DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING
NATIONAL INSTITUTE OF TECHNOLOGY, ROURKELA

Design and Development of Intelligent Sensors

UNDER THE GUIDANCE OF :
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CONTENT

ABSTRACT

In this project, we make an extensive study of Intelligent Sensors and devise methods for analyzing them through various proposed algorithms broadly classified into Direct and Inverse Modeling. Also we look at the analysis of Blind Equalization in any sensor. A regular sensor is a device which simply measures a signal and converts it into another signal which can be read by an observer and an instrument. A sensor's sensitivity indicates how much the sensor's output changes when the measured quantity changes. Ideal sensors are designed to be linear. The output signal of such a sensor is linearly proportional to the value of the measured property. The sensitivity is then defined as the ratio between output signal and measured property. For example, if a sensor measures temperature and gives a voltage output, the sensitivity is a constant with the unit [V/K]; this sensor is linear because the ratio is constant at all points of measurement. If the sensor is not ideal, several types of deviations can occur which render the sensor results inaccurate. On the other hand, an intelligent sensor takes some predefined action when it senses the appropriate input (light, heat, sound, motion, touch, etc.).A sensor is intelligent when it is capable of correcting errors occurred during measurement both at the input and output ends. It generally processes the signal by means of suitable methods implemented in the device before communicating it.

As we discussed an ideal sensor should have linear relationship with the measures quantity. But since in practice there are several factors which introduce non-linearity in a system, we need intelligent sensors. This particular project concentrates on the compensation of difficulties faced due to the non-linear response characteristics of a capacitive pressure sensor (CPS).It studies the design of an intelligent CPS using direct and inverse modeling switched-capacitor circuit(SCC) converts the change in capacitance of the pressure-sensor into an equivalent voltage output . The effect of change in environmental conditions on the CPS and subsequently on the output of the SCC is such that it makes the output non-linear in nature. Especially change in ambient temperature causes response characteristics of the CPS to become highly nonlinear, and complex signal processing may be required to obtain correct results.

The performance of the control system depends on the performance of the sensing element. It is observed that many sensors exhibit nonlinear input-output characteristics. Due to such nonlinearities direct digital readout is not possible. As a result we are forced to employ the sensors only in the linear region of their characteristics. In other words their usable range gets restricted due to the presence of nonlinearity. If a sensor is used for full range of its nonlinear characteristics, accuracy of measurement is severely affected. Similar effect is also observed in case of LVDT. 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 sensors also introduces nonlinearity.*

The proposed scheme incorporates intelligence into the sensor. We use many algorithms and ANN models to make the sensor 'intelligent'. Also there is an analysis of the Blind Deconvolution Techniques that maybe used for Channel Estimation. As it is a relatively new field of work, the challenges are huge but opportunities are many as well.

We try to make sensors more intelligent as they would allow a varied application of them in industry, academic and domestic environments.

1 Introduction

A sensor is a device that measures a physical quantity and converts it into a signal which can be read by an observer or by an instrument. A sensor's sensitivity is determined by the ratio output to the input i.e. it is measured by how much the sensor's output changes when the measurement quantity changes.

An intelligent sensor is a sensor but it is extended such that it has advance learning and adaptation abilities. A sensor is intelligent when it is capable of correcting errors occurred during measurement both at the input and output ends. An ideal sensor should have linear relationship with the measured quantity. But since in practice there are several factors which introduce non-linearity in a system, we need intelligent sensors.

An intelligent sensor takes some predefined action when it senses the appropriate input (light, heat, sound, motion, touch, etc.). It should be able to compensate the input value such that it appears to be untouched. Compensation is the ability to detect and respond to changes in the environment through diagnostic routines, self-calibration and adaptation. An intelligent sensor must be able to evaluate the validity of collected data, compare them with that of other sensors and confirm accuracy of any data variation.

An ideal sensor should be such that it is sensitive to the measured property, insensitive to any other property and should not influence the measured property.

Ideal sensors are designed to be linear. The output signal of such a sensor is linearly proportional to the value of the measured property. However if the sensor is not ideal, a number of deviations can occur like, the sensitivity may differ from the value specified; the output signal is not zero when the measured input is zero. The above aberrations are not very serious as they can be removed by re-calibration. These however do not make a sensor non-linear. Non-linearity comes into play when the sensitivity of a sensor is not constant over a range. To introduce non-linearity, the algorithm runs and it makes sure that the error content is reduced to a minimum.

Sensors based upon the capacitive sensing technique are strain-based sensors. In a typical configuration the sensor capacitances are arranged in a push-pull, half-bridge configuration where both capacitors are parameter modulated. Simple media isolation is achieved when one capacitance is parameter-modulated and the other capacitance within the half-bridge circuit is an un-modulated reference capacitance. Capacitive sensors require a dynamic excitation and all capacitive designs contain an internal oscillator and signal demodulator to provide static capable outputs.

In order to work to make a capacitive pressure sensor, intelligent we have to run many algorithms so that the system is trained before it makes any measurement. This is done by various mathematical computational methods. A computational model is a mathematical model in computational science that requires extensive computational resources to study the behavior of a complex system by computer simulation. The system under study is often a complex nonlinear system for which simple, intuitive analytical solutions are not readily available. Rather than deriving a mathematical analytical solution to the problem, experimentation with the model is done by changing the parameters of the system in the computer, and study the differences in the outcome of the experiments. Theories of operation of the model can be derived/deduced from these computational experiments. Examples of common computational models are weather forecasting models, earth simulator models, flight simulator models, molecular protein folding models, and neural network models.

2 Types of Sensors

2.1 CAPACITIVE PRESSURE SENSORS

Sensors based upon the capacitive sensing technique are strain-based sensors. The typical configuration is shown below where the sensor capacitances are arranged in a push-pull, half-bridge configuration where both capacitors are parameter modulated. Simple media isolation is achieved when one capacitance is parameter-modulated and the other capacitance within the half-bridge circuit is an un-modulated reference capacitance.

We have chosen a CPS in the study because of its wide applicability. The CPS has lower power dissipation and higher sensitivity than other types of pressure sensors. A CPS senses the applied pressure due to the 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)** maybe approximated by,

$$C(P) = C_0 + \Delta C(P)$$

$$= C_0(1 + \gamma)$$

(equation 1).

Where, C_0 is the sensor capacitance when P= 0,

$\Delta C(P)$ = Change in capacitance due to applied pressure.

$\gamma = P_n (1 - \alpha)/ (1 - P_n);$

α is the sensitivity parameter, which depends on the geometrical structure of the sensor.

P_n is the normalized applied pressure given by $P_n = (P/ P_{max})$. P_{max} is the maximum permissible input pressure.

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,

$$C(P, T) = C_0 f_1(T) + \Delta C(P, T_0) f_2(T)$$

(Equation 2)

Where, $\Delta C(P, T_0)$ represents the change in capacitance due to applied pressure at the reference temperature T_0 as given in equation 1.

The functions $f_1(T)$ and $f_2(T)$ are given by

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

(Equation 3)

Where the coefficients, β_1 and β_2 have different values depending upon the CPS chosen. The normalized capacitance of the CPS, C_N is obtained by dividing equation 2 by C_0 and maybe expressed as

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

(Equation 4)

SCC for interfacing the CPS is shown below in Fig 2.1, where **C (P)** represents the CPS. The circuit operation can be controlled by a reset signal **Φ**. When **Φ = 1** (logic 1), $C(P)$ charges to the reference voltage V_R while the capacitor is discharged to ground. Whereas, when, the total charge $C(P).V_R$ stored in the $C(P)$ is transferred to C_S producing an output voltage given by $V_0 = K.\ C(P),$ where $K = V_R / C_S$. It may be noted that if ambient temperature changes, then the SCC output also changes although the applied pressure remains the same. By choosing proper values of C_S and V_R, the normalized SCC output can be adjusted in such a way that $V_N = C_N$.

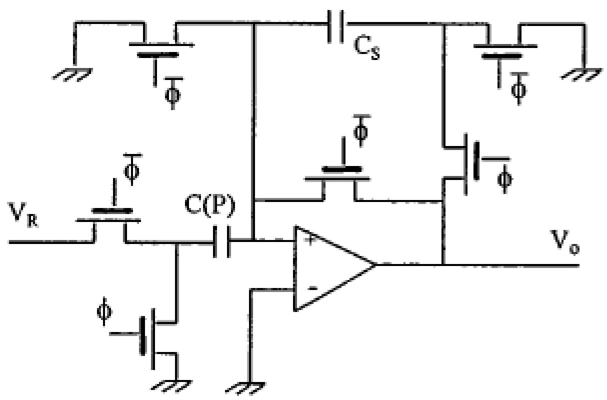


FIG 2.1 CIRCUIT DIAGRAM OF A CAPACITIVE PRESSURE SENSOR

Capacitive sensors require a dynamic excitation and all capacitive designs contain an internal oscillator and signal demodulator to provide static capable outputs. In most cases these components will limit the useful operating temperature range from -40ºC to +120ºC.

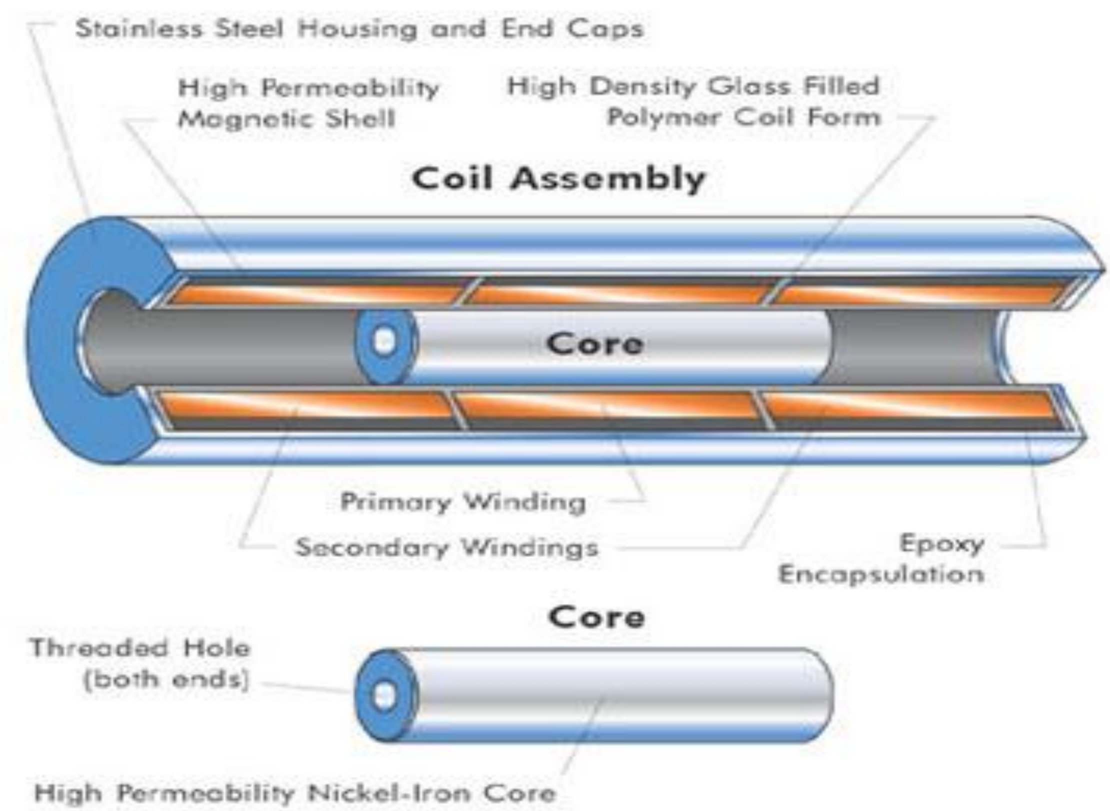
Under transient thermal conditions some differential expansion of the capacitance structures is to be expected although the very low expansion coefficient of the alumina capacitance modules limits transient outputs.

