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A Smart Displacement Measuring Technique Using Linear Variable Displacement Transducer

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Abstract

This paper aims to design of a smart displacement measuring technique using Linear Variable Differential Transformer (LVDT). The objectives of this work are to (i) extend the linearity range of LVDT, (ii) eliminate the dependence of physical parameters of LVDT, (iii) eliminate the affect of input frequency and (iv) eliminate the effect of working temperature on the output of LVDT. The output of LVDT is differential ac voltages in secondary coils. It is converted to dc voltage by using a suitable data conversion circuit. An ANN block is added in cascade to data conversion unit. This arrangement helps to extend linearity range of the overall system and makes it independent of physical parameters of LVDT, input frequency and working temperature. Since the proposed smart displacement measuring technique produces output independent of physical parameters of LVDT, input frequency and working temperature, thus the present work avoids the requirement of repeated calibration every time the LVDT, input frequency or working temperature is varying.

Keywords: LVDT, Artificial Neural Network,Sensor modelling, Temperature compensation

1. Introduction

Measuring displacement is a critical need in many processes. Many sensors are used for this purpose like potentiometer, capacitance picks, LVDT etc; LVDT finds a very wide application because of its high sensitivity and ruggedness. However, the problems of offset, non-linear response characteristics, dependence of output on the physical parameters of LVDT and the effect of ambient temperature have restricted its use and further impose some difficulties. Several techniques have been suggested in literature to overcome the difficulties faced due to the nonlinear response characteristics of the LVDT, but these are tedious and time consuming. Further, the process of calibration needs to be repeated every time the physical parameters like the number of primary and secondary winding, dimensions of primary and secondary winding etc are changed. The problem of nonlinear response characteristics of an LVDT further aggravates the situation when there is a change in environmental conditions as the output of LVDT depends on ambient temperature as well.

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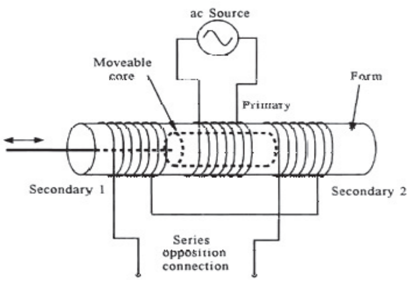
To overcome the above difficulties, a smart displacement measurement technique is proposed in this paper using artificial neural network. This network is trained to obtain linearity and make the output independent of physical parameters of LVDT, input frequency and temperature.

Literature review suggests that a numerical method of designing the LVDT is discussed to compensate the effect of temperature in [5]. In [6], the computational algorithm for LVDT is discussed. Signal conditioning circuit with the help of FFT & DSP algorithms are discussed in [7] & [8]. In [9]&[12], linearization of LVDT is discussed using ANN algorithms. In [10], LVDT is made linear using the least mean square method. In [11], non linearity of LVDT is compensated using radial basis function.

The paper is organised as follows: after introduction in Section-1, a brief description on LVDT model is given in Section-2. The output of the LVDT is AC voltage; summary on data conversion i.e. RMS to DC converter is presented in Section-3. Section-4 deals with the problem statement followed by proposed solution in Section-5. Finally, result and conclusion is given in Section-6

2. LVDT

LVDT is used to measure linear displacement. LVDT operates on the principle of a transformer. As shown in Fig 1, an LVDT consists of a coil assembly and a core. The coil assembly is typically mounted to a stationary form, while the core is secured to the object whose position is being measured. The coil assembly consists of three coils of wire wound on the hollow form. A core of permeable material can slide freely through the center of the form. The centre coil is the primary, which is excited by an AC source as shown. Magnetic flux produced by the primary is coupled to the two secondary coils placed on both sides of primary coil, inducing an AC voltage in each secondary coil.



