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A Novel Method of Designing LVDT using Artificial Neural Network

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Abstract

This paper proposes a simple and novel method of designing and developing LVDT based sensing system. Conventionally, precise adjustment of windings is made to enhance the linearity range of LVDT. The tedious job of pitch adjustment of windings of LVDT can be overcome by use of the proposed method. Functional link artificial neural network has been successfully used in the paper for nonlinear compensation of LVDT. The effectiveness of the proposed method is demonstrated through computer simulation with the experimental data of a simple LVDT. The complete algorithm with practical set-up for development of LVDT is presented in the paper.

1. INTRODUCTION

In many practical control systems Linear Variable Differential Transformer (LVDT) is used as the sensing element for displacement [1]-[4]. The performance of the control system depends upon the performance of the sensing elements. Many sensors exhibit inherent nonlinear input-output characteristics. Lot of researchers have worked to achieve LVDT with high linearity [1]-[4]. In its conventional design methodology achieving high linearity involves complex design task. Sophisticated and precise winding machines are used to achieve that. It is difficult to have all LVDT fabricated in a factory at a time to be equally linear. LVDT having different nonlinearity present in a control system malfunctions at times because of the difference in sensor characteristics. Nonlinearity also creeps in due to change in environmental conditions such as temperature and humidity. In addition aging of the sensors also introduce nonlinearity. As a result we are forced to use the devices or sensors only in the linear region of characteristics. In other words the usable range of these devices gets restricted due to nonlinearity. The accuracy of measurement is also affected if the full range of the instrument is used. The nonlinearity present is usually time varying and unpredictable as it depends on many uncertain factors.

Many researchers have worked on LVDT based systems. In [1], the linearity is achieved with square coil method where the core moves perpendicular to the axis instead of along the axis. A self-compensated LVDT is developed using dual secondary coils which is insensitive to the variation in excitation current and frequency [2]. In [3], detailed mathematical treatment of an LVDT is made. Recently some DSP techniques are being used along with LVDT to achieve better sensitivity and implementing the single conditioning circuits [4], [5]. The nonlinearity estimation and its compensation in case of a capacitive pressure sensor using artificial neural network (ANN) is proposed in [6], [7]. It is shown there that ANN implements another nonlinearity in cascaded with the nonlinear sensor to achieve overall linearity. LVDT shows nonlinearity when the core is moved any one of the secondary coils. At the middle portion of the core movement it shows almost linear characteristics. Because of that the range of operation is limited. By using similar method used in [6], the linearity of the LVDT can be enhanced. Hence the prime objective of this paper is to study the nonlinearity problem of these devices in depth and suggest novel methods of circumventing the effect of this problem. In this paper, we have given a novel design methodology where an electronics element is concatenated with the LVDT to extend the linearity. The electronics element is to realize an artificial neural network (ANN) to enhance the linearity of the conventional LVDT. It is also shown that the proposed method of enhancing the linearity is much simpler than the conventional methods. A variant of

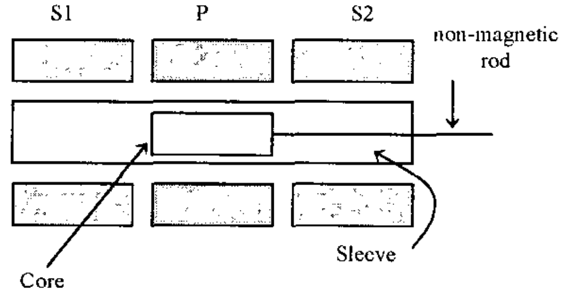

Fig. 1 Scheme of an LVDT

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neural network called functional link artificial neural network (FLANN) [8] is used in this problem as it is simple and involves simple calculations and easier for hardware implementations.

The rest of the paper is organized as follows. Section II discuses about the electrical characteristics of LVDT and the conventional methods used to extend the linearity range. Section III discuses the proposed algorithm and the experimental set-up. Section IV discuses about the FLANN structure and the corresponding mathematical analysis. FLANN based nonlinear compensation of LVDT is established in Section V. Section VI deals with the computer simulation study of the proposed model to demonstrate the effectiveness of the structure. Section VII concludes the paper with some future prospects.

2. LINEAR VARIABLE DIFFERENTIAL TRANSFORMER

Generally, LVDT is arranged with two sets of coil, one as the primary and the other secondary having two coils connected differentially for providing the output. It is thus a differential transformer. The coupling between the primary and the two secondary coils varies with the core plunger moving linearly as in the case of the plunger type. The two secondary coils are located on the two sides of the primary coil on the bobbin or sleeve. The scheme is shown in Fig. 1.

