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Artificial Neural Networks based Approach for Predicting LVDT Output Characteristics

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Abstract

This paper presents a novel approach for training and output prediction of data of a Linear variable differential transformer (LVDT). LVDT is a commonly used device used in laboratories for measuring linear displacements in specific situations. This article considers application of Artificial Neural Networks (ANNs) for learning and output estimation of LVDT. Real-time experiments were conducted and results were collected for training of ANNs. The Regression results and outputs verified the learning and prediction capability of ANNs.

Index Terms: Artificial neural network, LVDT, Matlab, Simulink, Mean square error, Regression.

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1. Introduction

A Linear variable differential transformer (LVDT) is an electromechanical transducer which is capable of measuring very small linear movements [1]. The transducer converts mechanical motion of the system into electrical signals which can be easily recorded and analysed [2]. LVDT can be considered as a differential transformer having one primary coil and two secondary coils connected such that the induced voltages are 180° out of phase [3]. The assembly comprises of a cylindrical core which can move linearly between the two coils. The output signal produced indicates direction of core movements from the centre position [4]. These devices have capabilities of contact-less sensing, tolerance against radiations, infinite resolution, good linearity and are cost effective [5]. Researchers have been showing keen interest in studying and analysing performance of LVDT's due to their vast engineering applications. In a multi-objective study by Santhosh & Roy [6], the authors aimed at extending the linear range of LVDT alongwith eliminating its dependency on physical parameters and working temperature. The study further added an artificial neural network block in cascade for

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data conversion. Liu et al. [7] constructed an on-machine learning measuring system having an air-bearing capacitive LVDT contact sensor mounted on a desktop machine tool. The proposed system was capable of decoding the digital signals of linear encoders and also acquires the analog signal of contact sensor. In an article by Meydan & Healey [8] a linear variable transducer having a metallic glass ribbon as the core material rather than nickel-iron material has been used. The authors investigated the suitability of metallic glass ribbon over other conventional material in terms of excitation magnitude and frequency. Tian et al. [9] proposed an equivalent magnetic circuit for a solenoid type LVDT. The authors considered magnetic circuit theory to calculate its magnetic reluctance, mutual inductance, output voltage and sensitivity. Muhammad & Umar [10] developed a small scale LVDT to detect level of different fluids. The fluids which were considered for analysis were water, petroleum and gasoline. The results showed that transducers works with good precision and has high sensitivity for all three fluids.

Nomenclature	
ANN	Artificial neural network
LVDT	Linear variable differential transformer

2. System Description

The setup includes a LVDT mounted on a panel provided with a capability of fine movement of core with the help of a lead screw. The lead screw is further coupled with a dial gauge with the help of a thumb and wheel arrangement as shown in Fig.1. The setup includes a low noise carrier frequency signal amplifier of 5 KHz, a demodulator, 3.5 inch digital LED indicator and an I.C. regulated power supply housed in a wooden box. A complete set of system specification are highlighted in Table 1. The circuit diagram of LVDT setup is shown in Fig.2.

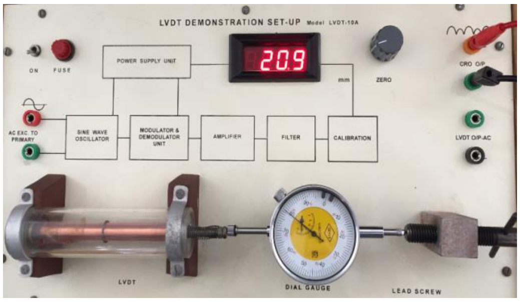

Fig.1. LVDT Setup

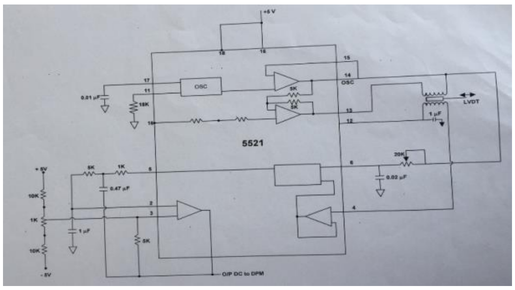

Fig.2. Circuit diagram of LVDT Setup

Table 1. Specifications of LVDT Setup

Specification	value
Core displacement	+/- 10 mm
Carrier frequency	5 KHz
Carrier voltage	1.0 Volt r.m.s
LVDT output	190 mVolt
Demodulator output	1.5 Volt D.C.
Power	220 Volt/50 Hz