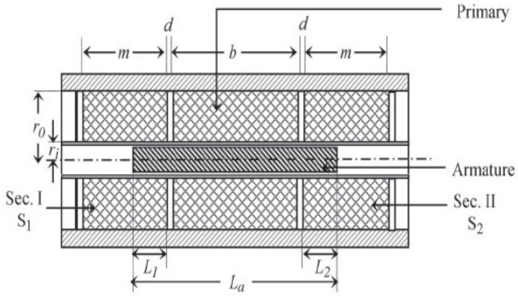


Fig 1. (a)LVDT schematic diagram (b) cross-section of LVDT

The relations of LVDT can be given by following equations [1-3]. The RMS value of secondary coil 1 and 2 are given by eqn (1) and eqn (2), with respect to Fig 1.

$$v_1 = \frac{4\pi^3}{10^7} \cdot \frac{f I_p n_p n_s}{\ln(r_0/r_i)} \cdot \frac{2L_2 + b}{m L_a} x_1^2 \tag{1}$$

$$v_2 = \frac{4\pi^3}{10^7} \cdot \frac{f I_p n_p n_s}{\ln(r_0/r_i)} \cdot \frac{2L_1 + b}{m L_a} x_2^2 \tag{2}$$

where I_p is the primary current for the excitation V_p

x_1- distance penetrated by the armature towards the secondary coil 1
x_2- distance penetrated by the armature towards the secondary coil 2
n_p- number of primary windings
n_s- number of secondary winding
f – frequency of primary excitation

Taking L_a = 3b, the differential voltage v is thus given by $v_1 \sim v_2$

$$v = \frac{(32 * 10^{-7})\pi^3 f I_p n_p n_s b x}{3m \ln\left(\frac{r_o}{r_i}\right)}\left(1 - \frac{x^2}{2b^2}\right) \quad (3) \qquad ; x = (x_1 - x_2)/2$$

$$I_p = \frac{v_p}{\sqrt{(R_p{}^2 + (2\pi f L_p)^2)}} \quad (4)$$

L_p- primary inductance
R_p – Primary resistance

The relation of inductance on variation of temperature [4] can be given by

$L_t = L_{to}(1+\alpha\,(t-t_o))$
L_t – Inductance at t °C
L_{to} – Inductance at t_o °C
α – temperature coefficient

The variation of R_p for change in temperature is not considered, since R_p itself is very small.

3. Data Conversion Unit

The block diagram representation of the proposed smart displacement measuring technique is given in Fig 2

Fig 2. Block diagram of the proposed technique

LVDT's output signal is converted by a 'LTC1967 true RMS to DC converter' to a DC signal that is linearly proportional to the displacement of the LVDT core. The LTC1967 is a true RMS-to-DC converter that uses an innovative delta-sigma computational technique. The benefits of the LTC1967 proprietary architecture are higher linearity & accuracy, bandwidth independent of amplitude and improved temperature behavior when compared to conventional log-antilog RMS-to-DC converters.

4. Problem Statement

In this section characteristics of LVDT are simulated to understand the difficulties associated with the available measuring scheme. For this purpose, simulation is carried out with three different ratios of coil outer and inner. These are (r_o/r_i) = 2, 4 and 6. Three different values of ratio of length of primary coil and secondary coil (b/m) are considered. These are b/m = 0.25, 0.5 and 0.75. Three different primary winding turns are taken. These are n_p = 100, 200 and 300. Three different secondary windings are taken. These are n_s = 100, 200 and 300. Three different frequencies are considered. These are f = 2.5 KHz, 5 KHz and 7.5

KHz. Different temperatures, like t = 25 ^oC, 50 ^oC and 75 ^oC are used to find the output of LVDT with respect to various values of input displacement considering a particular set of parameter of LVDT, frequency and temperature. These output voltages from LVDT and voltage after conversion using RMS to DC converter are plotted below.

The MATLAB environment is used for simulation.

