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Nonlinearity Compensation of Linear Variable Displacement Transducer based on Differential Evolution Algorithm

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ABSTRACT

Background: Transducers rarely possess a perfectly linear transfer characteristic, but always have some degree of non-linearity over their range of operation. Attempts have been made by many researchers to increase the range of linearity of transducers. **Objective:** This paper presents a method to compensate nonlinearity of Linear Variable Displacement Transducer (LVDT) based on Differential Evolution (DE) algorithm. Because of the mechanism structure, LVDT often exhibit inherent nonlinear input-output characteristics. The best approximation capability of optimized ANN technique is beneficial to this. The use of this proposed method is demonstrated through computer simulation with the experimental data of two different LVDT. **Results:** The results reveal that the proposed method compensated the presence of nonlinearity in the displacement transducer with very low Mean Square Error (MSE) and better linearity. **Conclusion:** This research work involves less computational complexity and it behaves a good performance for nonlinearity compensation for LVDT and has good application prospect.

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INTRODUCTION

Linear Variable Displacement Transducer (LVDT), a patent by G.B.Hoadley in 1940. It is arranged with two sets of coil, one as the primary and the other secondary having two coils connected differentially for providing the output. The coupling between the primary and the secondary coils varies with the core plunger moving linearly and the output differential voltage varies linearly. The displacement produced by the plunger will be gained by calculating the differential voltage. So LVDT is widely used in the measurement and control system which is associated with displacement. Because of the mechanism structure and others, LVDT often exhibit inherent nonlinear input-output characteristics. Complicated and accurate winding machines are used to solve this. It is difficult to have all LVDT to be equally linear. Nonlinearity also arises in due to change in environment conditions such as temperature and humidity. Due to such nonlinearities direct digital readout is not possible. Their usable range gets restricted due to the presence of nonlinearity. If a transducer is used for full range of its nonlinear characteristics, accuracy and sensitivity of measurement is severely affected. The nonlinearity present is usually time-varying and unpredictable as it depends on many uncertain factors.

A Functional Link Artificial Neural Network (FLANN) with the practical setup for the development of a linear LVDT (Saroj Kumar Mishra and Ganapati Panda, 2010). In the conventional design, sophisticated and precise winding machines are used to achieve the nonlinearity compensation (G. Y. Tian *et al.*, 1997). Some digital signal processing techniques have been suggested to achieve better sensitivity and to implement the signal conditioning circuits (A. Flammini *et al.*, 2007). It is reported that the artificial neural network (ANN)-based inverse model can effectively compensate for the nonlinearity effect of the sensors (J. C. Patra *et al.*, 2000). LVDTs show a nonlinearity behavior when the core is moved toward any one of the secondary coils. In the primary coil region (middle) of the characteristics, core movement is almost linear. Because of that, the range of operation is limited within the primary coil. The nonlinearity estimation and its compensation in the case of a capacitive pressure sensor and an LVDT using different ANNs are proposed. Compensation of

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Capacitive Pressure Sensor (CPS) nonlinearities is done using neuro-fuzzy algorithms (Jun Li and Feng Zhao, 2006). Calibration of CPS is discussed using circuits (Yi Leng *et al*., 2007). Calibration of CPS is done using least square support vector regression, and for temperature compensation one more CPS is used (Xiaoh Wang, 2008). Extension of linearity is achieved using Hermite neural network algorithm (Jagdish C. Patra *et al*., 2009). Chebyshev neural network algorithm is used for extension of linearity (Jagadish.C. Patra, and Cedric Bornand, 2010). Nonlinearity of CPS is compensated by using Hybrid Genetic Algorithm- Radial Basis Function neural network (Zhiqiang Wang *et al*., 2010). Calibration of CPS is done using DSP algorithms (Yang Chuan and Li Chen, 2010). Functional Link ANN (FLANN) algorithm is used for calibrations of CPS (Jiaoying Huang *et al*., 2010). Laguerre neural network is used for calibration of CPS (Jagadish Chandra Patra *et al*., 2011). An intelligent pressure measurement technique is proposed as an improvement to the earlier reported works (Santhosh K V and B K Roy, 2011). The technique is designed to obtain full scale linearity of input range and makes the output adaptive to variations in physical properties of diaphragm, dielectric constant, and temperature, all using the optimized ANN model.