An alternating supply of appropriate voltage V_i and frequency f is impressed across the primary coil and depending on the position of the core with respect to the primary and the two secondary coils, an output voltage V_o is obtained from the secondary coils as shown in Fig. 2. The induction in one secondary coil, according to the law, is

$$V_{os} = -nd\phi/dt = -Mdi_p/dt \quad (1)$$

where n = number of turns in the coil of the secondary, ϕ = magnetic flux, M = mutual inductance between primary and the concerned secondary and i_p = primary current. For the two coils differentially connected,

$$V_o = V_{os2} - V_{os1} = (M_1 - M_2)\frac{di_p}{dt} \quad (2)$$

Both M_1 and M_2 being functions of displacement x, $M_1 - M_2 = M(x)$. If the function is linear over a certain range, $M(x) = kx$, so that

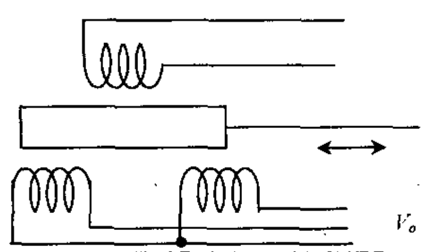

Fig. 2 Equivalent model of LVDT

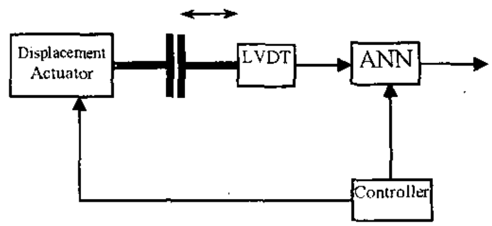

Fig. 3 Set-up for compensating nonlinearity of LVDT

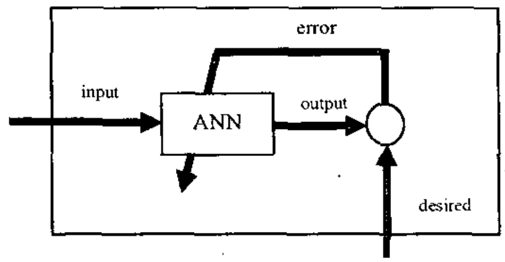

Fig. 4 Internal diagram of ANN block

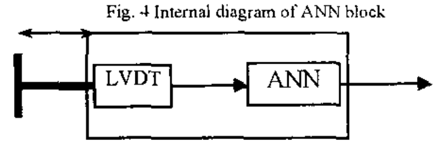

Fig. 5 LVDT after nonlinear compensated

$$x = \frac{V_0}{(kdi_p/dt)} \quad (3)$$

As the sensor basically forms a transformer, the loss components are also to be considered for obtaining the output V_o per unit displacement of the core. The loss components are to be considered for all the transducers of the inductive type. When arranged in a bridge in a differential way, they can, however, be compensated by appropriate circuit components. The equivalent circuit of the LVDT, in that light is shown in Fig. 2. Solving for the magnitude ratio per unit displacement $|V_0/V_i|/x$ and angle by which the output voltage V_o lags the input voltage V_i at a frequency $f = \omega/2\pi$ and, if the meter load is R_m, one gets,

$$\left|\frac{V_o}{V_i}\right| \cdot \frac{1}{x} = \frac{k\omega R_m/\{(R_s + R_m)R_p\}}{\sqrt{\left[\{1-\omega^2(\tau_m^2 + \tau_p\tau_s)\}^2 + \omega^2(\tau_p + \tau_s)^2\right]}} \quad (4)$$

and

$$\phi = 90^\circ - \tan^{-1}\frac{\omega(\tau_p + \tau_s)}{1-\omega^2(\tau_m^2 + \tau_p\tau_s)} \quad (5)$$

where $\tau_m = \frac{M_1 - M_2}{\sqrt{(R_m + R_p)R_p}}$,

$$\tau_p = L_p / R_p \text{ and } \tau_s = L_s / (R_s + R_m).$$

The phase-rectified secondary output voltage V_o with x is nonlinear for a given V_i where the linear range limits are indicated by x_m. This limitation is inherent in all differential systems and methods of extending the range have been proposed mainly by appropriate design and arrangement of the coils. Some of these:

(i) Balanced linear tapered secondary coils. But the improvement is not significant in this method.