The mechanical qualities of the fired-alumina spring member are excellent, in possessing high stiffness, low thermal expansion coefficients, high stability, and low hysteretic losses. The inert nature and zero porosity of the alumina renders it useful in a wide variety of environments.

2.2 LINEAR VARIABLE DIFFERENTIAL TRANSFORMER

The LVDT stands for Linear Variable Differential Transformer, a common type of electromechanical transducer that can convert the rectilinear motion of an object to which it is coupled mechanically into a corresponding electrical signal. LVDT linear position sensors are readily available that can measure movements as small as a few millionths of an inch up to several inches, but are also capable of measuring positions up to ±20 inches (±0.5 m).

The features that make an LVDT environmentally robust are evident in this cutaway view.



The transformer's internal structure consists of a primary winding centered between a pair of identically wound secondary windings, symmetrically spaced about the primary. The coils are wound on a one-piece hollow form of thermally stable glass reinforced polymer, encapsulated against moisture, wrapped in a high permeability magnetic shield, and then secured in cylindrical stainless steel housing. This coil assembly is usually the stationary element of the position sensor.

The moving element of an LVDT is a separate tubular armature of magnetically permeable material called the core, which is free to move axially within the coil's hollow bore, and mechanically coupled to the object whose position is being measured. This bore is typically large enough to provide substantial radial clearance between the core and bore, with no physical contact between it and the coil.

In operation, the LVDT's primary winding is energized by alternating current of appropriate amplitude and frequency, known as the primary excitation. The LVDT's electrical output signal is the differential AC voltage between the two secondary windings, which varies with the axial position of the core within the LVDT coil. Usually this AC output voltage is converted by suitable electronic circuitry to high level DC voltage or current that is more convenient to use.

Linear Variable Differential Transformer (LVDT) plays an important role to measure the displacement in control system applications. The performance of the control system depends on the performance of the sensing element. It is observed that many sensors exhibit nonlinear input-output characteristics. Due to such nonlinearities direct digital readout is not possible. As a result we are forced to employ the sensors only in the linear region of their characteristics. In other words their usable range gets restricted due to the presence of nonlinearity. If a sensor is used for full range of its nonlinear characteristics, accuracy of measurement is severely affected. Similar effect is also observed in case of LVDT. 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 sensors also introduces nonlinearity.

The LVDT consists of a primary coil and two secondary coils. The secondary coils itself has two coils connected differentially for providing the output. The two 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 [10]. The lengths of primary and two identical halves of the secondary coils are *b* and *m* respectively. The coils have an inside radius *ri* and an outside radius of *r0.* The spacing between the coils is *d*. Inside the coils a ferromagnetic armature of length *La* and radius *ri* (neglecting the bobbin thickness) moves in an axial direction. The number of turns in the primary coil is *np* and *ns* are the number of turns in each secondary coil. The cross-sectional view of LVDT is shown

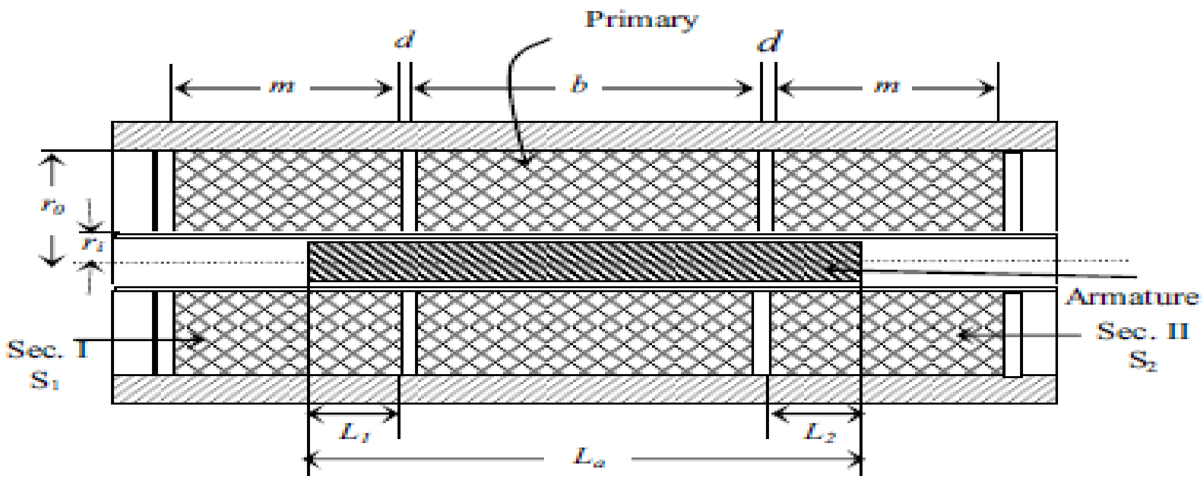


Fig. 1 Cross-sectional view of LVDT

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With a primary sinusoidal excitation voltage, *Vp* and the current *Ip* (r.m.s.) of frequency *f*, the r.m.s. voltage *e1* induced in the secondary coil S1 is,

$$e_1 = \frac{4\pi^3}{10^7} \cdot \frac{fI_p n_p n_s}{\ln(r_0/r_i)} \cdot \frac{2L_2 + b}{mL_a} x_1^2,$$

and in coil S_2,

$$e_2 = \frac{4\pi^3}{10^7} \cdot \frac{fI_p n_p n_s}{\ln(r_0/r_i)} \cdot \frac{2L_1 + b}{mL_a} x_2^2.$$

where

x_1 = Distance penetrated by the armature towards the secondary coil S_1,

x_2 = Distance penetrated by the armature towards the secondary coil S_2,

The differential voltage $e = e_1 - e_2$ is thus given by

$$e = k_1 x\left(1 - k_2 x^2\right) \tag{1}$$

where $x = \frac{1}{2}(x_1 - x_2)$ is the armature displacement and,

$$k_1 = \frac{16\pi^3 fI_p n_p n_s (b + 2d + x_0)x_0}{10^7 \ln(r_0/r_i)mL_a}\left(Vm^{-1}\right) \tag{2}$$

with $x_0 = \frac{1}{2}(x_1 + x_2)$ and

$$k_2 = 1/(b + 2d + x_0)x_0, \tag{3}$$

k_2 is a nonlinearity factor in (1), the non-linearity term ε being

$$\varepsilon = k_2 x^2 \tag{4}$$

For a given accuracy and maximum displacement the over-all length of the transducer is minimum for $x0 = b$ assuming that at maximum displacement the armature does not emerge from the secondary coils. Taking the length of armature $La = 3b + 2d$, neglecting $2d$ compared with b and using (2), (1) can be simplified as

$$e = \frac{16\pi^3 f I_p n_p n_s}{10^7 \ln(r_0/r_i)} \cdot \frac{2b}{3m}\left(1 - \frac{x^2}{2b^2}\right) \quad (5)$$

For a given primary sinusoidal excitation, the secondary output voltage e is nonlinear with respect to displacement x.

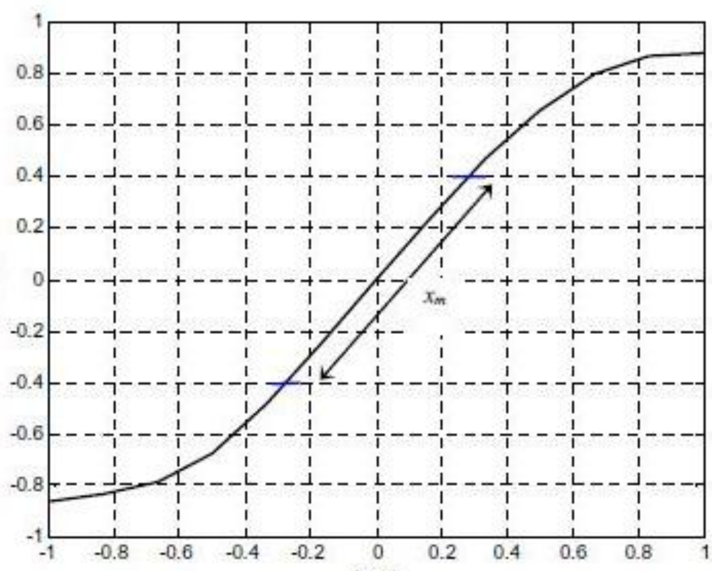


Fig. 2 Range of linear region of LVDT

3 Analysis of Sensors

GENERAL PROBLEM:-

A. Design models of CPS and LVDT (System Identification) by Direct Modeling.

B. Estimate the Channel Equalizer using Inverse Modeling when channel is noisy.

C. Removal of non-linearity present in CPS and LVDT outputs.

D. Blind Deconvolution of CPS and LVDT output to get Channel Estimate.

4 Artificial Neural Networks

An artificial neural network (ANN), often just called a "neural network" (NN), is a mathematical model or computational model based on biological neural networks. It consists of an interconnected group of artificial neurons and processes information using a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase.

In more practical terms neural networks are non-linear statistical data modeling tools.

They can be used to model complex relationships between inputs and outputs or to find patterns in data.

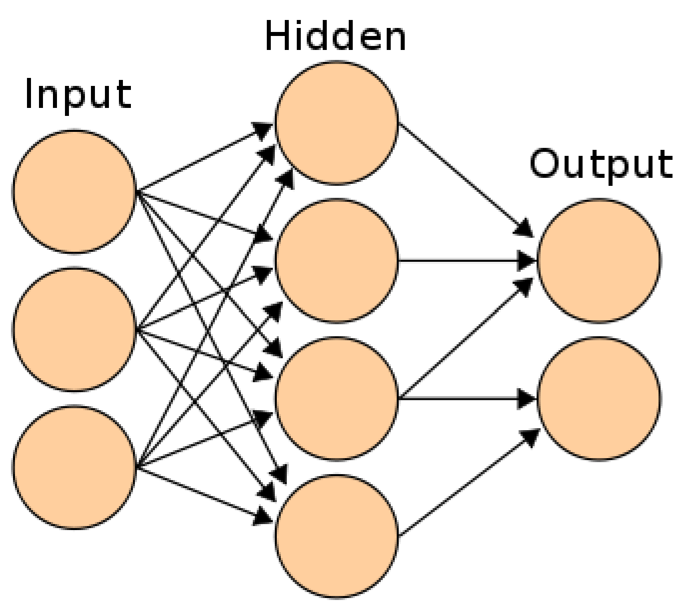


Fig – Artificial Neural Network

The various types of ANN are as follows:

- Functional Link Artificial Neural Network
- Feed-forward Neural Network.
- Radial Basis Function Network

4.1 MULTILAYER PERCEPTRON (MLP):-

A multilayer perceptron is a feed-forward artificial neural network model that maps sets of input data onto a set of appropriate output. It is a modification of the standard linear perceptron in that it uses three or more layers of neurons (nodes) with nonlinear activation functions, and is more powerful than the perceptron in that it can distinguish data that is not linearly separable, or separable by a hyperplane.