This paper is organized as follows: after introduction, a brief description on LVDT is given in Section 2.0. Specifications and experimental observations of two different LVDTs are also discussed in this section. Section 3.0 deals with the mathematical analysis of Differential Evolution (DE) algorithm. The computer simulation study of the proposed models by using the experimental data of two different LVDTs are carried out in this Section. Results and discussion with output performance curves before and after compensation of nonlinearity using the specified algorithms are mentioned in Section 4.0. Finally conclusion and future scope are discussed in Section 5.0.

2.0 Linear Variable Displacement Transducer (LVDT):

The LVDT consists of a primary coil and two secondary coils. The two secondary coils are connected differentially for providing the output. The secondary coils are located on the two sides of the primary coil on the bobbin or sleeve, and these two output windings (secondary coils) are connected in opposition to produce zero output at the middle position of the armature.

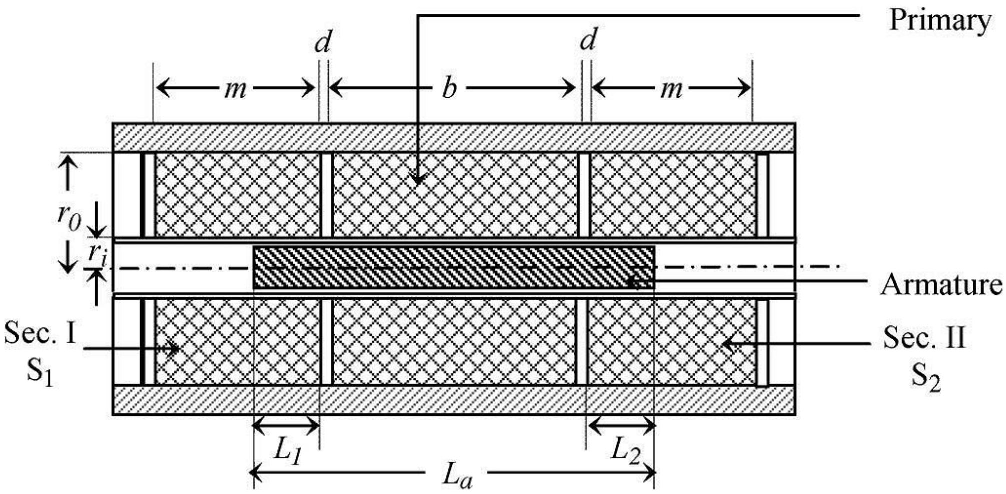

Fig. 1: Cross-sectional view of LVDT.

The lengths of primary and two identical halves of the secondary coils are b and m, respectively. The coils have an inside radius r_i and an outside radius of r_o. The spacing between the coils is d. Inside the coils, a ferromagnetic armature of length L_a and radius r_i (neglecting the bobbin thickness) moves in an axial direction. The number of turns in the primary coil is n_p, and n_s is the number of turns in each secondary coils. The cross-sectional view of LVDT is shown in Fig. 1. With a primary sinusoidal excitation voltage V_p and a current I_p (RMS) of frequency f, the RMS voltage v_1 induced in the secondary coil S_1 is

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

and that in coil S_2 is

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

Where

$x_1 -$ distance penetrated by the armature toward the secondary coil S_1 ;

$x_2 -$ distance penetrated by the armature toward the secondary coil S_2

The differential voltage $v = v_1 - v_2$ is thus given by

$$v = k_1 x(1 - k_2 x^2) \quad (3)$$

Where $x = (1/2)(x_1 - x_2)$ is the armature displacement and

$$k_1 = \frac{16\pi^3 f I_p n_p n_s (b+2d+x_0)x_0}{10^7 \ln(r_o/r_i) m L_a} (Vm^{-1}) \quad (4)$$