(ii) Over-wound linear tapered secondary coils, improves the linearity to a certain extent.

(iii) Balanced over-wound linear tapered secondary coils – a little unbalanced detected case (ii) is eliminated here, range specification is similar to case (ii).

(iv) Balanced profile secondary coils helps in extending linearity range by proper profiling of the secondary coils.

(v) Complementary tapered windings method extends the linearity range as well but the winding is quite complicated as sectionalised winding is done.

3. Proposed Algorithm

The experimental set-up for the proposed model is as shown in Fig. 3. In the set-up the displacement actuator, which is essentially a stepper motor controlled displacer, displaces the core of the LVDT in a controlled manner. The main controller gives an actuating signal to the displacement actuator, which displaces the core of the LVDT. The differential voltage output of the LVDT after being demodulated, which does not keep linear relationship with the displacement, is fed to the input of the neural network. At the same time the actuating signal is used as the desired signal by the neural network. With the input and the desired signal the neural network weights are trained to minimize the over all error. This process is repeated till the error is minimized. The training model of the neural network is shown in Fig. 4. Once the training is complete, the LVDT with this neural network being concatenated behaves like a linear sensor. This structure is shown in Fig. 5.

4. Functional Link Artificial Neural Network

The functional link artificial neural network (FLANN) [5] is a useful alternative to the multilayer artificial neural network (MLANN). It has the advantage of involving less computational complexity and a simple structure for hardware implementation. The conventional MLANN involves linear links. An alternative approach is also possible, whereby the functional link concept is used, which acts on an element of a pattern or the entire pattern itself and generates a set of linearly independent functions. By this process, no new ad hoc information is inserted into the process but the representation gets enhanced. In the functional link model an element v_k, $1 \le k \le N$ is expanded to $f_l(v_k), 1 \le l \le M$. The representative examples of functional expansion are power series expansion, trigonometry expansion, and tensor or outer product [5].

Let us consider the problem of learning with a flat net, which is a net with no hidden layers. Let V be the Q input patterns each with N elements. Let the net configuration have one output. For the qth pattern, the input components are $v_i^{(q)}$, $1 \le i \le N$ and the corresponding output is $y^{(q)}$. The connecting weights are w_i, $1 \le i \le N$ and the threshold is denoted by α. Thus $y^{(q)}$ is given by

$$y^q = \sum_{i=1}^{N} v_i^q w_i + \alpha,\ q = 1, 2, \ldots, Q. \quad (6)$$

or in matrix form,

$$\mathbf{y} = \mathbf{V}\,\mathbf{w}. \quad (7)$$

The dimension of $\mathbf{V}$ is $Q\times(N+1)$.

If $Q = (N+1)$ and Det($\mathbf{V}$) $\neq 0$, then

$$\mathbf{w} = \mathbf{V}^{-1}\mathbf{y}. \quad (8)$$

Thus, finding the weights for a flat net consists of solving a system of simultaneous linear equations for the weights $\mathbf{w}$.

If $Q < (N+1)$, $\mathbf{V}$ can be partitioned into a functional matrix $\mathbf{V}_F$ of dimension $Q\times Q$. By setting $w_{Q+1} = w_{Q+2} = \ldots\ldots = w_N = \alpha = 0$, and since Det($\mathbf{V}_F$) $\neq 0$, $\mathbf{w}$ may be expressed as

$$\mathbf{w} = \mathbf{V}_F^{-1}\mathbf{y}. \quad (9)$$

Equation (9) yields only one solution. But if the matrix $\mathbf{V}$ is not partitioned explicitly, then (8) yields a large number of solutions, all of which satisfy the given constraints.

But if $Q > (N+1)$, then we have

$$\mathbf{V}\mathbf{w} = \mathbf{y}, \quad (10)$$

where $\mathbf{V}$, $\mathbf{w}$, $\mathbf{y}$ are of dimensions $Q\times(N+1)$, $(N+1)\times 1$ and $Q\times 1$, respectively.