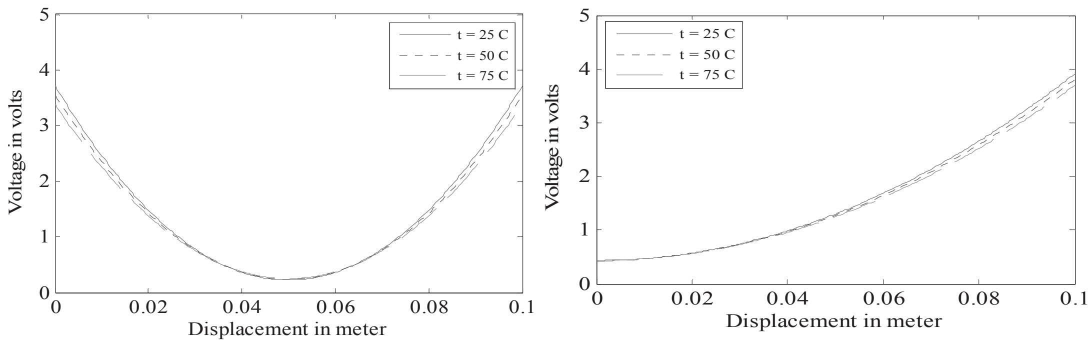


Fig 3. (a) Output of LVDT and (b) data conversion circuit for variation of displacement and temperature with frequency = 7.5 KHz, r_o/r_i = 2 , b/m= 0.75, n_p = 300, n_s= 300.

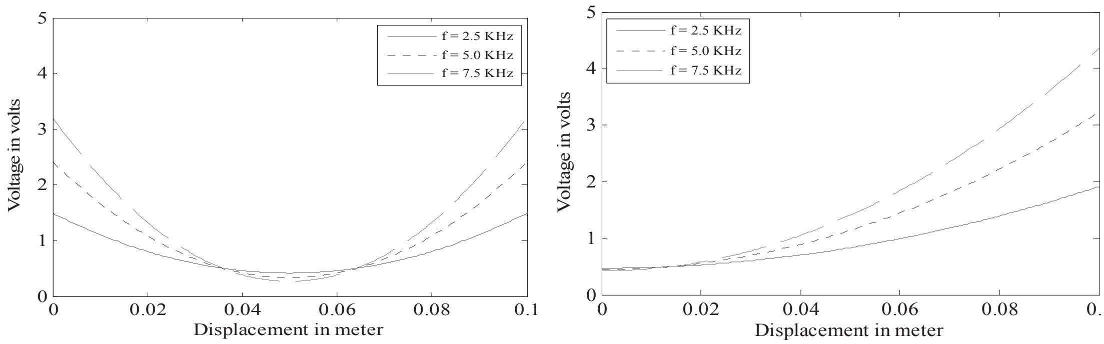


Fig 4. (a) Output of LVDT and (b) data conversion circuit for variation of displacement and frequency with, r_o/r_i = 2, b/m=0.75, n_p = 300, n_s= 300, temperature = 75 ^oC.

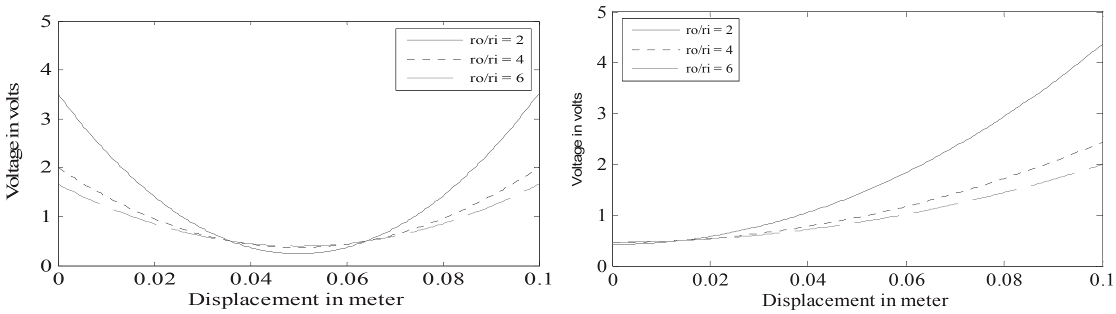


Fig 5. (a) Output of LVDT and (b) data conversion circuit for variation of displacement and r_o/r_i, with b/m=0.75, n_p = 100, n_s= 300, temperature= 75^{o}C, frequency = 7.5 KHz.