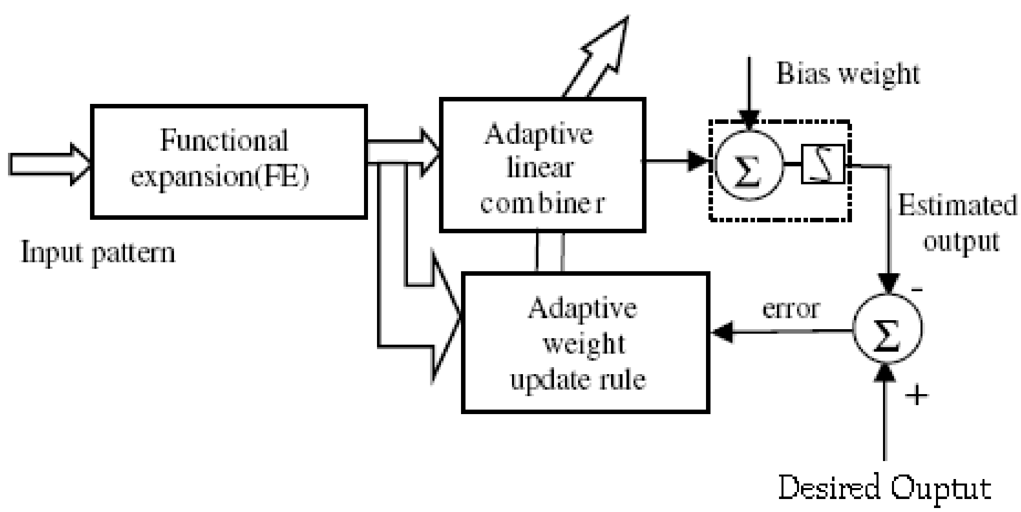
Multilayer perceptrons using a back-propagation algorithm are the standard algorithm for any supervised-learning pattern recognition process and the subject of ongoing research in computational neuroscience and parallel distributed processing. They are useful in research in terms of their ability to solve problems stochastically, which often allows one to get approximate solutions for extremely complex problems.

4.2 FUNCTIONAL LINK ARTIFICIAL NEURAL NETWORK:-

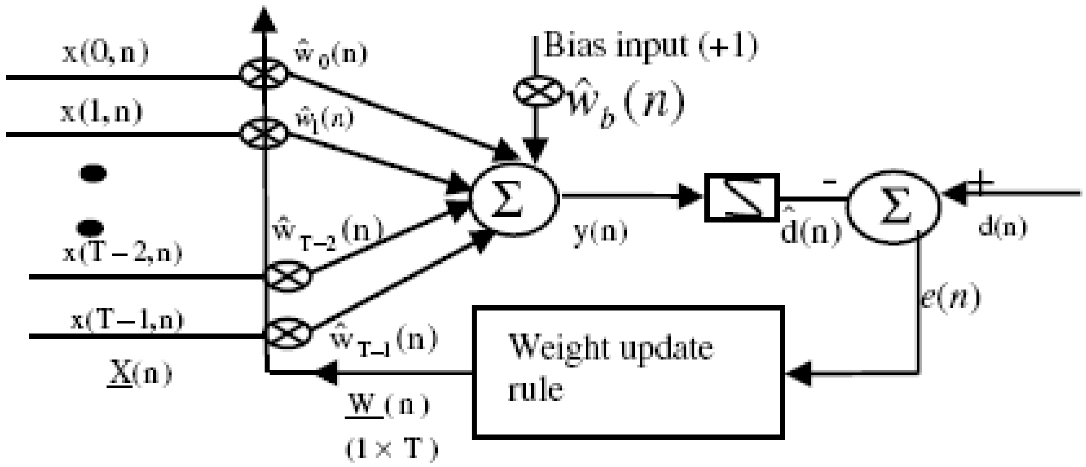
The FLANN is a single layered neural network with nonlinear input and a single neuron at the output. This network is a useful substitute of multilayer artificial neural network

(MLANN) .However, it is structurally simple and involves less computations compared to those of MLANN. It is also reported that for some applications the FLANN performs better than the MLANN. The nonlinear input is generated by functionally expanding the input vector in a nonlinear manner. Different nonlinear expansions may be employed. These are trigonometric(sine and cosine), Chebyshev and power series. In this paper the trigonometric expansion based financial model is developed for exchange rate prediction as it offers better performance compared to when other expansions are used. The proposed model consists of three basic processes:-

- Non-linear functional expansion.
- Estimation of outputs in response to non-linear elements.
- Adaptive adjustment of connecting weights.



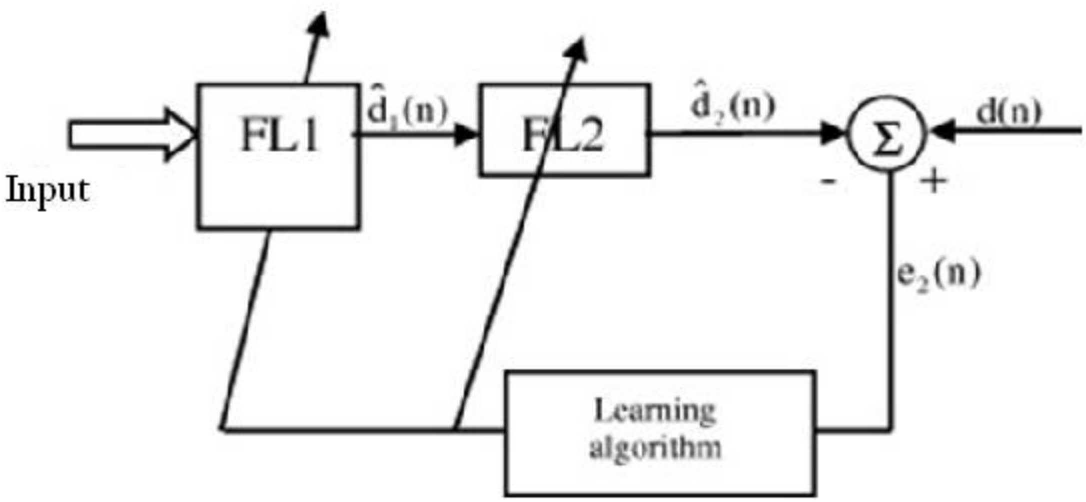
(FLANN model)



BASIC REPRESENTATION OF INTRODUCTION OF NON-LINEARITY BY FLANN

4.3 CASCADED FLANN:-

In this model two single layer FLANN structures are cascaded in series. Fig below shows the block diagram representation of a two stage cascaded FLANN adaptive model. In this figure *FL*1 represents the first FLANN model as detailed in FLANN model. Let its output be $\hat{d}_1(n)$. This estimated value once again is expanded nonlinearly either by using trigonometric or exponential functions. As stated earlier this expansion introduces additional nonlinearity to the model. Unlike multilayer ANN (MLANN), there is only one neuron in each of $FL1$ and $FL2$ blocks. Hence the computational complexity of CFLANN model is significantly reduced compared to the MLANN model. The number of inputs to *FL*1 is equal to the number of extracted features obtained from the given financial time series, which is only three in the present case. However, since *FL*1 provides only one output, the expanded values in *FL*2 is only due to one input.



SCHEMATIC REPRESENTATION OF CASCADED FLANN

5 Learning Algorithms

Learning algorithms (LAs) are tools used to train an ANN. The various parameters of the systems are updates by using appropriate LA. They are mathematically designed to converge and give the most appropriate result. The Las should be converging, have less computational complexity , not be susceptible to local maxima and minima ,exhaustive and expansive in order to be successful. Different LA s are used for different purposes. For example- Least Mean Squares, Recursive Least Squares, Least Mean Fourth, Recursive Mean Forth, Apriori algorithm, Bayesian Functions, etc.

5.1 LEAST MEAN SQUARE ALGORITHM:-

The Least Mean Square (LMS) algorithm, introduced by Widrow and Hoff in 1959 [12] is an adaptive algorithm, which uses a gradient-based method of steepest decent [10]. LMS algorithm uses the estimates of the gradient vector from the available data. LMS incorporates an iterative procedure that makes successive corrections to the weight vector in the direction of the negative of the gradient vector which eventually leads to the minimum mean square error. Compared to other algorithms LMS algorithm is relatively simple; it does not require correlation function calculation nor does it require matrix inversions.

The various equations used in the computation of Least Mean Square Algorithm are mentioned below

$$\mathbf{X}_k = \begin{bmatrix} x_k & x_{k-1} & \dots & x_{k-L+1} \end{bmatrix}^{\mathrm{T}} \qquad L\text{-by-1 tap input vector.}$$

$$\mathbf{W}_k = \begin{bmatrix} w_{0k} & w_{1k} & \dots & w_{(L-1)k} \end{bmatrix}^{\mathrm{T}} \qquad L\text{-by-1 tap weight vector.}$$

$$y_k = \sum_{l=0}^{L-1} w_{lk} x_{k-l}$$

$$y_k = \mathbf{X}_k^{\mathrm{T}} \mathbf{W}_k = \mathbf{W}_k^{\mathrm{T}} \mathbf{X}_k \qquad \text{output}$$

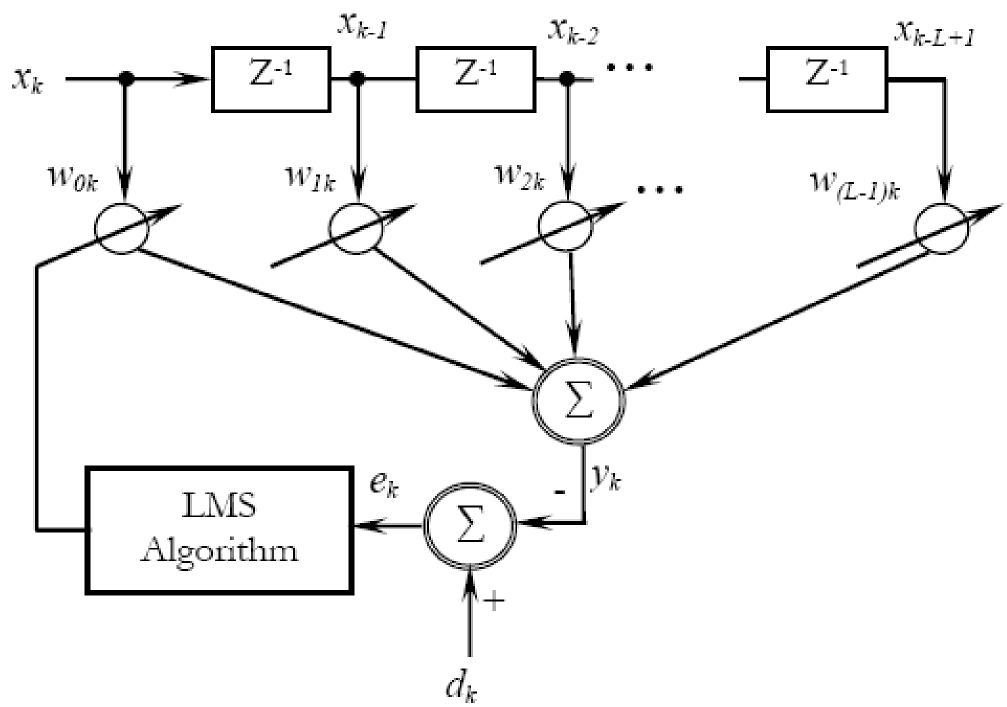
The weight updates equation for n^{th} instant

$$w_k(n+1) = w_k(n) + \Delta w_k(n)$$

$$w_k(n+1) = w_k(n) + 2 \cdot \eta \cdot e_k(n) \cdot \mathbf{X}_k^{\mathrm{T}}$$

where η is the learning rate parameter ($0 \leq \eta \leq 1$).