By the functional expansion scheme, a column of $\mathbf{V}$ is enhanced from $(N+1)$ elements to M, producing a matrix $\mathbf{S}$ so that $M \ge Q$. Under this circumstance, we have

$$\mathbf{S}\,\mathbf{w}_F = \mathbf{y}, \quad (11)$$

where $\mathbf{S}$, $\mathbf{w}_F$, $\mathbf{y}$ are of dimensions $Q\times M$, $M\times 1$, $Q\times 1$, respectively. If $M = Q$ and Det ($\mathbf{S}$) $\neq 0$, then

$$\mathbf{w}_F = \mathbf{S}^{-1}\mathbf{y}. \quad (12)$$

Equation (12) is an exact flat net solution. However, if $M > Q$, the solution is similar to that of (9). This analysis indicates that the functional expansion model always yields a flat net solution if a sufficient number of additional functions is used in the expansion.

Figure 6 represents a simple FLANN structure, which is essentially a flat net with no hidden layer. In FLANN, N inputs are fed to the functional expansion block to generate M functionally expanded signals, which are linearly combined with the M-element weight vector to generate a single output. In this paper, the trigonometric functional expansion is chosen for the FLANN structure bec of the below-mentioned reason.

Basis of using trigonometric functional expansion:

Of all the polynomials of Pth order with respect to an orthogonal system, the best approximation in the metric space is given by the Pth partial sum of its Fourier series with respect to the system. Therefore, the trigonometric polynomial basis functions given by

$$\mathbf{s} = \{v, \sin(\pi v), \cos(\pi v), \sin(2\pi v), \cos(2\pi v), \ldots, \sin(P\pi v), \cos(P\pi v)\}$$

provide a compact representation of the function in the mean square sense.

5. FLANN Based Nonlinear Compensation of LVDT

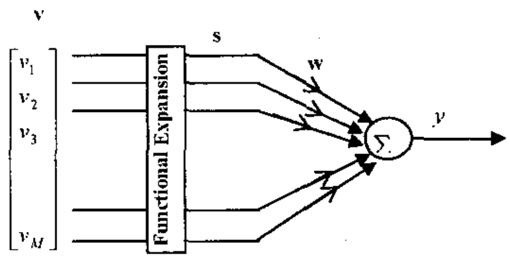

Fig. 6 The structure of a FLANN

The output of the LVDT V_o is functionally expanded as **s** vector. The functionally expanded **s** vector is linearly combined with the weight matrix by the following relationship

$$y = \sum_{i=1}^{M} s_i w_i + \alpha \qquad (13)$$

where α is the bias term, and s_i is defined as

$$s_i = \begin{cases} v_o, & i = 1 \\ \sin(l\pi v_o), & i > 1, i \text{ even} \\ \cos(l\pi v_o), & i > 1, i \text{ odd} \end{cases} \qquad (14)$$

where $1 \le l \le P$, P is the order of expansion. Let us define the error signal as

$$e(n) = d(n) - \sum_{i=1}^{M} w_i s_i \qquad (15)$$

where $d(n)$ is the desired signal which is same as the control signal given to the displacement actuator and n is the time index.

Let us define the cost function ξ as the residual noise power, i.e.

$$\xi = E[e^2(n)] \qquad (16)$$

The weight vector $\mathbf{w}(n)$ may be adjusted according to the following update equation which minimizes the mean square error ξ:

$$\mathbf{w}(n+1) = \mathbf{w}(n) - \frac{\mu}{2}\hat{\nabla}(n) \qquad (17)$$

where $\hat{\nabla}(n)$ is an instantaneous estimate of the gradient of ξ with respect to the weight vector $\mathbf{w}(n)$. Now

$$\hat{\nabla}(n) = \frac{\partial \xi}{\partial \mathbf{w}} = -2e(n)\frac{\partial y(n)}{\partial \mathbf{w}} = -2e(n)\frac{\partial[\mathbf{w}(n)\mathbf{s}(n)]}{\partial \mathbf{w}}$$
$$= 2e(n)s(n) \qquad (18)$$

Substituting the values of $\hat{\nabla}(n)$ in (24) we get

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu e(n)s(n) \qquad (19)$$

where μ denotes the step-size, which controls the convergence speed of the FSLMS algorithm.

6. Computer Simulation

To demonstrate the effectiveness of the FLANN based nonlinear compensator, computer simulation study has been undertaken using experimental data set. The experimental data is collected from an LVDT of the following specification. The LVDT is having two secondary coils (3300 turns) each wound over it uniformly with the two coils separated by a Teflon ring. The core diameter is 4.4 mm, core length is 4.5 mm and the core length is 45 mm. Excitation frequency, and voltage given to primary coil are 5 kHz and 10V (peak-to-peak), respectively. V_p given in this expt. was 6.712 V_{rms}. Primary winding resistance = 260 ohm. Secondary winding resistance (S_1) = 426.8 ohm. Secondary winding resistance (S_2) = 414 ohm. Two secondaries are wound in opposite directions (one clockwise and the other anticlockwise). The pitch was kept around 0.02-0.03 mm. The experimental measured data is presented in Table 1.