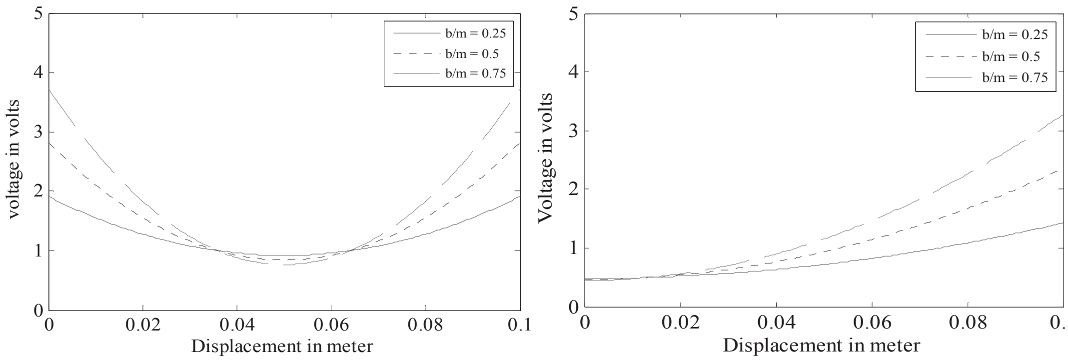


Fig 6. (a) Output of LVDT and (b) data conversion circuit for variation of displacement and b/m with n_p = 300, n_s= 300 temperature = 25°C, frequency = 2.5 KHz, r_o/r_i = 2.

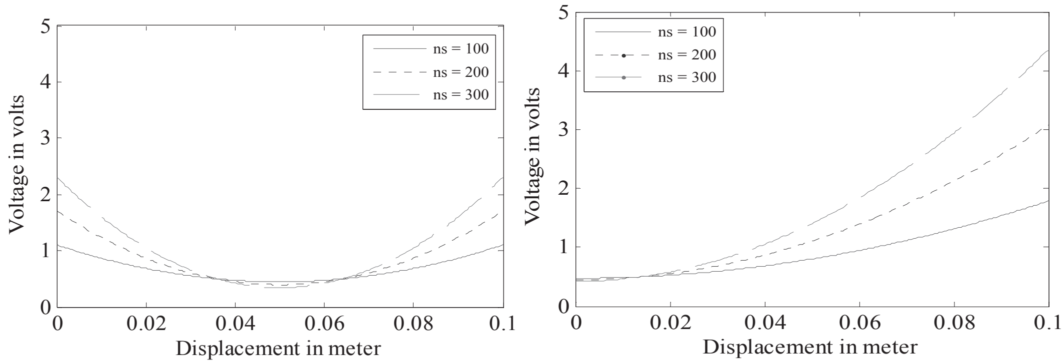


Fig 7. (a) Output of LVDT and (b) data conversion circuit for variation of displacement and n_s with temperature = 75 °C, frequency = 2.5 KHz, r_o/r_i = 2, b/m = 0.75, n_p = 100.

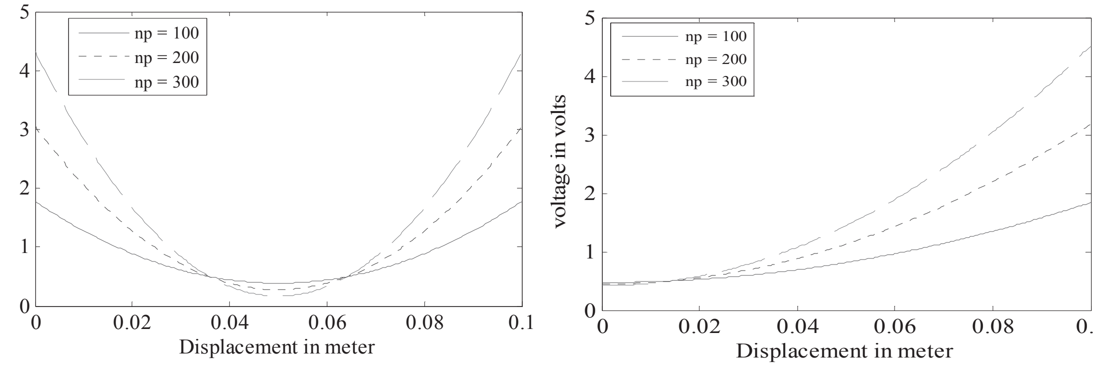


Fig 8. (a) Output of LVDT and (b) data conversion circuit for variation of displacement and n_p with temperature = 50 °C, frequency = 5 KHz, r_o/r_i = 2, b/m = 0.75, n_s = 200.