MSE at the time index k $\quad \xi = E\left[e_k^2\right]$



Adaptive filter using LMS algorithm

5.2 BUSSGANG ALGORITHM

The Bussgang Algorithm for blind deconvolution uses the Bayes estimator (conditional expectation) of the source given the equalized output as its non-linear function. It is used when there is a non-linearity in the output of the adaptive equalization filter. It has the function g(z) which is used to construct the desired signal and there by get channel equalization. It does not use higher order statistical parameters. The ease by which blind convolution is achieved is one of the prime reasons why a Bussgang Algorithm is used .It uses the celebrated LMS algorithm for updating parameters. Like other algorithms used for blind deconvolution it has a tendency to miscalculate the answer but it can be overcome by appropriate estimate of the non-linear memoryless function g(z). The main steps of the algorithm can be shown as below.

UNKNOWN : source signal $\underset{\rightharpoonup}{s}(t)$

linear channel with impulse response $\bar{h}$,

KNOWN : output vector ***x(t)***

$$x(t),\ x(t-1),\ x(t-2),\ \ldots,\ x(t-m+1)$$

$$x(t) = \vec{h}^T \vec{s}(t) + N(t)\ ,$$

where $\vec{s}(t)$ is a vector containing the input samples:

$$s(t),\ s(t-1),\ s(t-2),\ \ldots,\ s(t-\ell+1)\ ,$$

$N(t)$ additive noise

A transversal filter described by its impulse response $\vec{w}$ is a channel equalizer if $\vec{w}$ cancels the effects of $\vec{h}$ on the source signal.

$$z(t) = \vec{w}^T(t)\vec{x}(t)\ ,$$

m is the number of tap-weights in $\vec{w}$, $z(t)$ output of the filter

Since $\vec{h}$ and $s(t)$ are unknown, the equalizer $\vec{w}_\star$ such that $z(t) \sim s(t)$ has to be *blindly* found usually by means of an iterative algorithm

$$z(t) = cs(t-\delta) + n(t)\ ,$$

$n(t)$ is the so-called *deconvolution noise*, c is an amplitude factor and δ is a finite delay.

WEIGHT UPDATE

$$\Delta\vec{w} = \mu[g(z) - z]\vec{x} \ ,$$

$$\Delta\vec{w} = -\eta E[(g'(z) - 1)(g(z) - z)\vec{x}]$$

$$\mu(z) \stackrel{\text{def}}{=} -\eta[g'(z) - 1]$$

The function $g(z)$ provides an estimate of the source signal

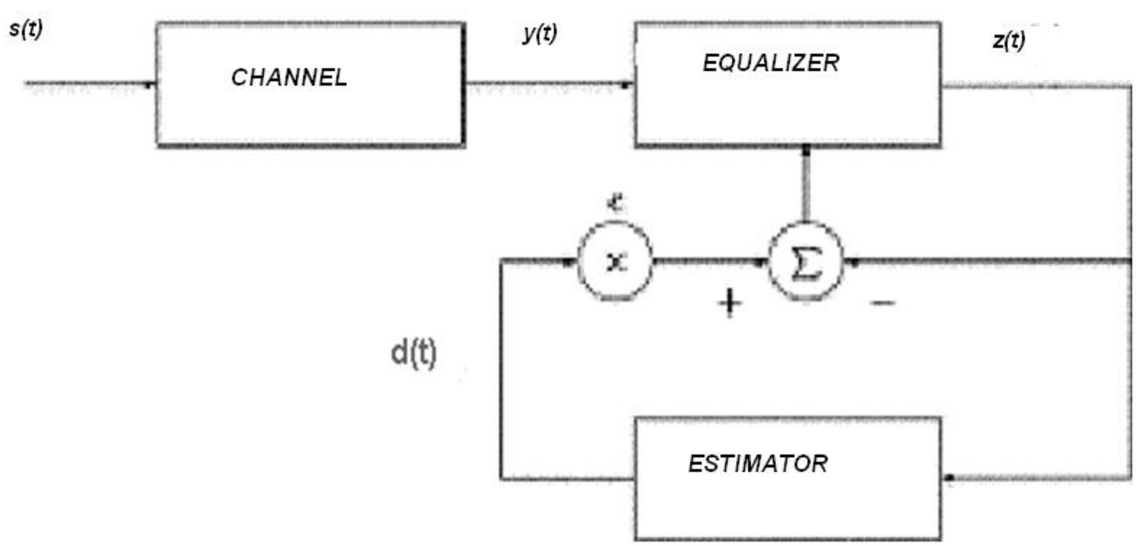
$$g(z) \stackrel{\text{def}}{=} a\tanh(bz) \ ,$$

$$\Delta a = -\alpha\frac{\partial U}{\partial a} = -\alpha E\left[(g - z)\frac{g}{a}\right] \ ,$$

$$\Delta b = -\beta\frac{\partial U}{\partial b} = -\beta E\left[(g - z)(a^2 - g^2)\frac{z}{a}\right]$$

where α and β are constant positive learning stepsizes.

The Bussgang Algorithm can be schematically shown as below

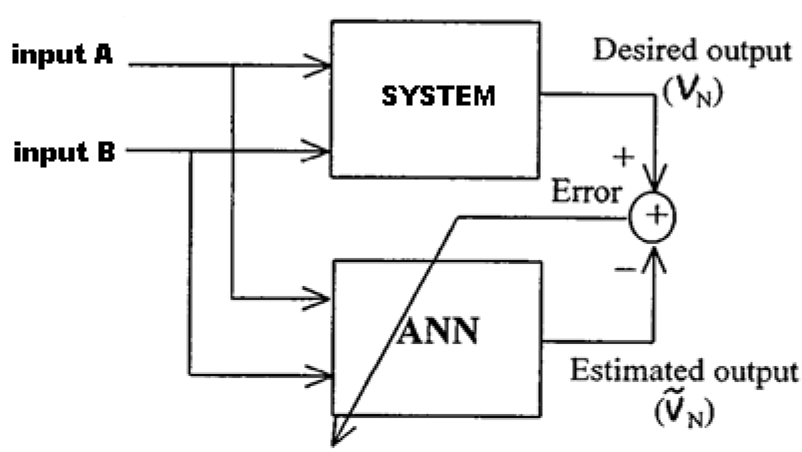


SCHEMATIC REPRESENTATIONOFBUSSGANG ALGORITHM

6 Direct Modeling

GENERAL DESCRIPTION:-

Direct Modeling is used for system identification. System identification is a general term to describe mathematical tools and algorithms that build dynamical models from measured data. A dynamical mathematical model in this context is a mathematical description of the dynamic behavior of a system or process in either the time or frequency domain.

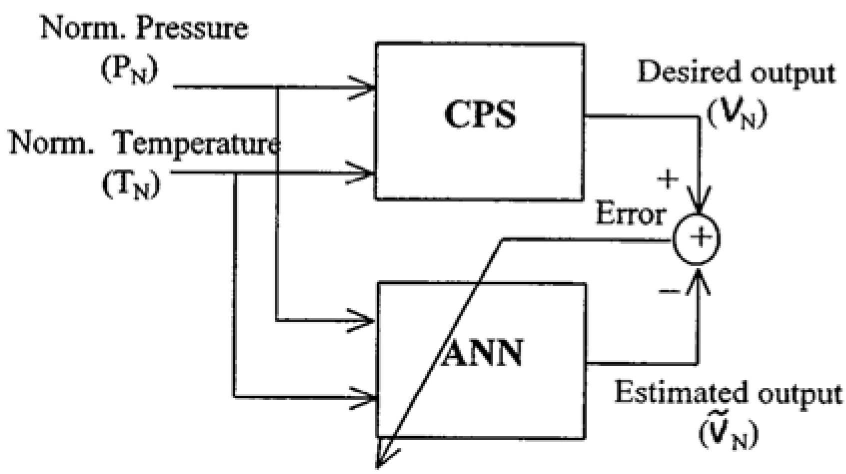


SCHEMATIC REPRESENTATION OF DIRECT MODELING

DIRECT MODELING AS APPLIED TO THE PROBLEM :-

(A) CPS:-

A scheme of direct modeling of a CPS is shown in Fig below. This scheme is analogous to that of the system identification problem in control engineering. The purpose of the direct modeling is to obtain an ANN model of the CPS in such a way that the outputs of the CPS and the ANN match closely. Once a model of the CPS is available, it may be used for fault detection of the sensor. An ANN based on the MLP is a feed-forward network with one or more layers of nodes between its input and output layers. The popular back-propagation (BP) algorithm, which is a generalization of the LMS algorithm, is used to train the MLP. Simulation studies were carried out to obtain a direct model of the CPS. The SCC output voltage was obtained experimentally at the reference temperature of 25 C for different values of normalized pressure **Pn** chosen between 0.0 and 0.6 with an interval of 0.05. Thus, these 13 pairs of input-output data constitute a set of patterns at the reference temperature. Using (3), the functions $f1$ (T) and $f2$ (T) were generated by setting the values of β 1 and β 2 to -2.0 x 10^-3 and 7.0 x 10^-3, respectively. From the available CPS pattern set at the reference temperature, i.e., PN ~ CN, and with the knowledge of functions *f* 1 (T) and *f* 2(T) eight sets of patterns (each containing 13 pairs of input-output data) were obtained at an interval of 10 C ranging from 10 C to 60 C.



DIRECT MODELING OF CPS USING ANN

PROGRESS

The CPS was designed using system identification to obtain a linear filter with weights such that it would replicate the results as obtained in the CPS. The algorithms used have been outlined below:-

Type of models:-

- 3 tap FIR filter

- 3 tap FIR filter with Trigonometric FLANN

Algorithms used: - LMS and BP

<u>PROCEDURE</u>:-

- To begin with, the results of the CPS were determined as per the capacitance – pressure relationship.
- The weights of the filter to be modeled were initialized to zeros.
- The outputs of the filter for every pressure input were determined simultaneously with the CPS results.
- The errors were calculated for each input value.
- The weight update was performed using the suitable algorithm corresponding to each error and input value until the optimum filter with a nearly identical output as CPS was obtained.
- Several iterations were performed in order to minimize the error to a negligible value.
- The final filter obtained was an accurate model for the CPS.