With

$$x_0 = (1/2)(x_1 + x_2) \quad (5)$$

and

$$k_2 = 1/(b + 2d + x_o)x_o \quad (6)$$

k_2 is a nonlinearity factor in (3), with the nonlinearity term $\in$ being

$$\in = k_2 x^2 \quad (7)$$

For a given accuracy and maximum displacement, the overall length of the transducer is minimum for $x_0 = b$, assuming that at maximum displacement, the armature does not emerge from the secondary coils. Taking the length of armature $L_a = 3b + 2d$, neglecting $2d$ compared with b, and using (4), (3) can be simplified as

$$v = \frac{16\pi^3 f I_p n_p n_s}{10^7 \ln(r_o/r_i)} \cdot \frac{2b}{3m} \left(1 - \frac{x^2}{2b^2}\right) \quad (8)$$

For a given primary sinusoidal excitation, the secondary output voltage v is nonlinear with respect to displacement x. This is shown in Fig.2 in which the linear region of the plot is indicated as x_m.

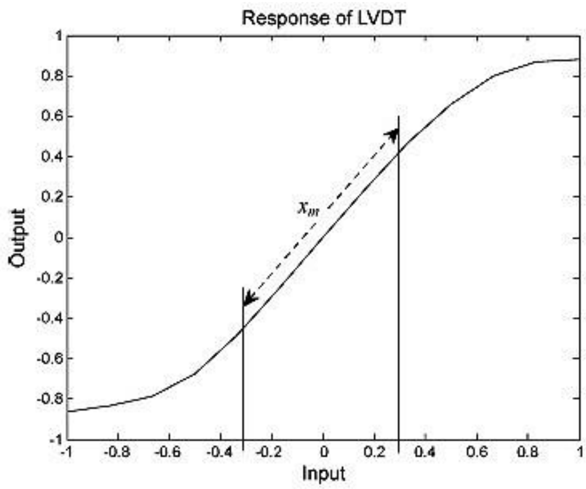

Fig. 2: Range of linear region of LVDT

This limitation is inherent in all differential systems, and methods of nonlinearity compensation are proposed mainly by appropriate design and arrangement of the coils. Some of these are given as follows.

- Balanced linear tapered secondary coils: improvement in linearity range is not significant
- Over-wound linear tapered secondary coils: linearity is improved to a certain range
- Balanced over-wound linear tapered secondary coils
- Balanced profile secondary coils: helps in extending linearity range by proper profiling of the secondary coils
- Complementary tapered windings method: extends the linearity range as well, but the winding is quite complicated as sectionalized winding is done

2.1 Linearity:

One of the best characteristics of a transducer is considered to be linearity, that is, the output is linearly proportional to the input. The computation of linearity is done with reference to a straight line showing the relationship between output and input. This straight line is drawn by using the method of least squares from the given calibration data. This straight line is sometimes called an idealized straight line expressing the input-output relationship. The linearity is simply a measure of maximum deviation of any of the calibration points from this straight line.

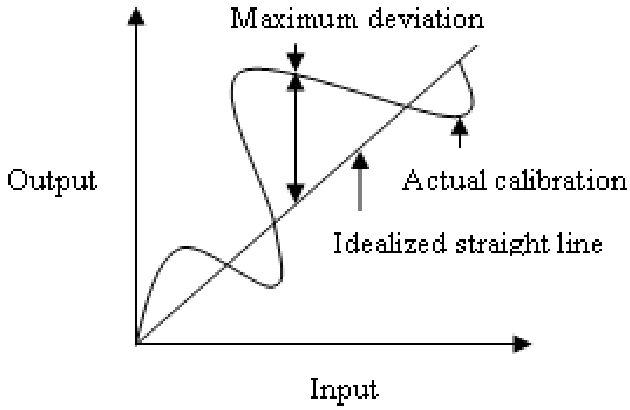

Fig. 3: Actual calibration curve

Fig.3 shows the actual calibration curve i.e., a relationship between input and output and a straight line drawn from the origin using the method of least squares.

$$Percentage\ of\ Nonlinearity = \frac{Max\ deviation\ \ from\ the\ idealized\ \ straig\ ht\ line}{Full\ scale\ \ deviation} \times 100 \quad (9)$$

Equation (9) expresses the nonlinearity as a percentage of full scale reading. It is desirable to keep the nonlinearity as small as possible as it would in that case result in small errors.

