A Review on Enhancing the Linearity Characteristic of Different Types of Transducers-A Comparative Study

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Abstract: *Many types of sensors and transducers have a nonlinear response. Ideal transducers are designed to be linear. But since in practice there are several factors which introduce non-linearity in a system. Due to such nonlinearities, transducer's usable range gets restricted and also accuracy of measurement is severely affected. Similar effect is observed in different types of transducers. The nonlinearity present is usually time-varying and unpredictable as it depends on many uncertain factors. Nonlinearity also creeps in due to change in environmental conditions such as temperature and humidity. In addition ageing of the transducers also introduces nonlinearity. This particular paper concentrates a review on the compensation of difficulties faced due to the non-linear response characteristics of different types of sensors like resistive (thermocouple), capacitive (capacitive pressure sensor),inductive(LVDT) and humidity transducers. In this review, we identified many algorithms and ANN models like Functional Link Artificial Neural Network (FLANN), Radial Basis Function based ANN, Multi Layer Perceptron and Back Propagation Network to enhance the linearity performance of resistive, capacitive and inductive transducers. On comparison of different ANN models for non-linearity correction in different types of transducers, we identified FLANN model is used as a useful alternative to the MLP, BPN and the radial basis function (RBF)-based ANN. It has the advantage of lower computational complexity than the MLP, BPN and RBF structures and is, hence, easily implementable. Throughout the paper, we described the effects produced by each kind of nonlinearity, emphasizing their variations for different types of transducers with different ANN models.*

Keywords: *ANN, Thermocouple, Linear Variable Differential Transformer (LVDT), Capacitive Pressure Sensor (CPS), Humidity sensor*

I. Introduction

While still retaining the time independence assumption we can introduce non-linearity in the model of the sensor:

$Y'(x) = Ax + b_2x^2 + b_3x^3 + \ldots\ldots = A\,x + g\,(x)$….. (1)

The function *g(x)* describes how much the sensor response deviates from its linearised description. There are several ways to describe linearity or nonlinearity, each one of them described by a different term. The terms linearity and nonlinearity are conjugate, are used interchangeably, and often a value of linearity is quoted as non-linearity, and vice-versa. Nonlinearity is usually measured in relative units, either as a percentage of the maximum full scale reading of the sensor or the instrument, or locally as a percentage of a reading. Ideally we wish the nonlinearity to vanish, so it must be proportional to $|g(x)|$.

II. Nonlinearity Correction

This Chapter.2 deals with the nonlinearity compensation and correction of various transducers like Thermocouple, LVDT, and Capacitive Pressure Sensor and Humidity sensor.

A.BPN based Thermocouple

The types, specifications, and structures of thermocouple variety, almost all have the serious problem of non-linear, and there is a non-linear relationship between its output and the measured temperature. In K-type thermocouple when the temperature ranges between 0 and 200°C,basing on the table of thermoelectric potential and temperature,we can fit the following E ~ t relationship by the least squares principle

$$E = c_0 + c_1t + c_2t^2 + \ldots \quad (2)$$

E is potential thermoelectric when the c_0= 0.0311*mv*, c_1 = 0.0415*mv / °C*, c_2 = - 3.5x10^{-6} *mv/ °C*^{2}. The equation (1) tells us that the *E-t* relationship is nonlinear. The temperature at the cold point of the thermocouple is zero [1].

The non-linear correction model structure established by BP neural network can be described by the weighted values and the threshold values, the threshold values and the weighted values are shown as follows:

The weighted values between the entering layer and the hidden layer:

*w*1 = [-30.473488 -38.820904 -1.644704 -2.235481 0.099258 95.799098]

The weighted values between the outputting layer and the hidden layer:

*w*2 = [-20.979834 31.472969 -6.901741 1.78862 1014.294648 -254.668243]

Hidden threshold values:

$b1$ = [-47.329741 -25.972066 12.099975 4.515939 -0.050021 86.879988]
The threshold of the outputting layer:
$b2$ = -234.662545
We can easily get an equality of t ' - *E*
The output of the entering layer: $O_i = E(t,0)$.
Hidden output: $\mathrm{Oj} = \mathrm{f(Ij)} = \frac{1}{1+\mathrm{e}-\mathrm{I}\lambda}$
The total input of the hidden layer j-node:

$$I_j = O_i * w_{1j} + b_j$$

The output of the outputting layer: t' =I,
While $\mathrm{I} = \sum_{j-1}^{6} \mathrm{oj.\,w2j} + \mathrm{b2}$;

$$t' = \frac{w2}{1+e^{-(w1E(t,0)+b1)}} + b2$$

So any thermoelectric potential E can be passed on a t' corresponding temperature, which is the temperature after non-linear correction.
The testing samples with data on BP to build the network model were tested, and the testing results were shown in table 1.