Fig 3 to Fig 8 show the variation of voltages with the change in input displacement considering different values of frequency, physical parameters of the LVDT and temperature. It has been observed from the above graphs that the relation between input displacement and voltage output has a non linear relation. Datasheet of LVDT suggests that the input range of 10% to 80% of full scale is used in practice as linear range. The output voltage also varies with the change in mutual inductance, frequency and temperature. These are the reasons which have made the user to go for calibration techniques using some circuits. These conventional techniques have a drawback that its time consuming and need to be calibrated every time an LVDT is changed in the system, variation of environment conditions like temperature and the use is restricted only to a portion of full scale for linear operation.

To overcome these drawbacks, this paper makes an attempt to design a smart displacement measuring technique incorporating intelligence to produce linear output and to make the system independent of physical parameter of LVDT, input frequency and temperature using the concept of artificial neural network.

5. Problem Solution

The problem stated above is solved by using an ANN. The first step in developing a neural network is to create a database to train and validate the network. The output voltages of the system for the change in displacement, physical parameters of LVDT, frequency and temperature form the input matrix; target matrix would be the expected linear response of LVDT as shown in Fig 9(b). After many tests of different ANN models the present model as shown in Fig 9(a) is obtained with 5 number of layers having 6, 5, 7, 6 and 6 neurons in each layer respectively. For training Levenberg–Marquardt algorithm (LMA) is used**.** LMA provides a numerical solution to the problem of minimizing a function, generally nonlinear, over a space of parameters of the function [13], [14].

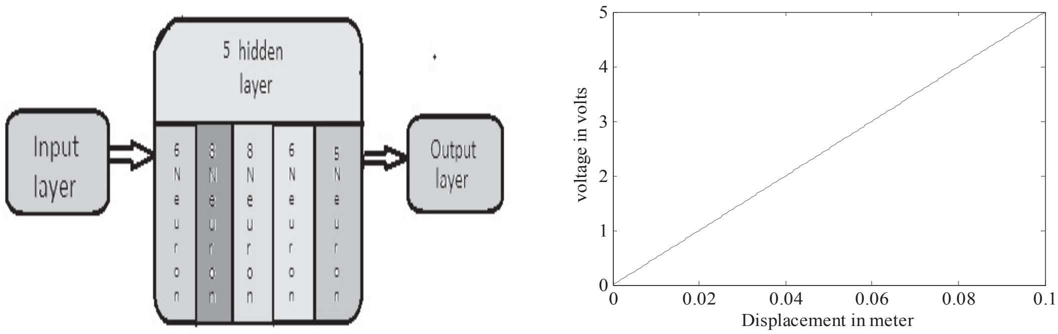


Fig 9.(a) Neural Network Architecture, (b) Target graph

The functionality of ANN can be explained as given below. First the data is initialized; like training base (70%), test base (15%), validation base (15%), number of layers and neurons, type of the transfer functions, number of iteration and estimate error threshold. The network is trained to compute the weights. Once the weights are computed, it is verified to have mean square error (MSE) is less than estimate error threshold (Th) for at least 10 consecutive readings. If the above condition is satisfied the whole model is saved, else the iteration for updates of ANN parameters continue till it reaches the maximum value and then the model is saved with cautioned that desired performance has not reached. Else the system will accept a new set of data to satisfy the conditions. After the network is trained, **Th** is the estimate error threshold, and Mean Squared Error (MSE) is the average squared difference between outputs and targets. Lower value of MSE is better. Zero MSE means no error. Regression R measures the correlation between outputs and targets. An R value of 1 means a close relationship, 0 a random relationship. With these details the network is trained, validated and tested. Table 1 summarises the various parameters of the measured network model.