The study considered the data samples collected by real-time experiments. The results are obtained by rotating the lead screw through 1mm each time and noting down the modulated output voltage. A set of 25 such reading were obtained and stored in .MAT file for further training of Artificial neural networks (ANNs).

3. Application of ANN for Output Prediction

Neural networks are computational models which are inspired by biological neurons present in human brain and are used for processing information [11-12]. These networks are widely used in machine learning, speech recognition, computer vision, medicines, text processing processes [13-18]. A basic architecture of ANN is shown in Fig.3. ANN architecture comprises of various nodes and biases whose weights can be adjusted during the learning process. The system comprises of three different layers namely input layer, hidden layer and output layer. All the inputs are fed to the network through input layer. These inputs are processed in the hidden layers and further supplied to output layer as output [19].

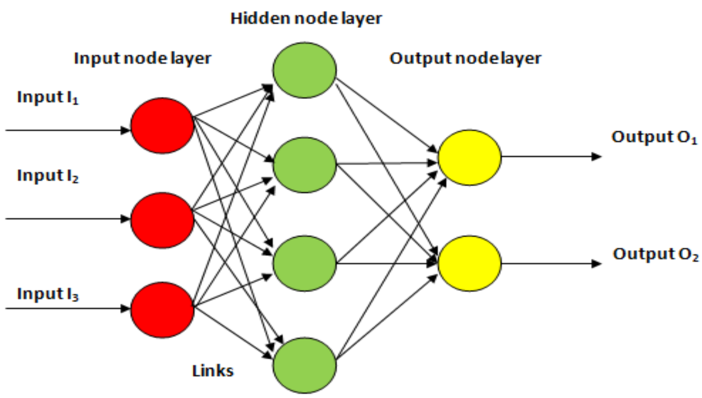

Fig.3. ANN Architecture

The training of ANNs was performed using 25 data samples collected from real-time results of LVDT. These samples were then randomly divided into training, validation and testing samples [20-21]. The training samples aids in tuning of network whereas validation samples were used for measuring network generalization and halts training as generalization stops improving. The testing samples have no effect on training and provide an independent measure of network performance during and after training. The number of neurons considered in hidden and output layer considered was 10 and 1 respectively [22]. A view of neural network architecture consisting of 4-inputs and 1-output is shown in Fig.4.

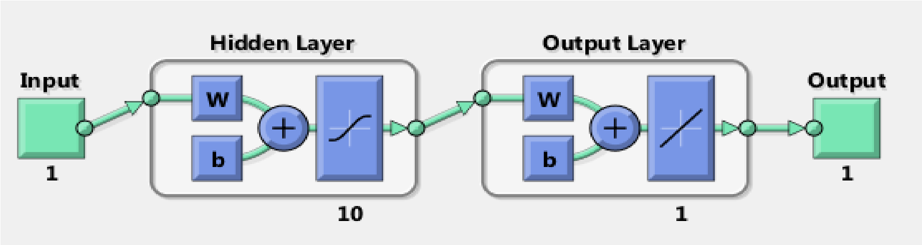

Fig.4. ANN having 4-inputs and 1-output

The network was trained using Levenberg-Marquardt learning algorithm which takes more memory and less time for computation [23]. The number of data samples taken for analysis, Mean Squared Error (MSE) and Regression (R) values obtained after training are shown in Table 2. MSE is the average squared difference between outputs and targets. Lower values of MSE are better whereas zero indicates no error. Regression values are used for measuring the correlation between outputs and targets. R value of 1 means close relationship whereas 0 means random relationship [24]. Training of samples different times yields different results due to different initial conditions and samplings. Training of samples is carried via 1000 iterations and 6 validation checks were performed to obtain optimal results.