Table 1.Theory Temperature and the Temperature Of Test Results

Theoretical values/°C	0.0	5.0	200.0
Test Results/°C	0.002668	4.973522	199.967966

The actual temperature curve and calculated curve based on BP networks are provided by figure 1.The largest fitting deviation is 0.8347°C.

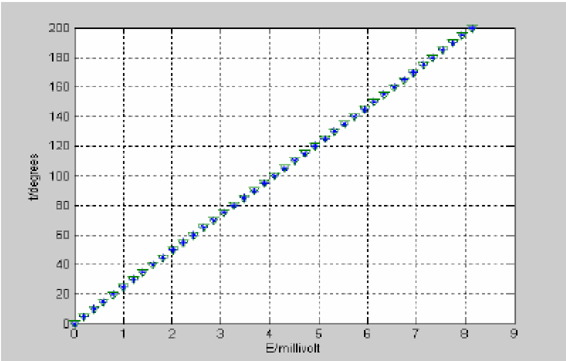

Figure 1 Comparisons between the actual temperature curve and calculated curve based on BP networks Before the neural network training, according to test sample data (E, t) can be obtained an equation by the linear least-squares fitting:
t = 24.4412 x E+0.2628

The largest fitting deviation can be obtained = 0.8347°C, then the linearity of K-type thermocouple:

$$\delta_L = \frac{\Delta Lm}{YFS} \times 100\% = 0.0421\%$$

Comparing specific linearity is shown in table 2

Table. 2 The Performance Comparison Before and After Nn Training

	The largest fitting deviation/°C	The Linearity
Before Training	0.8347	0.41%
After Training	0.0842	0.0421%

After the neural network training, the nonlinear of thermocouple has been significantly improved between temperatures of 0 and 200.

B.FLANN Based LVDT

The Functional Link Artificial Neural Network (FLANN) is a single layer network in which there are no hidden layers. The functional link acts as on an element of a pattern or on the entire pattern itself by generating a set of linearly independent functions and then evaluating these functions with the pattern as the argument. The differential voltage v at the output of the LVDT is fed to the FLANN model as the input. In this paper authors have used trigonometric expansion because it provides better nonlinearity compensation compared to other types of section.
Mathematical analysis of FLANN:

Let us consider the problem of learning with a flat net, which is a network with no hidden layers. Let V be the input vector of N elements. Let the net configuration have one output. Each element undergoes trigonometric nonlinear expansion to form P elements such that the resultant matrix has the dimension of N×P. Since the nth input elements is v_n ,1≤ n≤N, the functional expansion is carried out as

$$s_i = \begin{cases} v_{n,} & i=1 \\ \sin(l\pi v_n), & i > 1, i \text{ is even} \\ \cos(l\pi v_n) & , i > 1, i \text{ is odd} \end{cases}$$

Let the weight vector is represented as W having Q elements. The output, y is given as

$$y = \sum_{i=1}^{Q} w_i s_i$$

In matrix notation, the output can be

$$Y=S.W^T$$

At the K^{th} iteration, the error signal e (k) can be computed as

$$e(k) = d(k) - y(k)$$

Where d (k) is the desired signal that is the same as the control signal given to the displacement actuator. Furthermore the above equation can be written as

$$\epsilon(k) = \frac{1}{2}\sum_{j\in P} e_j^2(k)$$

The weight vector can be updated by LMS algorithm as

$$w(k+1) = w(k) - \frac{\mu}{2}\hat{\nabla}(k)$$

Where $\hat{\nabla}(k)$ is an instantaneous estimate of the gradient of ϵ with respect to the weight vector w(k).

Now

$$\hat{\nabla}(k) = \frac{\partial \varepsilon}{\partial \omega} = -2e(k)\frac{\partial y(k)}{\partial \omega}$$

$$= -2e(k)\frac{\partial[\omega(k)s(k)]}{\partial w} \qquad = 2e(k)s(k).$$

By substituting the values of $\hat{\nabla}(k)$ in ( ), we get

$$\omega(k+1) = \omega(k) + \mu e(k)s(k)$$

Where μ denotes the step size $(0 \le \mu \le 1)$, which controls the convergence of speed of LMS algorithm.