(B)LVDT:-

To demonstrate the usefulness of the CFLANN based nonlinear compensator, computer simulation study is carried out using experimental data obtained from a typical LVDT having following specifications.

Number of turns in two secondary coils, S1 and S2,

ns =3300 turns each wound over it uniformly with the two coils

Core diameter is, *2ri* = 4.4 mm,

Core length is, *La* = 4.5 mm.

The primary sinusoidal excitation voltage, Vp = 10V (peak- peak) of frequency, *f* = 5kHz.

Vp is 6.712 Vrms.

Primary winding resistance, *rp* = 260ohm.

Secondary winding resistance, *sr1* = 426.8 ohm.

Secondary winding resistance, *sr2* = 414 ohm.

Two secondaries are wound in opposite directions. The pitch is kept around 0.02-0.03 mm. The experimentally measured data is presented in Table-I. With this data the LVDT is modeled into a dynamic system .

Table-I: Experimental Measured Data of LVDT

EXPERIMENTAL MEASURED DATA

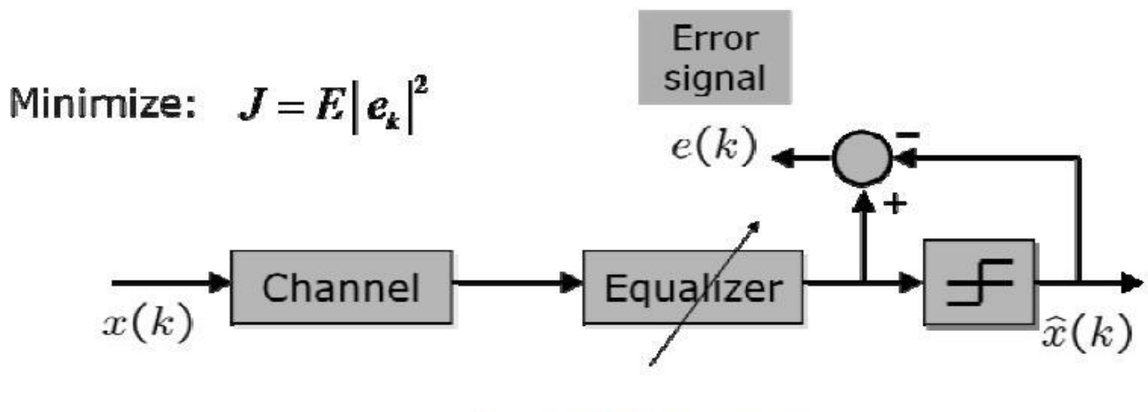
Displacement (x in mm)	Differential Output voltage (e_{rms})	Demodulated voltage output (e)
-30	4.085	-5.185
-25	3.956	-5.017
-20	3.731	-4.717
-15	3.221	-4.039
-10	2.359	-2.896
-5	1.273	-1.494
Null position, 0	0.204	0.001
5	1.153	1.462
10	2.226	1.810
15	3.118	3.962
20	3.748	4.799
25	4.050	5.225
30	4.085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

7 Inverse Modeling

GENERAL DESCRIPTION:-

Inverse modeling is implemented for Channel Equalization. Channel equalization is the process of compensating for the effect of the physical channel between a transmitter and a receiver. It is an important area in communications as it can greatly improve the quality of transmission which in turn leads to more efficient communication. In this the transmission channel is modeled as a non-linear time-varying system. By using Inverse Modeling we compensate the channel so as to get an error-free channel.

To combat the distortive channel effects, or in other words, invert the FIR filter (time or time-varying) representing the channel, a so-called equalizer is needed. In a communication system, the transmitter sends the information over an RF channel. On passing through the channel, the signal gets distorted before actually it gets received at the receiver end. Hence, it is the receiver ”task” is to figure out what signal was transmitted and turn the received signal in understandable information. The purpose of an equalizer is to reduce the ISI as much as possible to maximize the probability of correct decisions.

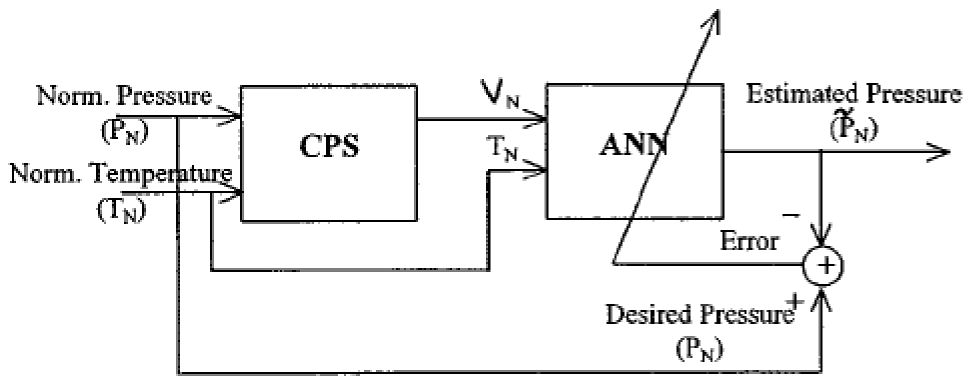


SCHEMATIC REPRESENTATION OF INVERSE MODELING

INVERSE MODELING AS APPLIED TO THE PROBLEM:-

(A)CPS:-

A scheme of inverse modeling of a CPS using an MLP for estimation of applied pressure is shown in Fig.This is analogous to the channel equalization scheme used in a digital communication receiver to cancel the adverse effects of the channel on the data being transmitted. To obtain a direct digital readout of the applied pressure, an inverse model of the CPS may be used in cascade with it to compensate for the adverse effects on the CPS output due to the nonlinear response characteristics and the variations with ambient temperature. The generation of training-set and test-set patterns is similar to that of the direct modeling scheme. However, in the inverse modeling scheme, the normalized temperature **T N** and the CSS output **V N** are taken as input patterns, and the normalized input pressure **P N** is taken as the desired output pattern in the ANN model.



INVERSE MODELING OF CPS USING ANN

PROGRESS:-

This is similar to direct modeling but here normalized temperature and capacitance are taken as inputs and pressure is treated as the output of the model. The analysis was performed in the following way:-

- The desired pressure samples were collected and stored as reference samples.

- These samples were then passed through the CPS which acted as the channel and the output capacitance values were passed into an equalizer which is a filter with a transfer function that is the inverse of the channel transfer function.
- The equalizer has a length of weights twice the length of the channel.
- The outputs of the equalizer are then compared with the reference pressure samples which have been delayed through some time units generally half of the length of the equalizer.
- The errors obtained at each step are used for updation of the weights of the equalizer using the LMS algorithm.
- Thus we obtain a model to remove non-linearities right at the input end without comparing the accuracy of outputs.

(B)LVDT:-

The proposed nonlinearity compensation scheme is shown in Fig. In this scheme the LVDT can be controlled by a displacement actuator. The main controller gives an actuating signal to the displacement actuator, which displaces the core of the LVDT. The differential voltage of the LVDT after being demodulated does not keep linear relationship with the displacement. For many applications the FLANN as a useful alternative to the multilayer artificial neural network (MLANN) and radial basis function (RBF) based ANN. It has the advantage of less computational complexity than the MLANN and RBF structure and hence easily implementable. But the FLANN model requires more numbers of expansions (typically number of expansion is 100) to achieve the desired percentage of linearity level .The linearity behaviour of LVDT can further be improved by the proposed method of CFLANN, which essentially consists of two-stage FLANN, each stage requiring less number of nonlinear expansions. In the present case only 12 and 4 expansions are used unlike 100 in case of FLANN.

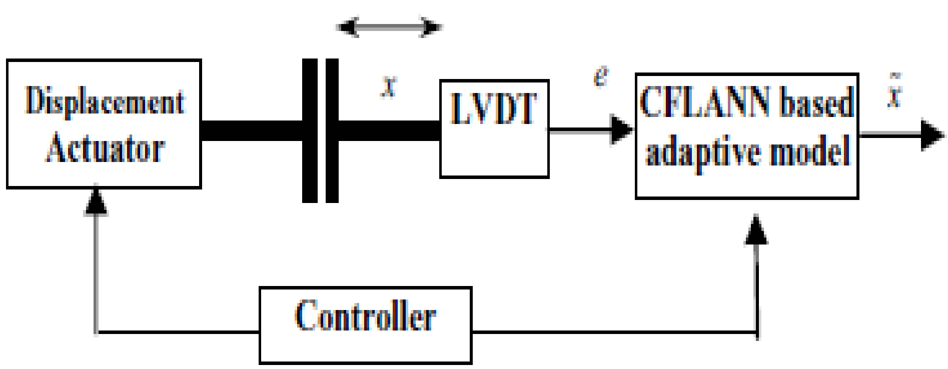


Fig. 3. Scheme of an intelligent nonlinearity compensation of LVDT

PROGRESS:-

The differential voltage *e* at the output of LVDT is subjected to trigonometric expansion (12 values) to achieve nonlinearly mapped values. These are then multiplied with a set of weights and then added to produce an intermediate output (stage-I). This output value undergoes further expansion (4 values) which are then weighted and summed to generate the final output (stage-II). It is compared with the desired signal (actuating signal of the displacement actuator) to produce an error signal. With this error signal, the weight vectors (2 sets) of the CFLANN model are updated. This process is repeated till the mean square error (MSE) is minimized. Once the training is complete, the LVDT together with the proposed model acts like a linear sensor with enhanced dynamic range. The algorithm used is backpropagation (gradient descent algorithm) as the CFLANN structure can give better performance then.

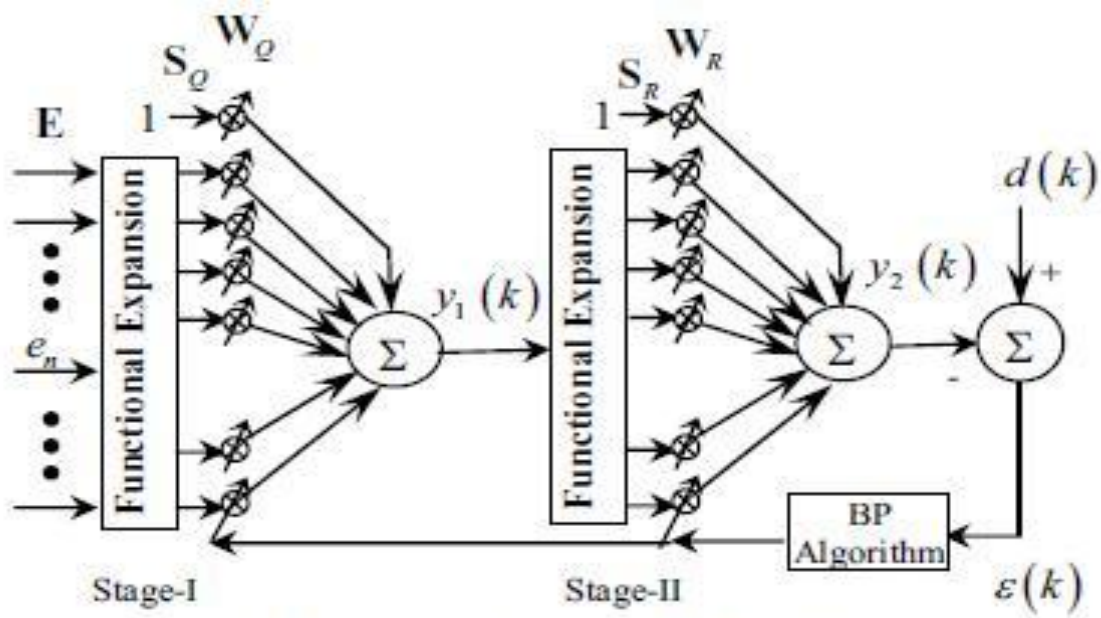


Fig. 4. The structure of CFLANN model

8 Blind Deconvolution

Blind deconvolution is a deconvolution technique that permits recovery of the target scene from a single or set of "blurred" images in the presence of a poorly determined or unknown point spread function (PSF). Blind deconvolution can be performed iteratively, whereby each iteration improves the estimation of the PSF and the scene, or non-iteratively, where one application of the algorithm, based on exterior information, extracts the PSF. Suppose we have a signal transmitted through a channel. The channel can usually be modeled as a linear system, so the receptor receives a convolution of the original signal with the impulse response of the channel. If we want to reverse the effect of the channel, to obtain the original signal, we must process the received signal by a second linear system, inverting the response of the channel. This system is called an equalizer.