2.2 Geometric parameters and Experimental observations of LVDT:

The performance of the LVDT is highly influenced by transducer geometry, arrangement of primary and secondary windings, quality of core material, variations in excitation current and frequency, and changes in ambient and winding temperatures. The geometric parameters and specifications of a conventional LVDT is listed in the below Table 1.

Table 1: Geometric parameters and specifications of LVDT.

Parameter	Range (mm)	Variable/Fixed	LVDT-1	LVDT-2
Coil diameter	5 – 20	Variable	5 mm	20 mm
Core length	62 – 216	Variable	60 mm	140 mm
Core diameter	4.1 – 10	Variable	4.4 mm	10 mm
Number of turns P	200-2000	Variable	1500	200
Number of turns S_1	100-4000	Variable	3300	100
Number of turns S_2	100-4000	Variable	3300	100
Excitation voltage	3V<Ve<15Vpp	Variable	10 Vpp	5 Vpp
Excitation Frequency	5kHz-10kHz	Variable	5 kHz	10kHz

In this research work, we have taken the performance of two different LVDTs. The experimental data are collected from two different LVDTs having the specifications listed in Table 1. The variable parameters of the conventional LVDT are chosen as lowest range for LVDT-1 and highest range for LVDT-2. The data obtained by conducting experiments on the two LVDTs are given in Table 2 and Table 3. The output response curves of two LVDTs are shown in Fig.4 and Fig.5. It is clear that the output response of the two LVDTs shows the presence of nonlinearity.

Table 2: Experimental observations of LVDT-1.

Core Displacement (in mm)	Signal conditioned output voltage (in mV)
-6.30	-2.91
-5.08	-2.38
-4.10	-1.87
-3.02	-1.35
-1.94	-0.84
-0.99	-0.34
0.05	0.15
1.20	0.90
2.21	1.90

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3.20	3.00
4.22	4.10
5.29	2.67
6.37	3.20
7.46	3.72
8.49	4.21
9.51	4.70
10.57	5.21
11.53	5.69
12.68	6.22
13.73	6.72
14.70	7.22

Table 3: Experimental observations of LVDT-2

Core Displacement (in mm)	Signal conditioned output voltage (in Volts)
-30	-5.185
-25	-5.017
-20	-4.717
-15	-4.039
-10	-2.896
-5	-1.494
0	0.001
5	1.462
10	1.810
15	3.962
20	4.799
25	5.225
30	5.276

The percentage of nonlinearity is calculated using the equation (9). The lowest range choosen LVDT (LVDT-1) having highest percentage of nonlinearity when compared with the highest range LVDT (LVDT-2). So it is necessary to compensate the percentage of nonlinearity present in both LVDTs.