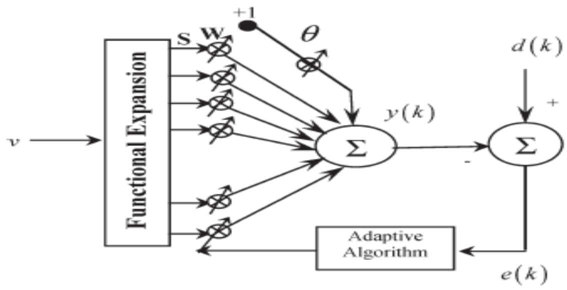

Figure 2. Structure of a FLANN

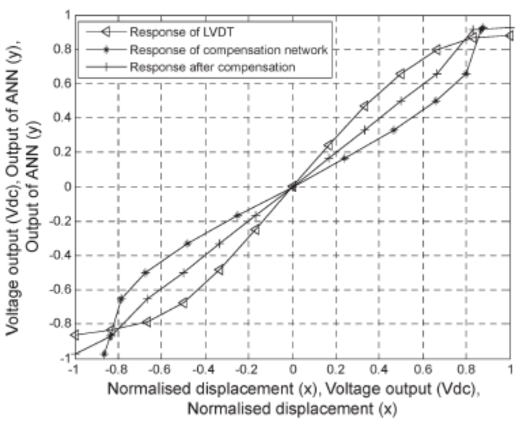

Figure 3. Compensation graph by FLANN

C.Mlp based Capacitive Pressure Sensor

A multilayer perceptron (MLP) is a feed forward artificial neural network model that maps sets of input data onto a set of appropriate output. An MLP consists of multiple layers of nodes in a directed graph, with each layer fully connected to the next one. Except for the input nodes, each node is a neuron (or processing element) with a nonlinear activation function. MLP utilizes a supervised learning technique called back propagation for training the network. MLP is a modification of the standard linear perceptron and can distinguish data that is not linearly separable

The problem of nonlinear response characteristics of a CPS further aggravates the situation when there is change in environmental conditions. This ANN model is capable of providing pressure readout with a maximum FS error of 2% over a wide variation of ambient temperature. Temperature range can be widened by training MLP with sufficient number of pattern sets covering the temperature range.

A CPS senses the applied pressure due to elastic deflection of its diaphragm. In the case of a simple structure, this deflection is proportional to the applied pressure P, and the sensor capacitance C (P) varies hyperbolically. Neglecting higher-order terms, C (P) may be approximated by

$$C(P) = C_o + \Delta C(P) = C_o(1 + \gamma)$$

where C_o is the sensor capacitance when$P = 0; \Delta C(P)$ is the change in capacitance due to applied pressure;$\gamma = P_N(1 - \alpha/(1\text{-}P_N)$ is the sensitivity parameter which depends upon the geometrical structure of the sensor; P_N is the normalized applied pressure given by $P_N = P/P_{max}$ and P_{max} is the maximum permissible input pressure.

In the 2-D problem discussed in this paper, the sensor capacitance is a function of the applied pressure and the ambient temperature. Assuming that the change in capacitance due to change in temperature is linear and independent of the applied pressure, the CPS model may be expressed as

$$C(P, T) = C_o f_1(T) + \Delta C(P, T_0) f_2(T)$$

Where $\Delta C(P, T_0)$represents the change in capacitance due to applied pressure at the reference temperature T_0 as given in (1).The functions $f_1(T)$ and$f_2(T)$ are given by

$$f_1(T) = 1 + \beta_1(T - T_0); \qquad f_2(T) = 1 + \beta_2(T - T_0)$$

Where the coefficients $\beta_1$and β_2 may have different values depending on the CPS chosen. The normalized capacitance of the CPS, C_N is obtained by dividing (2) by and may be expressed as

$$C_N = C(P, T)/C_0 = f_1(T) + \gamma f_2(T)$$

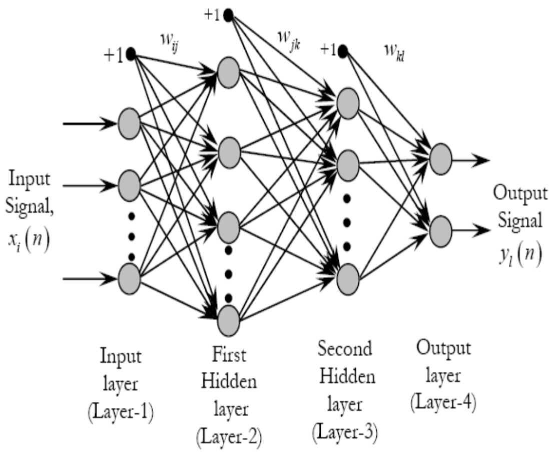

Figure.4. Structure of MLP Model

D.Rbf based Humidity Sensor

A radial basis function network is an artificial neural network that uses radial basis functions as activation functions. It is a linear combination of radial basis functions. They are used in function, time series prediction, and control.