Table 2. MSE and R Values Obtained for Different Samples

Sample	Number of samples	MSE	R
Training	17	2.94882e-8	9.9999e-1
Validation	4	3.07529e-2	9.9997e-1
Testing	4	2.68479e-4	9.9998e-1

The function fit obtained for outputs, targets and errors for different samples is shown with the help of Fig.5.

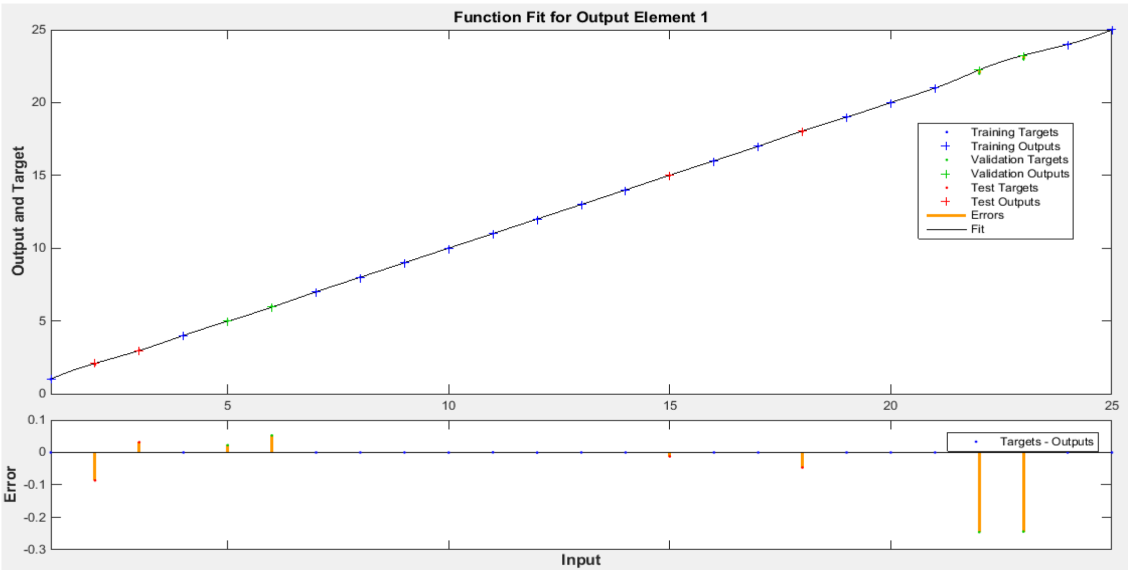

Fig.5. Function Fit Obtained for Different Samples

The Regression fit obtained for different samples are shown in Fig.6. It is clear from the figure that training and validation samples shows R value of 1 whereas testing samples gives R value of 0.99998. The R value obtained for all samples is 0.99996.