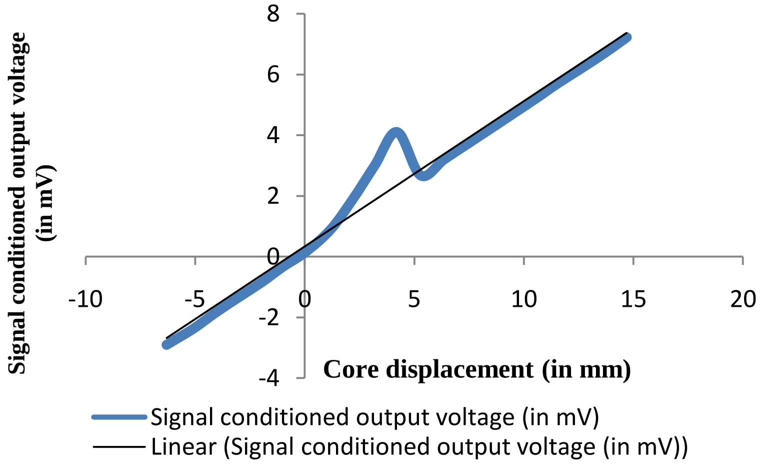

Fig. 4: Input-Output Response of LVDT-1

$$\%\ of\ Nonlinearity\ for\ LVDT\ 1 = \frac{2}{7.22} \times 100 = 27.70\%$$

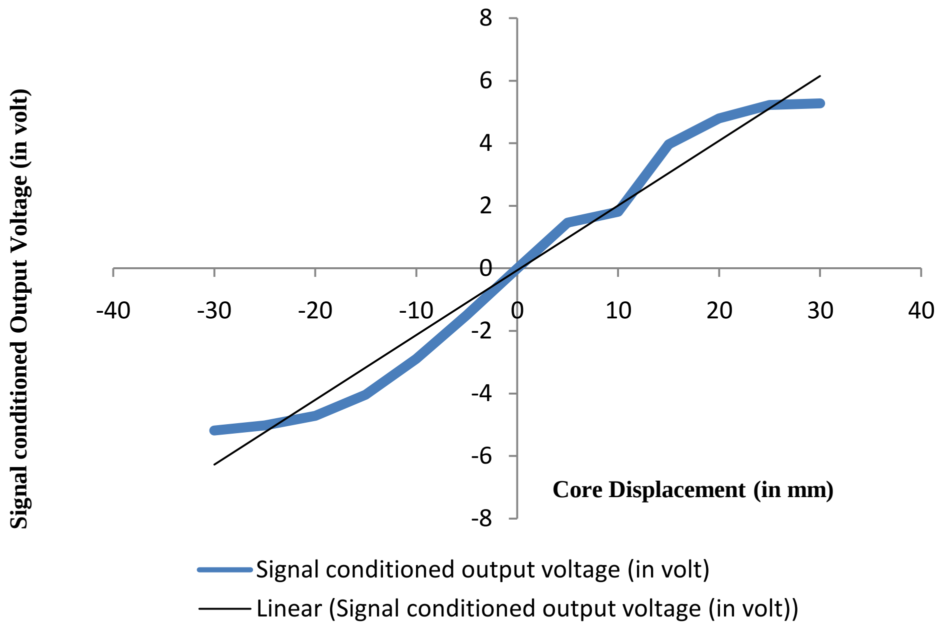

Fig. 5: Input-Output Response of LVDT-2

$$\%\ of\ Nonlinearity\ for\ LVDT\ 2 = \frac{1.143}{5.276} \times 100 = 21.66\%$$

It has been observed from the above graphs (Fig.4 and Fig.5), that the relation between input displacement and voltage output of LVDT are nonlinear.

3.0 Differential evolution algorithm based nonlinearity compensation:

The Differential Evolution (DE) algorithm is a stochastic, population-based optimization algorithm introduced by Storn and Price in 1996. It is developed to optimize real parameter and real valued functions. It is a population based algorithm like genetic algorithms using the similar operators; crossover, mutation and selection. The main difference in constructing better solutions is that genetic algorithms rely on crossover while DE relies on mutation operation. This main operation is based on the differences of randomly sampled pairs of solutions in the population. The algorithm uses mutation operation as a search mechanism and selection operation to direct the search toward the prospective regions in the search space. The DE algorithm also uses a non-uniform crossover that can take child vector parameters from one parent more often than it does from others. By using the components of the existing population members to construct trial vectors, the recombination (crossover) operator efficiently shuffles information about successful combinations, enabling the search for a better solution space. An optimization task consisting of D parameters can be represented by a D-dimensional vector. In DE, a population of NP solution vectors is randomly created at the start. This population is successfully improved by applying mutation, crossover and selection operators. The main steps of the DE algorithm are given as follows:

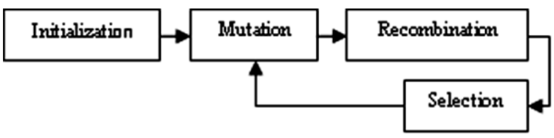

Fig. 6: General Evolutionary Algorithm Procedure

The general problem formulation is:

For an objective function $f: X \subseteq \mathbb{R}^D \longrightarrow \mathbb{R}$ where the feasible region $X \neq \emptyset$, the minimization problem is to find

$x^* \in X$ Such that $f(x^*) \leq f(x) \forall x \in X$ where $f(x^*) \neq -\infty$

Suppose we want to optimize a function with D real parameters, we must select the size of the population N (it must be at least 4). The parameter vectors have the form:

$$x_{i,G} = [x_{1,i,G}, x_{2,i,G}, \dots \dots . x_{D,i,G}] \qquad (10)$$

$i = 1,2, \dots \dots N$

Where, G is the generation number.

3.1 Initialization:

Define upper and lower bounds for each parameter:

$$x_j^L \le x_{j,i,1} \le x_j^U \quad (11)$$

Randomly select the initial parameter values uniformly on the intervals:

$$[x_j^L, x_j^U] \quad (12)$$

3.2 Mutation:

Each of the N parameter vectors undergoes mutation, recombination and selection. Mutation expands the search space.

For a given parameter vector $x_{i,G}$ randomly select three vectors $x_{r1,G}, x_{r2,G}$ *and* $x_{r3,G}$ such that the indices $i, r1, r2$ *and* $r3$ are distinct.

Add the weighted difference of two of the vectors to the third

$$v_{i,G+1} = x_{r1,G} + F(x_{r2,G} - x_{r3,G}) \quad (13)$$

The mutation factor F is a constant from $[0,2]$

$v_{i,G+1}$ is called the donor vector

3.3 Recombination:

Recombination incorporates successful solutions from the previous generation. The trial vector $u_{i,G+1}$ is developed from the elements of the target vector, $x_{i,G}$ and the elements of the donor vector, $v_{i,G+1}$

Elements of the donor vector enter the trial vector with probability CR

$$u_{j,i,G+1} = \begin{cases} v_{j,i,G+1}, & if\ rand_{j,i} \le CR\ or\ j = I_{rand} \\ x_{j,i,G}, & if\ rand_{j,i} > CR\ and\ j \ne I_{rand} \end{cases} \quad (14)$$

$i = 1,2, \dots \dots N; j = 1,2, \dots \dots D$

$rand_{j,i} \sim U[0,1], I_{rand}$ $is\ a\ random\ integer\ from$

$[1,2, \dots \dots D]$

I_{rand} ensures that $v_{i,G+1} \ne x_{i,G}$

3.4 Selection:

The target vector $x_{i,G}$ is compared with the trial vector $v_{i,G+1}$ and the one with the lowest function value is admitted to the next generation

$$x_{i,G+1} = \begin{cases} u_{i,G+1}, & if\ f(u_{i,G+1}) \le f(x_{i,G}) \\ x_{i,G}, & otherwise \end{cases} \quad (15)$$

$i = 1,2, \dots \dots, N$

Mutation, recombination and selection continue until some stopping criterion is reached. It has been observed from the above graphs (Fig.4 and Fig.5) that, the relation between input displacement and voltage output of LVDT are nonlinear before compensation. After compensation by DE algorithm, the nonlinearity is successfully compensated. The DE algorithm has a few control parameters: number of population NP, scaling factor F, combination coefficient *K*, and crossover rate *CR*. The problem specific parameters of the DE algorithm are the maximum generation numbers G_{max} and the number of parameters designing the problem dimension *D*. The values of these two parameters depend on the problem to be optimized. The following results were obtained by using DE algorithm in this research work. From the observed readings of LVDT-1 and LVDT-2 shown in Table 2 and Table 3, the simulation study has been carried out and the following results have been obtained.