The ANN employs radial basis function (RBF) network in the hidden layer, followed by an ADALINE network, for automatic adjustments of weights and biases to arrive within a desired maximum allowable error. This adaptive network, successfully trained, has been used as a neural linearizer for the sensor under consideration. The primary variable (humidity) values generated by the neural linearizer from the capacitance values of the sensor have been found to be in reasonably close agreement with those provided by the manufacturer.

A capacitive humidity sensor has a dielectric whose permittivity is dependent on humidity. Either one or both electrodes of the sensor are porous, which allow water molecules to pass into the dielectric. Thus the sensor capacitance depends on the humidity. For a typical capacitive humidity sensor, the relationship between capacitance C and relative humidity H_r can be approximated by:

$$C_s/C_{12} = 0.985 + 0.34(H_r/100)^{1.4}$$

Where C_{12} is the sensor capacitance at 12% relative humidity?

To make the artificial neural linearization most effective, input temperature range is equally divided into three segments (25^oC to 35^oC, 35^oC to 45^oC and 45^0C to55^0C) and for each of these temperature segment frequency range is divided into three segments (1 KHz to 10 KHz, l0KHz to l00KHz and 100 KHz to1MHz). Each segment covers the relative humidity range from 10% to 90%.

Radial basis function is a supervised learning algorithm that makes automatic adjustment of weights and biases to arrive within an expected maximum allowable sum squared error goal for the network. Then, using these trained sets of weights and biases, we can find output for any set of input values with reasonable accuracy. In RBFN, the hidden layer neurons actually simulate receptive fields which are locally tuned (bell shaped) and overlapping in nature. The activation level of receptive field unit is a function of exp [$-\|w1-p\|^2$] where p is the RxQ matrix of Q input (column) vectors and wl is SlxR weight matrix. Where R = number of inputs, S1 = number of neurons in the hidden layer of RBF, Q = number of input (or output) column vectors i.e. number of sets of input-output combination data, S2 =number of neurons in the output ADALINE layer.

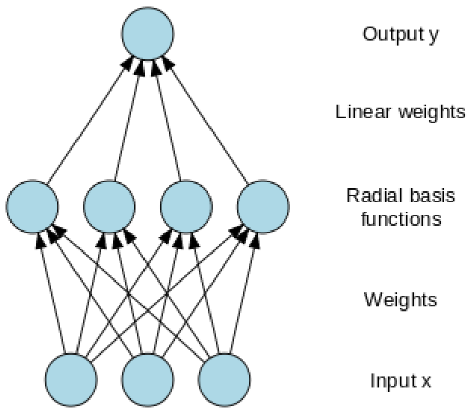

Figure 5. Structure of RBF Model

III. Comparative Analysis

Table.3.Comparative Analysis of Nn Techniques

Classification Technique	Resources/ Researcher	Notes
FLANN	[2]	Design and development of high linearity linear variable differential transformer based displacement sensing systems.
MLP	[7],[17] [9]	Extending the linear range of a negative temperature coefficient resistor sensor. The problem of nonlinear response characteristics of a CPS further aggravates the situation when there is change in environmental conditions. This ANN model is capable of providing pressure readout with a maximum FS error of 2% over a wide variation of ambient temperature.
RBF	[10]	Encountering the non linearity problems associated with the capacitive humidity sensor using ANN. Computations have been carried out with the manufacturers' data for an industrial capacitive humidity sensor.
BPN	[1],[7],[11]	The non linearity correction in input and output characteristics of thermocouple sensor.

IV. Conclusions

This review paper investigates on the nonlinearity issues relating to different types of transducers. The nonlinearity problem gives rise to the difficulties like Non accuracy in measurement; Limitation of dynamic range (linearity region).The nonlinearity problem also arises due to environmental changes such as change in temperature, humidity and atmospheric pressure, aging of transducers and constructional limitations. We reviewed different adaptive and intelligent methods for compensation of nonlinearities which have been applied to four typical sensors. The proposed review based on the structures like BPN, FLANN, MLP and RBFNN. The learning algorithms employed in this review are:LMS algorithm in FLANN,BP algorithm in MLP and RBF learning algorithm Exhaustive simulation studies of various methods show that RBFNN and FLANN structures provide improved non-linearity compensation performance but involves more computations and tedious to implement. Techniques used in Linearity enhancement of different transducers and classification has been briefly reviewed in this paper. Based on the review, FLANN is the most popular technique due to its accuracy.

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