Table 1: Network model

<table>
<tr><td colspan="9">OPTIMIZED PARAMETERS OF THE NEURAL NETWORKS MODEL</td></tr>
<tr><td colspan="2" rowspan="3">Database</td><td colspan="4">Training base</td><td colspan="3">140</td></tr>
<tr><td colspan="4">Validation base</td><td colspan="3">30</td></tr>
<tr><td colspan="4">Test base</td><td colspan="3">30</td></tr>
<tr><td colspan="2" rowspan="6">No of neurons</td><td colspan="4">Hidden layer 1</td><td colspan="3">6</td></tr>
<tr><td colspan="4">Hidden layer 2</td><td colspan="3">5</td></tr>
<tr><td colspan="4">Hidden layer 3</td><td colspan="3">7</td></tr>
<tr><td colspan="4">Hidden layer 4</td><td colspan="3">6</td></tr>
<tr><td colspan="4">Hidden layer 5</td><td colspan="3">6</td></tr>
<tr><td colspan="4">Output layer</td><td colspan="3">1</td></tr>
<tr><td colspan="2" rowspan="6">Transfer function</td><td colspan="4">Hidden layer 1</td><td colspan="3">tansig</td></tr>
<tr><td colspan="4">Hidden layer 2</td><td colspan="3">tansig</td></tr>
<tr><td colspan="4">Hidden layer 3</td><td colspan="3">tansig</td></tr>
<tr><td colspan="4">Hidden layer 4</td><td colspan="3">tansig</td></tr>
<tr><td colspan="4">Hidden layer 5</td><td colspan="3">tansig</td></tr>
<tr><td colspan="4">Output layer</td><td colspan="3">linear</td></tr>
<tr><td rowspan="3">Input</td><td></td><td>Displacement</td><td>r_o/r_i</td><td>b/m</td><td>Frequency</td><td>Temp</td><td>n_p</td><td>n_s</td></tr>
<tr><td>Min</td><td>0 mm</td><td>2</td><td>0.25</td><td>2.5 KHz</td><td>0^oC</td><td>100</td><td>100</td></tr>
<tr><td>Max</td><td>100 mm</td><td>6</td><td>0.75</td><td>7.5 KHz</td><td>75^oC</td><td>300</td><td>300</td></tr>
<tr><td colspan="2" rowspan="3">MSE</td><td colspan="4">Training</td><td colspan="3">8.41E-08</td></tr>
<tr><td colspan="4">Validation</td><td colspan="3">0.24E-07</td></tr>
<tr><td colspan="4">Test</td><td colspan="3">0.93E-08</td></tr>
<tr><td colspan="2" rowspan="3">R</td><td colspan="4">Training</td><td colspan="3">0.999985</td></tr>
<tr><td colspan="4">Validation</td><td colspan="3">0.9999687</td></tr>
<tr><td colspan="4">Test</td><td colspan="3">0.9999980</td></tr>
</table>

6. Result and Conclusion

As discussed, ANN is trained, validated and tested with the simulated data. Once the training is over, the system with LVDT along with other modules in cascade as shown in Fig. 2 is subjected to various test inputs corresponding to different displacement at a particular physical parameter of LVDT, excitation frequency and working temperature. For testing purposes the range of displacements is considered from 0 to 100 mm, the range of ratio of outer to inner coil diameter is 2 to 6, the range of ratio of length between primary to secondary coil is 0.25 to 0.75, range of frequency is 2.5 KHz to 7.5 KHz, range of primary winding turns 100 to 300, range of secondary winding turns 100 to 300, and the range of temperature is 0 ^oC to 75 ^oC. Variation in the output voltage of a particular displacement for variation of working temperature is taken and in the present measuring technique. The working voltage is measured and fed as an input to ANN. The outputs of system with ANN were noted corresponding to various input displacements with particular values of physical parameters, frequency and temperature within the range.

The input output result is plotted and is shown in Fig. 10. The output graph is matching with the target graph as shown in Fig. 9(b).