Table 4: DE based nonlinearity compensation for LVDT-1

Iterations	NP	F	CR	MSE	Average Training Time
1000	100	0.8	0.5	0.0097	7.141830e+02
		0.7	0.4	0.0108	7.282330e+02
		0.6	0.3	0.0084	7.358051e+02
		0.5	0.2	0.0102	7.280086e+02
		1.1	0.8	0.0301	7.326111e+02
		1.2	0.9	0.0094	7.285723e+02
		0.4	0.9	0.0118	7.306492e+02

Table 5: DE based nonlinearity compensation for LVDT-2

Iterations	NP	F	CR	MSE	Average Training Time
1000	100	0.8	0.5	0.0035	7.37e+01
		0.7	0.4	0.0044	7.51e+01
		0.6	0.3	0.0043	7.44e+01
		0.5	0.2	0.0032	7.56e+01
		0.4	0.1	0.0054	7.58e+01
		0.9	0.6	0.0062	7.58e+01
		1.0	0.7	0.0133	7.48e+01
		1.1	0.8	0.0083	7.71e+01
		1.2	0.9	0.0209	7.64e+01
		0.4	0.9	0.000311	1.49e+03

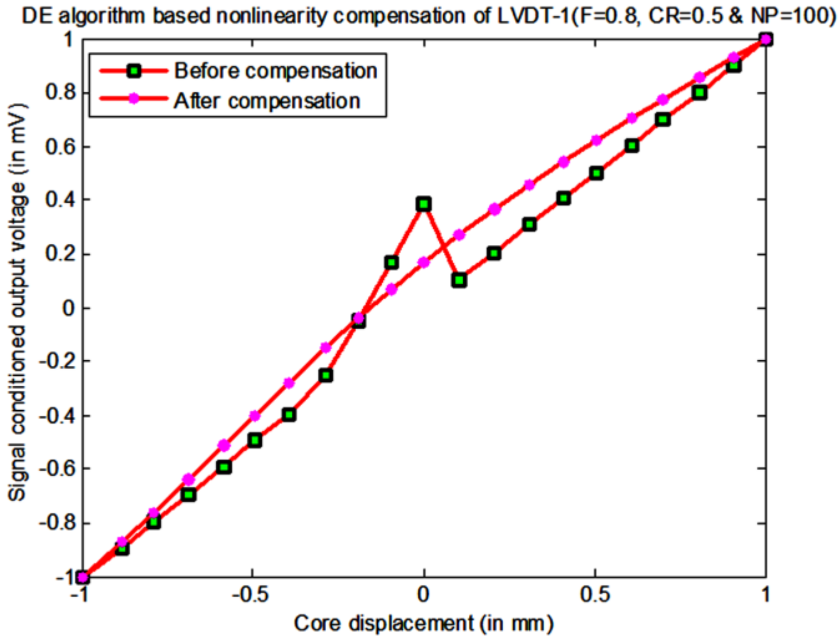

Fig. 7: DE algorithm based nonlinearity compensation of LVDT-1(F=0.8, CR=0.5 & NP=100)

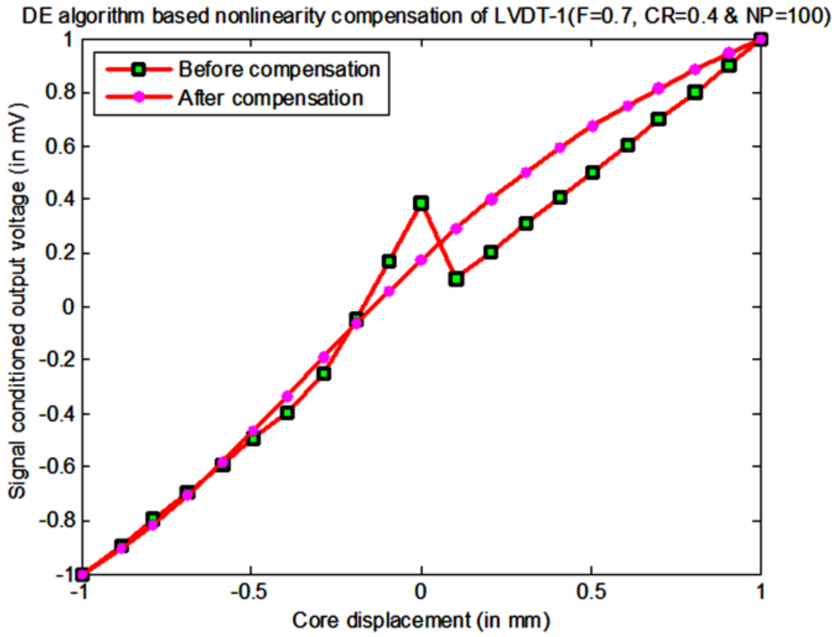

Fig. 8: DE algorithm based nonlinearity compensation of LVDT-1(F=0.7, CR=0.4 & NP=100)