If we are given the original signal, we can use a supervising technique, such as finding a Wiener filter, but without it, we can still explore what we do know about it to attempt its recovery. For example, we can filter the received signal to obtain the desired spectral power density. This is what happens, for example, when the original signal is known to have no auto correlation, and we "whiten" the received signal.

Whitening usually leaves some phase distortion in the results. Most blind deconvolution techniques use higher-order statistics of the signals, and permit the correction of such phase distortions

Blind equalization is a digital signal processing technique in which the transmitted signal is inferred from the received signal, while making use only of the transmitted signal statistics. Hence, the use of the word *blind* in the name.

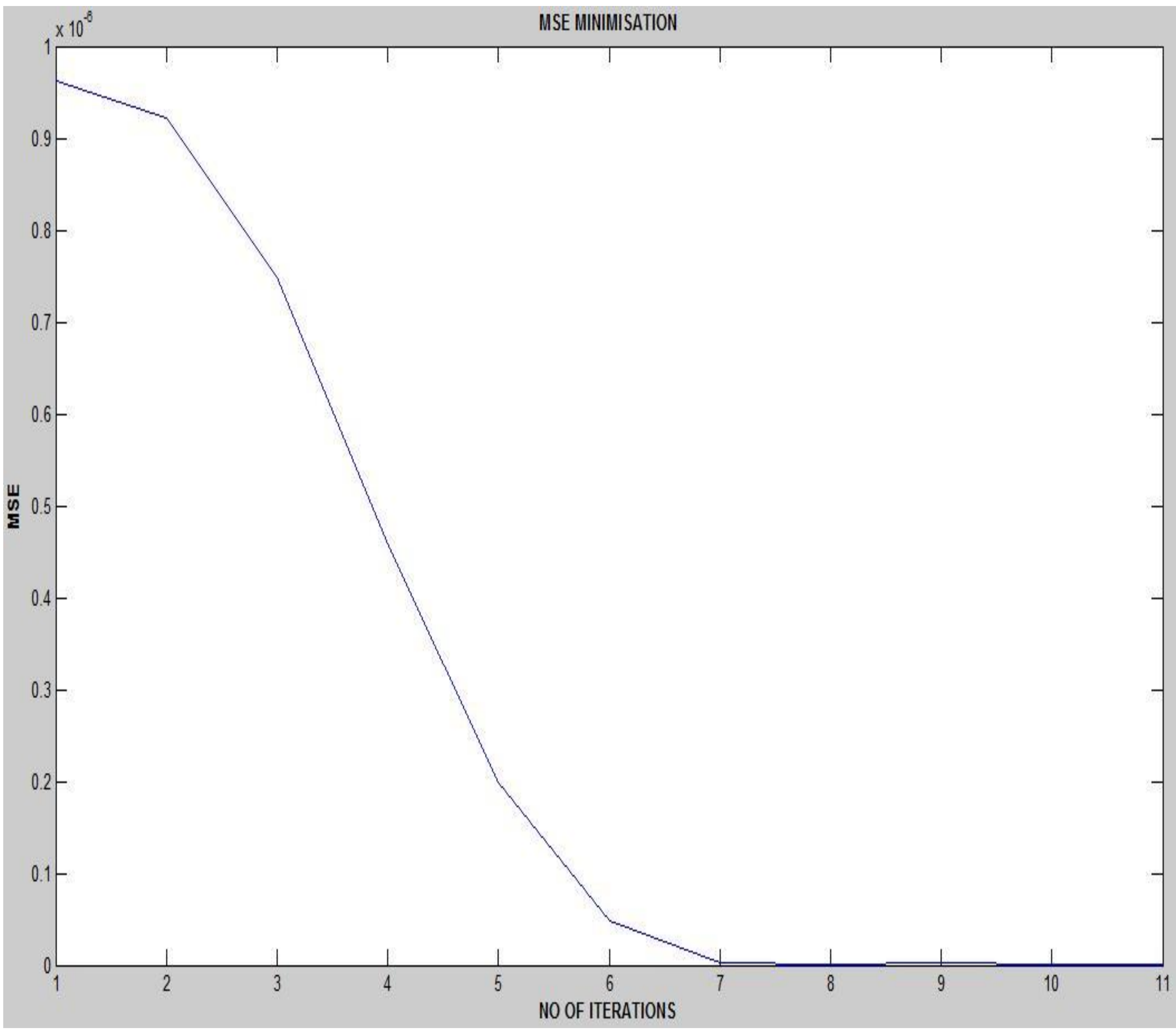
Blind equalization is essentially blind deconvolution applied to digital communications. Nonetheless, the emphasis in blind equalization is on online estimation of the equalizer filter, which is the inverse of the channel impulse response, rather than the estimation of the channel impulse response itself. This is due to blind deconvolution common mode of usage in digital communications systems, as a mean to extract the continuously transmitted signal from the received signal, with the channel impulse response being of secondary intrinsic importance.

The estimated equalizer is then convolved with the received signal to yield an estimation of the transmitted signal.

For the present analysis we have taken the LVDT output and tried to estimate the input signal blindly. The estimating function used is the tan hyperbolic function. The various parameters are updated using the algorithm as mentioned earlier. The result gave a converging MSE. The algorithm is run for 1000 iterations and the value of the learning rate is kept constant mu is kept constant at 0.08 which however can be make to vary iteratively.

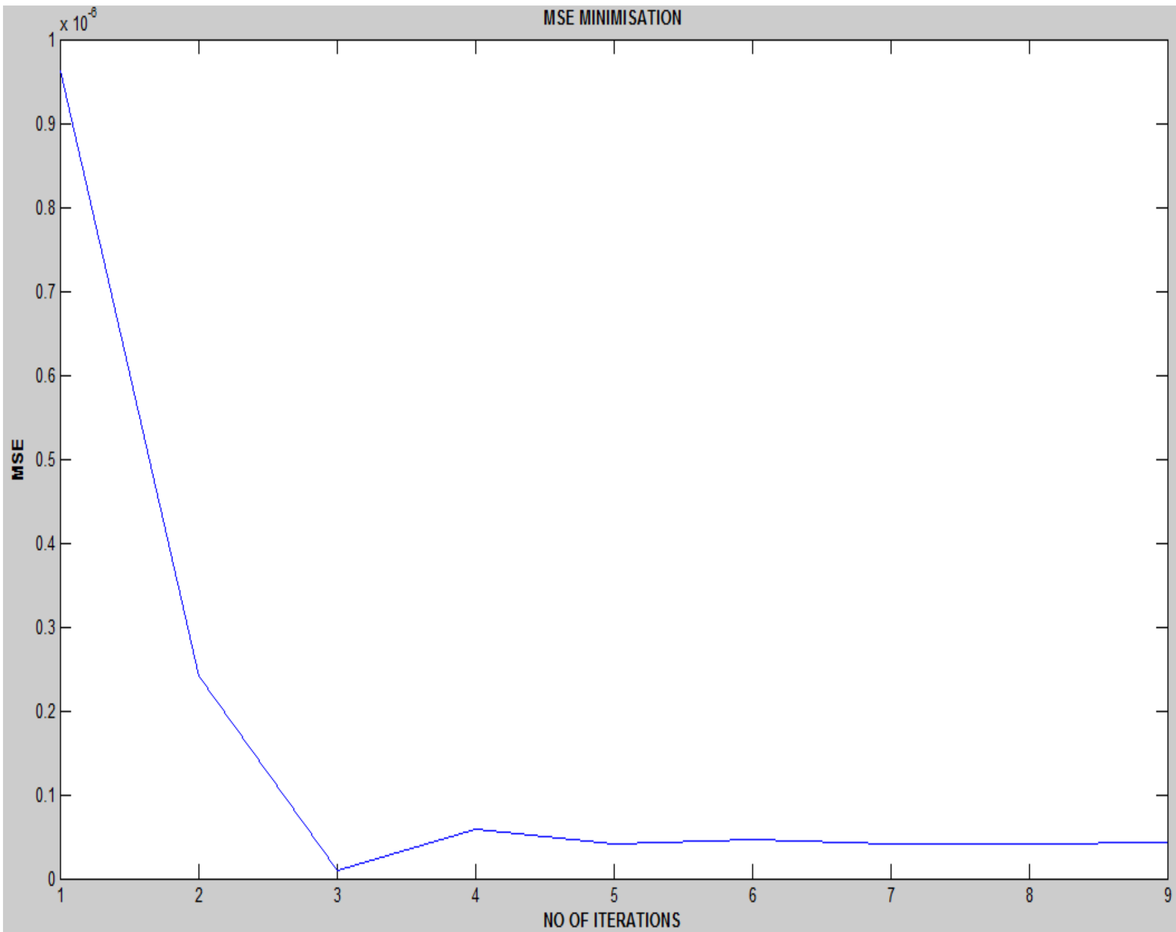
9 Simulation Results

Error Square Minimization using LMS in case of a 3 tap filter modeling of a CPS:-