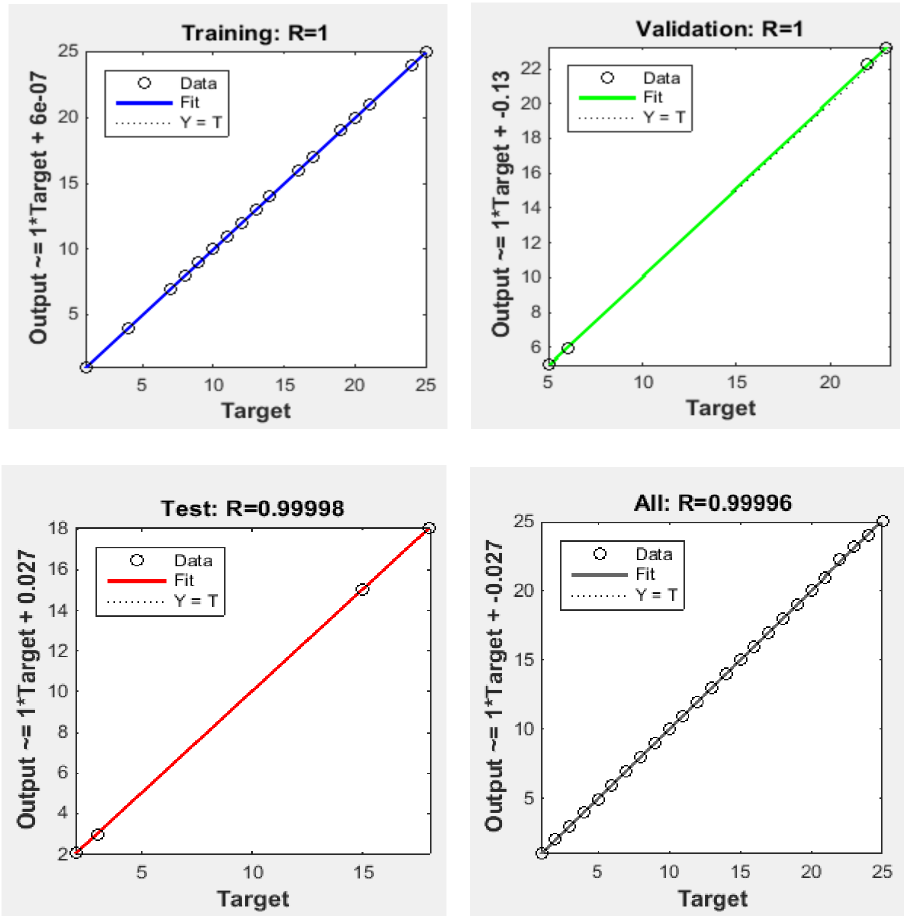

Fig.6. R-plots Obtained for all Samples

A complete detail of number of epochs, time taken for training, performance of network, gradient, validation checks etc are shown with the help of Figure 7. It is clear from the figure that network is trained after 13 iterations and 6 validation checks.

Epoch:	0	13 iterations	1000
Time:		0:00:02	
Performance:	1.56e+03	3.85	0.00
Gradient:	4.97e+03	5.11	1.00e-07
Mu:	0.00100	0.0100	1.00e+10
Validation Checks:	0	6	6

Fig.7. Performance Results Obtained for ANNs

After completion of training a Simulink-model of above system has been generated as shown in Fig.8. The results of Simulink are then compared to that of real-time experimental results. The results obtained showed good correlation between output and targets using ANNs.

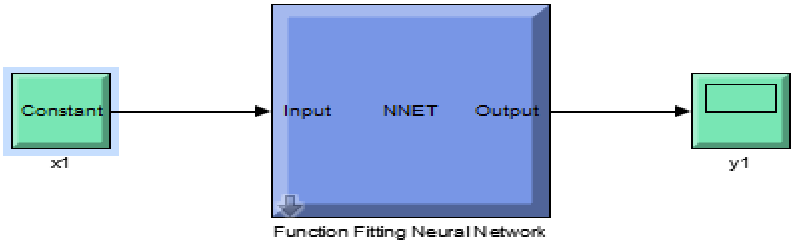

Fig.8. Simulink Model Developed after Training in ANN Toolbox

4. Conclusion

The paper successfully highlights a novel learning approach for data learning and prediction using ANNs. The study has considered Levenberg-Marquardt learning algorithm for training of neural networks. The proposed algorithm learns input-output characteristics of LVDT setup in an effective manner. The data pattern generated can be further used for prediction and estimation of output characteristics of LVDT for real-time applications. The values of MSE and regression showed excellent learning characteristics and need not to be further optimised. The training of ANNs has been completed using 10 neurons in the hidden layer and 1 neuron in the output layer. Finally, a Matlab based Simulink model has been developed which can be used for predicting the results LVDT in an effective manner. The output results verified the validity of proposed study.

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