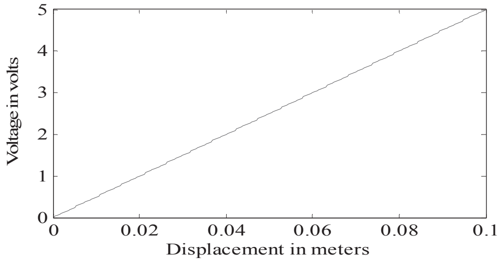


Fig 10 Response of the system for change in displacement

It is evident from the Fig. 10 that the proposed measuring technique presented here has incorporated smartness to the LVDT; it has increased the linearity range of the LVDT. Also the output has been made independent of the physical parameters of LVDT, excitation frequency and working temperature. Thus, if the LVDT is replaced having different physical parameters and or frequency of operation is changed and or working temperature, the system does not require any calibration. The present paper is compared with the similar reported works in [5-12]. In the present paper, output of LVDT has been made independent of physical parameters of LVDT, excitation frequency and working temperature which is substantive improvement over the earlier reported works.

Measurement noise is not considered in the present work. Performance of proposed measuring technique in presence of measurement noise will be taken up in future. An embedded system will be attempted incorporating the design technique to make it suitable for practical application.

References

1. H. K. P. Neubert. Instrument Transducers: An Introduction to Their Performance and Design. 2nd edition New Delhi, India, Oxford University Press, 2003.
2. Bela G Liptak. Instrument Engineers Handbook-Process Measurement and Analysis. 4th Edition, CRC Press, 2003.
3. DVS Murty. Transducers and Instrumentation. PHI publication India, 2003.
4. Janusz Groszkowski. The temperature coefficient of inductance. Proceedings of the Institute of Radio Engineers, pp 448-464, Vol 25, No 4, 1937.
5. S. C. Saxena and S. B. L. Seksena. A self-compensated smart LVDT transducer. IEEE Transactions on Instrument and Measurement. vol. 38, no. 3, pp. 748–753, Jun. 1989.
6. G. Y. Tian, Z. X. Zhao, R. W. Baines, and N. Zhang. Computational algorithms for linear variable differential transformers (LVDTs). *Proc. Inst. Elect. Eng.—Sci. Meas. Technol.*, vol. 144, no. 4, pp. 189–192, Jul. 1997.
7. D. Crescini, A. Flammini, D. Marioli, and A. Taroni. Application of an FFT-based algorithm to signal processing of LVDT position sensors. IEEE Transactions on Instrument and Measurement. vol. 47, no. 5, pp. 1119–1123, Oct. 1998.
8. R.M. Ford, R. S.Weissbach, and D. R. Loker,. A novel DSP-based LVDT signal conditioner. IEEE Transactions on Instrument and Measurement, vol. 50, no. 3, pp. 768–774, Jun. 2001.
9. S. K. Mishra, G. Panda, D. P. Das, S. K. Pattanaik, and M. R. Meher. A novel method of designing LVDT using artificial neural network. In Proceedings IEEE Conference, ICISIP, pp. 223–227, Jan. 2005.
10. A. Flammini, D. Marioli, E. Sisinni, and A. Taroni, “Least mean square method for LVDT signal processing. IEEE Transactions on Instrument and Measurement, vol. 56, no. 6, pp. 2294–2300, Dec. 2007.
11. Zhongxun Wang, Zhonghua Duan. The Research of LVDT Nonlinearity Data Compensation based on RBF Neural Network. Proceeding of World Congress on Intelligent Control and Automation, Chongqing, China, June 25-27, 2008.
12. Saroj Kumar Mishra, Ganapati Panda, Debi Prasad Das. A Novel Method of Extending the Linearity Range of Linear Variable Differential Transformer Using Artificial Neural Network.IEEE Transactions on Instrument and Measurement, Vol 59, No 4, pp 947-953, 2010.
13. Fernando Morgado Dias, Ana Antunes1, José Vieira, Alexandre Manuel Mota. Implementing The Levenberg-Marquardt Algorithm On-line: a sliding window approach with early stopping. 2004 IFAC
14. K. Madsen, H.B. Nielsen, O. Tingleff. Methods for Non-Linear Least Squares Problems. Information and Mathematical Modelling, Technical University of Denmark, 2nd Edition, April 2004.