl.NO	Input to ANN model (m volt)	Actual Displacement in mm d(n)	Output of ADALIN model	Error of ADALIN model	Output of MLP model	Error of MLP model	Output of RBFNN model	Error of RBFNN model
1	-5.0170	-25.00	-25.3630	0.3630	- 24.5550	-0.4450	-24.9626	-0.0374
2	-2.8960	-10.00	-9.34840	-0.6516	- 15.4966	0.4966	-10.9876	0.9876
3	0.0010	0	0.2590	-0.2590	-0.0108	0.0108	-0.0643	0.0643
4	1.4620	5.000	4.3040	0.6966	4.7072	0.2928	5.3526	-0.3526
5	4.7990	20.000	21.8853	-1.8853	21.6670	-1.6670	15.8476	-0.8476

Table 2 – Output y(n) of Diverse ANN model with their error value.

V. CONCLUSION

An experimental approach based investigation of Dynamic compensator is simulated for various Artificial Neural Network from the simulation upshot as listed in table 2, 3 and 4. It is untarnished that dynamic compensation of ADALIN and MLP is feeble when compared ANFIS based dynamic compensation when compare to all the simulated models RBFNN has acceptable accuracy but hybrid soft computing technique Adaptive Neuro – Fuzzy Inference System shows exceptional performance as a dynamic compensator.

VI. Appendices I.

Specification of used Available translational **L**inear **V**ariable **D**ifferential **T**ransformer.

Input	3 to 15 V(rms) sine wave
Frequency range	60 to 20,000 Hz
Most common signals	3V,2.5kHz and 6.3V, 60Hz
Full range Stroke ranges	± 125 µm to ±75 µm
Sensitivity	0.6 to 30mV per 25 µm (0.01in) under normal excitation of 3 to 6 Volt
Nonlinearity	0.5% in the order of Full scale

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