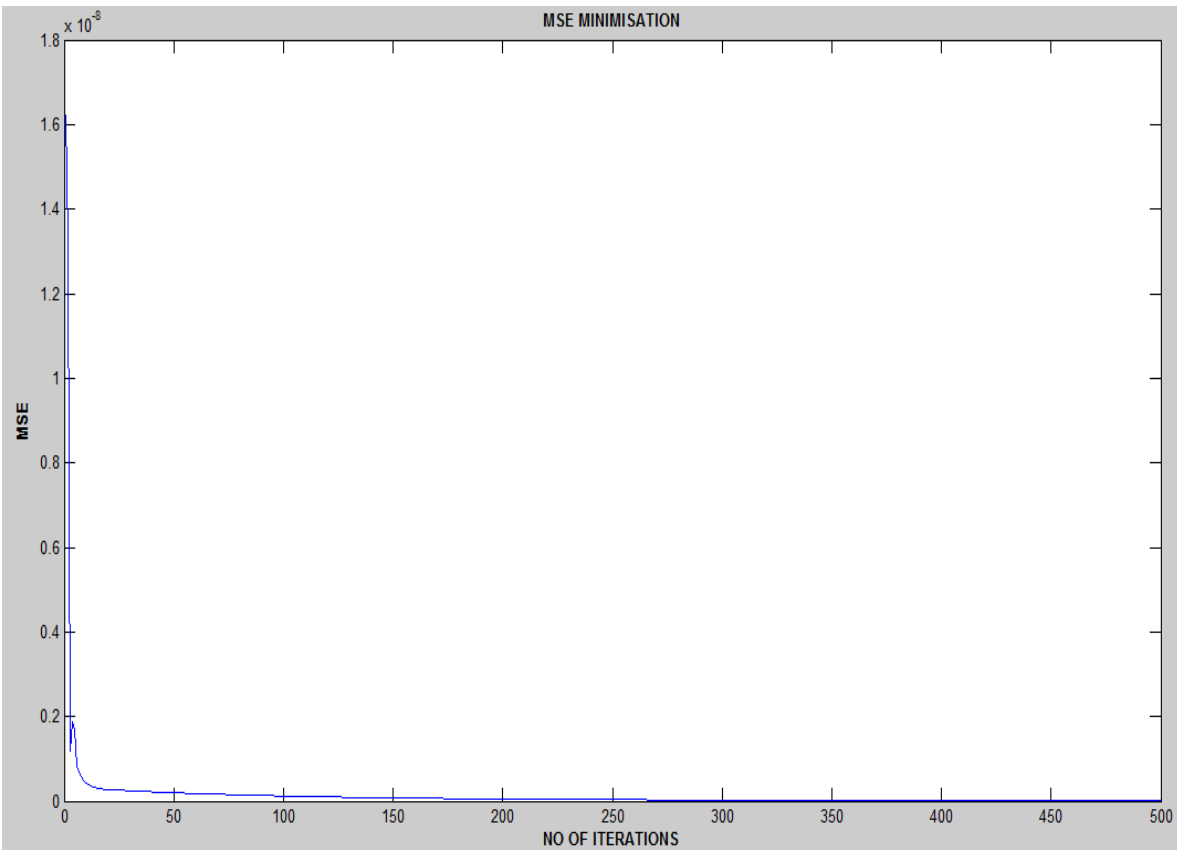
Using trigonometric FLANN trained by LMS at constant temperature:-

Error square minimization:-



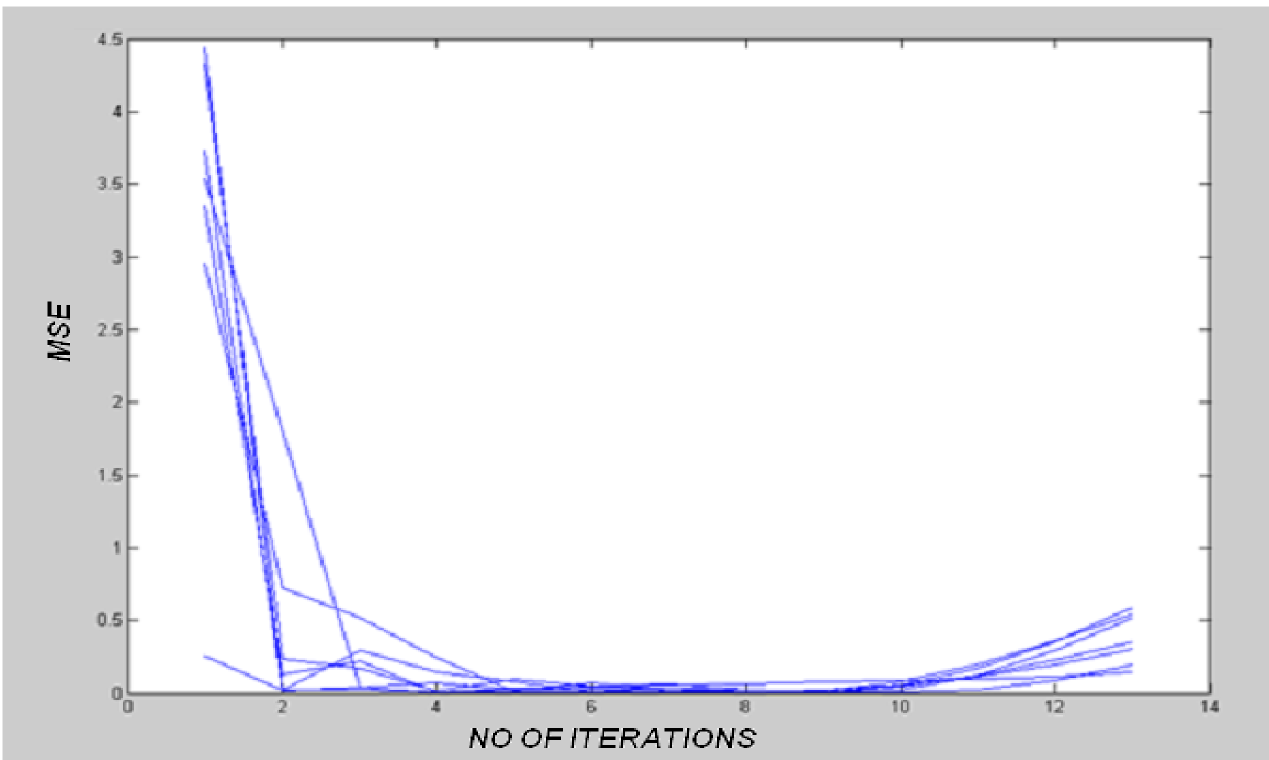
Using trigonometric FLANN trained by back propagation at constant temperature:-

Error square minimization:-



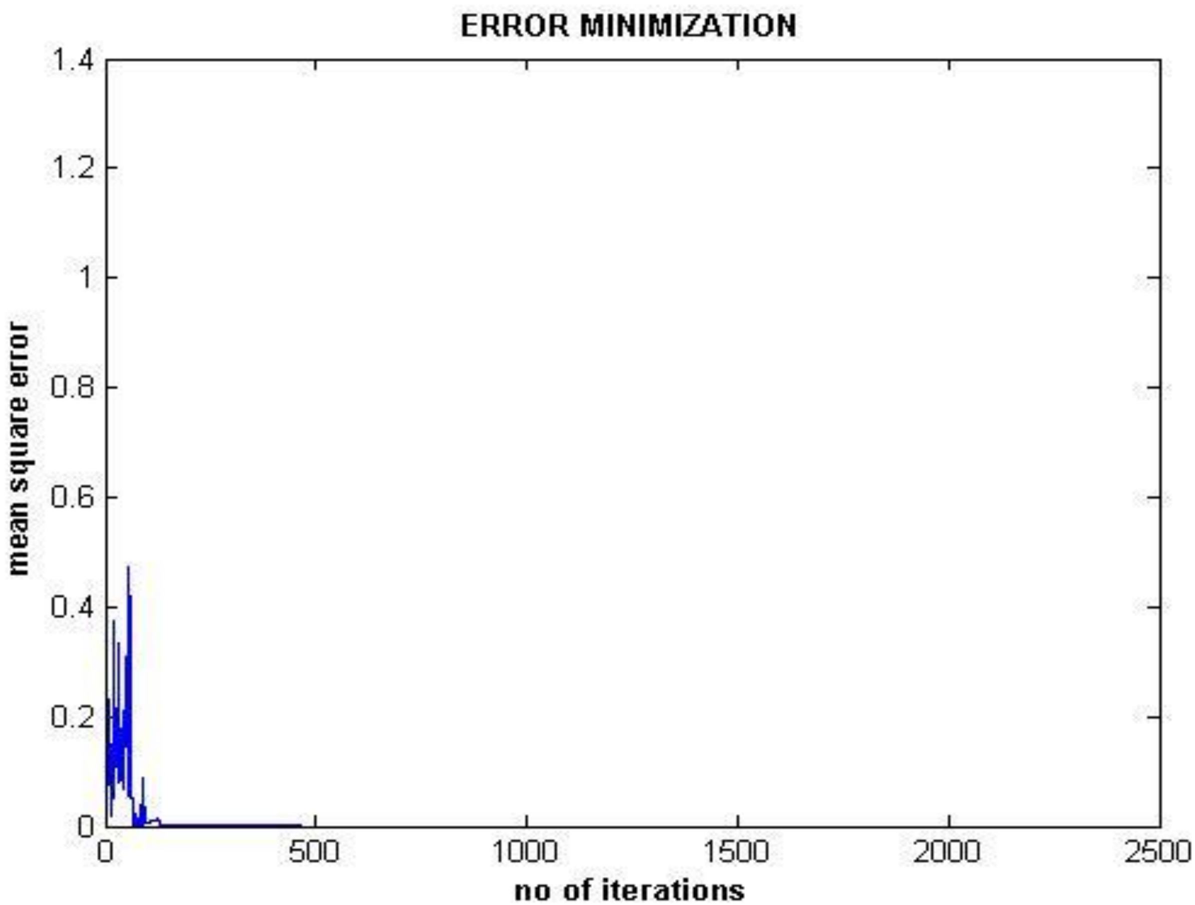
Using trigonometric FLANN trained by LMS at various temperatures:-

Error square minimization:-



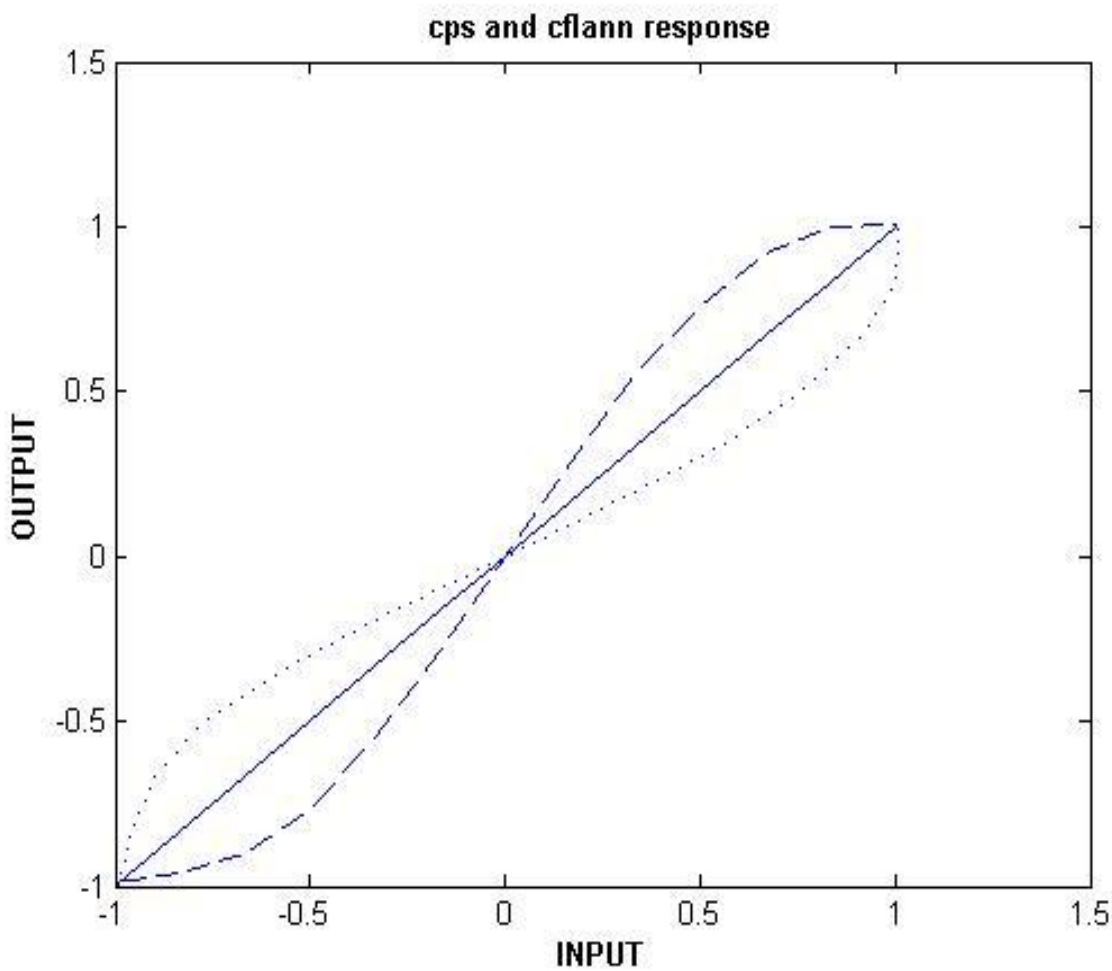
Non-linearity removal in CPS trigonometric CFLANN trained by back propagation:-