TABLE 1: EXPERIMENTAL MEASURED DATA

Displacement (mm)	Output voltage (V_{rms})	Demodulated output (V_{DC})
-30	4.085	-5.185
-25	3.956	-5.017
-20	3.731	-4.717
-15	3.221	-4.039
-10	2.359	-2.896
-5	1.273	-1.494
Null Position 0	0.204	0.001
5	1.153	1.462
10	2.226	1.810
15	3.118	3.962
20	3.748	4.799
25	4.050	5.225
30	4.085	5.276

These data are normalized and are used by FLANN. The normalized demodulated output of the LVDT is input to the

FLANN and the output of the FLANN is compared with the normalized displacement in Table 1. Two different experiments are carried out using the same data set. The first experiment is carried out with less number of functional expansion i.e. P=10. In second experiment large number of functional expansion is chosen. Here P is taken as 100. Fig. 7 shows the response of the LVDT and the nonlinear compensator for the first experiment. Fig. 8 shows the same for the second experiment. From the Figures it is seen that there is significant improvement of linearity by FLANN based compensator with more number of functional expansion. FLANN with 100 functional expansion is achieving linearity about 4.7×10^{-5}%. The computation involved in this case are: multiplications = 102, additions =101 and the Sin(.)/Cos(.) computation =100.

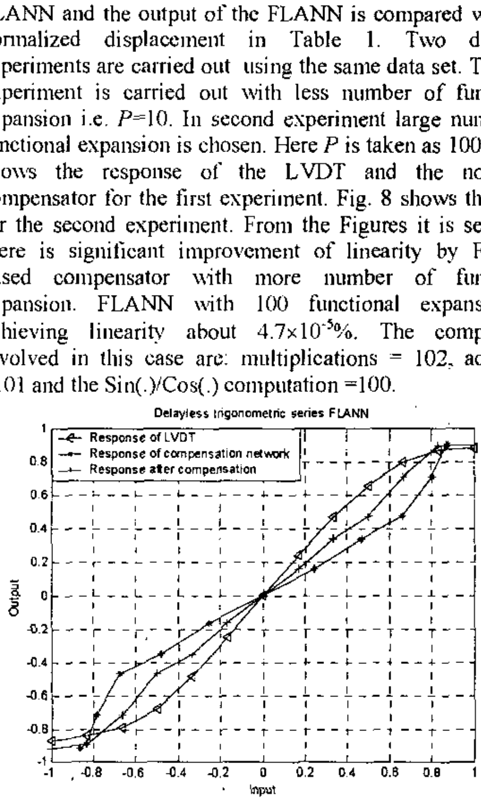

Fig.7 Response due to trigonometric series P=10

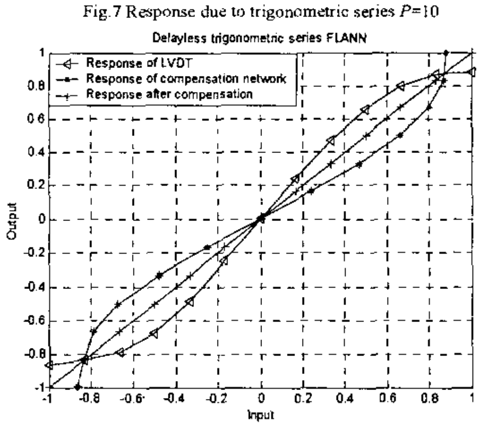

Fig.8 Response due to trigonometric series P=100

7. CONCLUSIONS

In this paper a simple and effective way of designing the high linearity LVDT based displacement sensing system is proposed. Traditional ways of pitch adjustment and specialized winding techniques are not used in this method. FLANN is successfully applied for nonlinear compensation of LVDT. Detailed implementation procedure for training the FLANN model before used in series with LVDT is presented. The same algorithm with slight modification can be used for hysteresis compensation also. This procedure can also be applied to any other types of transducer having nonlinear characteristic. If the nonlinearity of a sensor is time varying the compensator can also be made intelligent to keep track of the nonlinearity change and act accordingly so that linearity is maintained.

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