The DE algorithm has a few control parameters: number of population *NP*, scaling factor *F* and crossover rate *CR*. In the simulations, it was observed that the value of scaling factor significantly affected the performance of DE. This can be seen in Table 4 and Table 5. In order to get the best performance from the DE, the scaling factor value F and cross over value CR must be optimally tuned for each function. Of course, this is a time-consuming task. For the simplicity and flexibility, the value of F was randomly chosen between [0 2] and the value of CR was chosen between [0 1] for each generation instead of using a constant value. DE algorithm was run 1000 times for each function to achieve average results. For each run, the initial population was randomly created by means of using different seed numbers. The corresponding MSE values and average training time are calculated and listed in Table 4 and Table 5.

4.0 Results:

A computer simulation is carried out in the MATLAB.12 environment using an experimental dataset. The experimental data are collected from two different LVDTs having different specifications shown in Table 1. The data obtained by conducting experiments on the two LVDTs are given in Table 2 and Table 3. The observed simulation results are shown in various figures listed below. It is observed that DE algorithm produces the lowest MSE value of 0.000311 for F=0.4, CR=0.9 and NP=100.

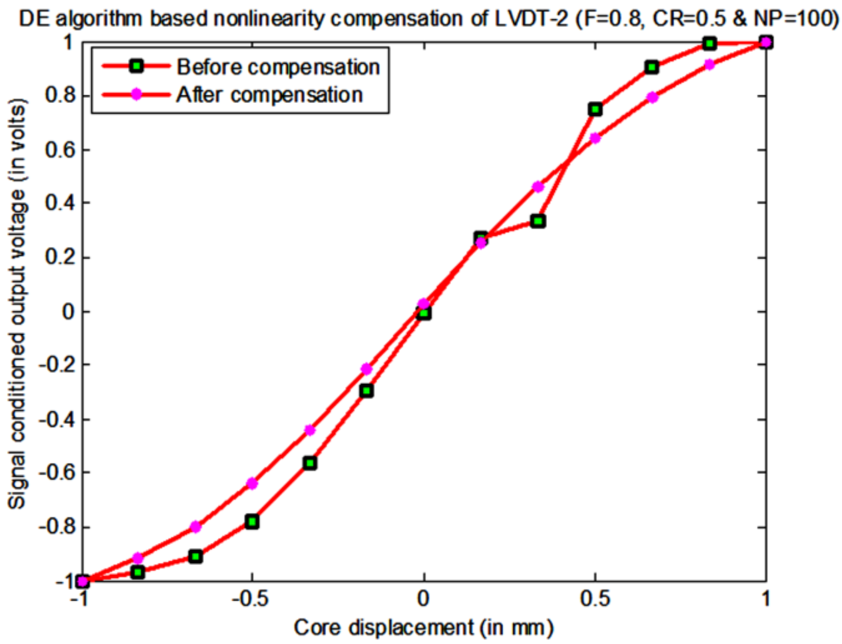

Fig. 14: DE algorithm based nonlinearity compensation of LVDT-2 (F=0.8, CR=0.5 & NP=100)

5.0 Conclusion and Future Scope:

This paper has proposed Differential Evolution (DE) algorithm to adaptively compensate for the nonlinearity offered by two different LVDTs. It yields better mean square error value when compared to others. The proposed algorithm offers a less complexity structure and simple in testing and validation procedure. This adaptive algorithm can also be applied to any transducer having a nonlinear characteristic. This hybrid technique is used to make a transducer output as more linear as possible. Further this adaptive algorithm is preferable for real time implementation also.

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