Error square minimization:-



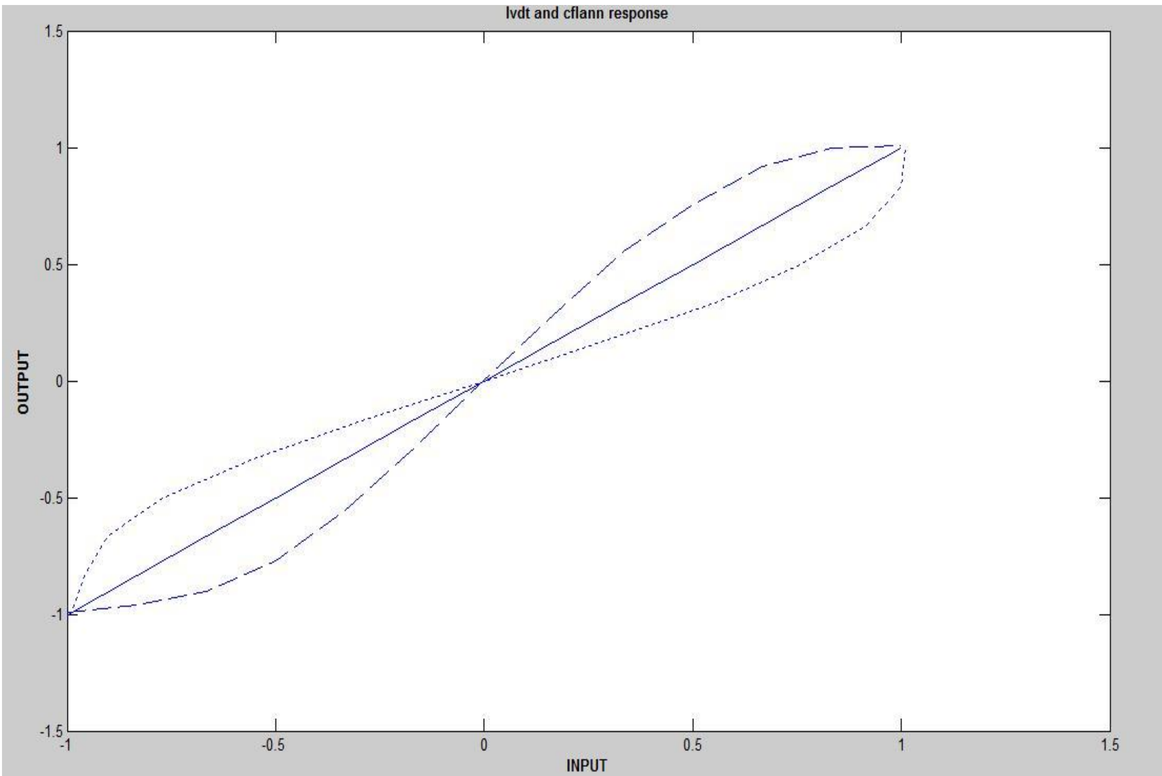
Non-linearity removal in CPS trigonometric CFLANN trained by back propagation:-

Output :-

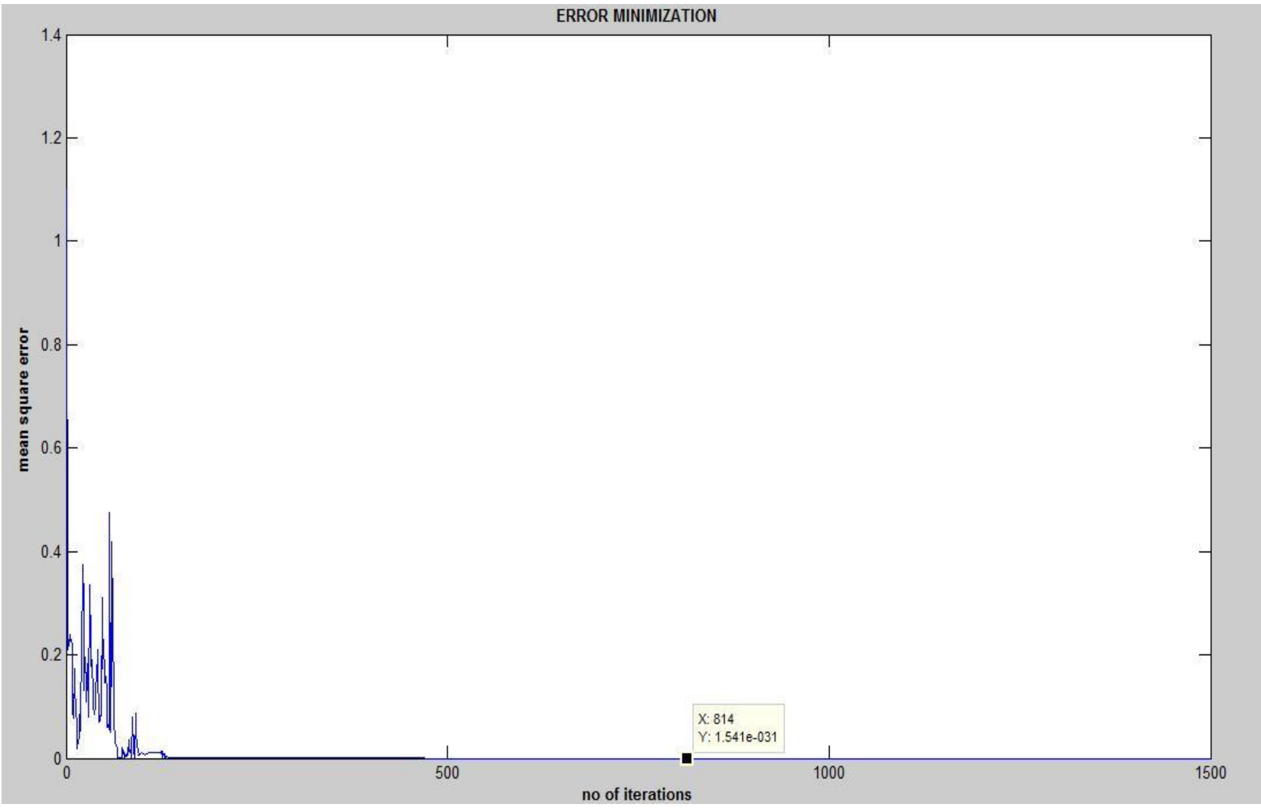


Non-linearity removal in CPS trigonometric CFLANN trained by back propagation:-

A :Output :-

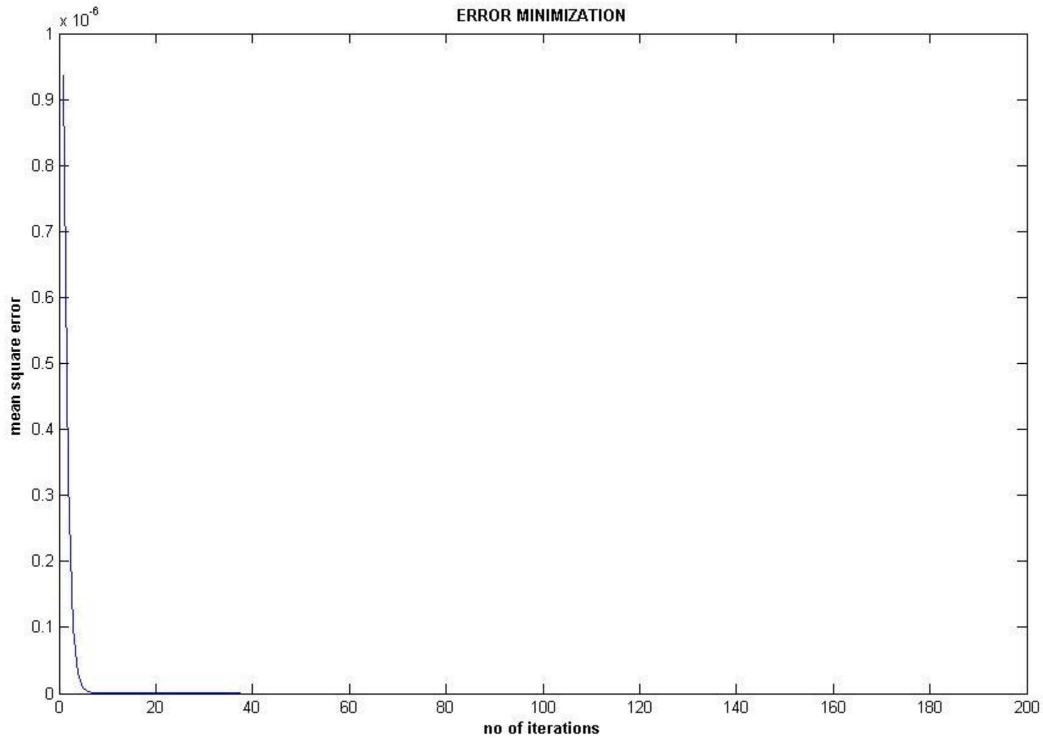


B: Error minimization in LVDT inverse model:-



Implementation of Blind Convolution using Bussgang Algorithm

ERROR MINIMIZATION FOR LVDT



10 Conclusion

In the course of our analysis it was found that the Cascaded FLANN when trained with Back Propagation algorithm, gave the best estimate of the Linear Variable Differential Transducer . It gave a faster convergence and a better result than the other models like FLANN.

For the Capacitive Pressure Sensor it was found that the FLANN model gave a suitable error minimization and output at various temperatures. It is found to be also giving accurate results on being modeled by FLANN trained by Back Propagation.

The Linear Variable Differential Transducer output when trained by Bussgang Algorithm gave a convergence of error. It gave a very accurate Inverse Equalizer for the channel.

Work can be extended in blind equalization using higher order statistics i.e. using the Tricepstrum Equalization Algorithm.

11 References

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