DYNAMIC SYSTEM IDENTIFICATION AND SENSOR LINEARIZATION USING NEURAL NETWORK TECHNIQUES

A Thesis Submitted in Partial Fulfillment

Of the Requirements for the Award of the Degree of

Master of Technology

In

Electronics and Instrumentation Engineering

By

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May 2014

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CERTIFICATE

This is to certify that the thesis report entitled **"SYSTEM IDENTIFICATION USING NEURAL NETWORK TECHNIQUES "** Submitted by **Mr. PRATEEK MISHRA** bearing roll no. **212EC3157** in partial fulfillment of the requirements for the award of Master of Technology in Electronics and Communication Engineering with specialization in **"Electronics and Instrumentation Engineering"** during session 2012-2014 at National Institute of Technology, Rourkela is an authentic work carried out by him under my supervision and guidance.

To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other University / Institute for the award of any Degree or Diploma.

Prof. Ajit Kumar Sahoo

Place: Assistant Professor

Date: Dept. of Electronics and Comm. Engineering

National Institute of Technology, Rourkela-769008

Dedicated to My Family,
Teachers and Friends

ACKNOWLEDGEMENTS

First of all, I would like to express my deep sense of respect and gratitude towards my advisor and guide **Prof. Ajit Kumar Sahoo**, who has been the guiding force behind this work. I am greatly indebted to him for his constant encouragement, invaluable advice and for propelling me further in every aspect of my academic life. His presence and optimism have provided an invaluable influence on my career and outlook for the future. I consider it my good fortune to have an opportunity to work with such a wonderful person.

Next, I want to express my respects to Prof. U.K. Sahoo, Prof U.C. Pati, Prof. S. K. Patra, Prof. T.K. Dan Prof. K. K. Mahapatra, Prof. S. Meher, Prof. A. Swain, Prof. Poonam Singh, Prof D.P. Acharya, Prof. L. P. Roy, Prof. Nihar Ranjan Panda and Prof. Sanad Kumar for teaching me and helping me how to learn. They have been great sources of inspiration to me and I thank them from the bottom of my heart.

I would like to thanks my friends Avinash Giri, Siba Prasad Mishra, Chandan Kumar, Saurabh Bansod, Ashish Singh, Vikram Javre, Shailesh Singh Badghare, Kuldeep Singh, Dipen Mondal, Abhishek Gupta, Nilima Samal and all other classmates for all the thoughtful and mind stimulating discussions we had, which prompted us to think beyond the obvious. I have enjoyed their companionship so much during my stay at NIT, Rourkela.

I am especially indebted to my parents for their love, sacrifice, and support. They are my first teachers after I came to this world and have set great examples for me about how to live, study, and work.

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ABSTRACT

Many techniques have been proposed for the identification of unknown system. The scope of the parameter approximation or estimation and system identification is growing day by day. Lots of research has been done in this field but it can be still considered as an open field for researchers.

The overall field of system identification is day by day growing in the field of research and lots of methods are coming time to time. This research presents a number of results, examples and applications of parameter identification techniques. Different Methods are introduced here with less and more complexities. For System Identification some of Neural Network techniques are studied. Least mean square technique is used for the final calculations of simulation results. Simulations are done with the help of Matlab programming.

Some Neural Network Techniques have been proposed here are multilayered neural Network, Functional link Layer Neural network Technique. Mainly Disadvantage of basic system identification techniques is that it use the back propagation techniques for the weight updating purpose which have a lots of computation complexity.

A single layer Artificial Neural Network has been studied which is known as Functional Link Artificial Neural Network (FLANN). In such type of System Identification technique hidden layers are wipe out by functional expansion of input pattern. The prominent advantage of such type of network is that the computation complexity is much less than complexity of the multilayered neural network.

In the field Control and Instrumentation there are some characteristics which are desirable for the sensors. Linearity is one of the prime characteristic which is highly desirable for a sensor. Many a time in the field of instrumentation it is highly desirable to reduce the nonlinearity. There are many techniques has been developed for sensor linearization like functional approximation techniques for digital system, embedded sensor interface and microcontroller based methods etc. Artificial neural Network has been emerged as one of alternating techniques for Linearization of sensor.

Linearization of thermistor with the help of ANN has been done in this research and result has been discussed.

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
MLP	Multilayer Perceptron
FLANN	Functional Link Layer Artificial Neural Network
Logsig	Continuous Log Sigmoid Function
FIR	Finite Impulse Response
IIR	Infinite Impulse response
DSP	Digital Signal processing
BP	Back Propagation
LMS	Least Mean Square
RLS	Recursive Least Square

CHAPTER 1

INTRODUCTION AND MOTIVATIO BEHIND SYSTEM IDENTIFICATION

- Introduction of System Identification
- Basic Building Function
- Motivation
- Thesis Layout

1. Introduction of System Identification

There are many types of systems are present in nature .They can have any characterization like linear or nonlinear, dynamic or static, time variant or time invariant as well as it can be mathematical or physical or any other. Some time we need to make a parallel system to a unknown system. To formulate such type of system first thing we need is to identify the system. if we have a well-defined system and we also have the sets of inputs to be applied to system then we can easily calculate or find the output characteristics of the system. For the system identification techniques we have the known input patterns and corresponding to that input pattern we have a set of output pattern which can be evaluated experimentally. So with the information of such input output pattern we can map the system. The Approach system identification may be different depends upon the system properties. One method can't be applicable for all systems so we need different types of approach for different types of system.

Recently many developments have been done in the field of system identification to accurately identify the complex nonlinear systems with much less computational complexities and with fewer efforts. One such technique is block adaptive digital filter technique.it simply calculate filter output from some block of inputs it comes with the saving of lots mathematical computation complexity. It enables the parallel processing of computation which enables the system to have a good processing speed.

In near years Artificial Neural Network Techniques has been developed as an efficient and fast learning technique for system identification [2] of very highly nonlinear dynamic as well as static system. These types of methods have some major advantages from traditional techniques like they are very good in approximation of highly nonlinear and complex system.

They have very high reliability for complex system and they have very good performance index for the highly nonlinear complex system.

Basic Building Block of Neural Network

Multilayered Neural Network is basic structure to perform such type of system identification but we have large number of hidden layers and very complex structure which slows down the speed of operation.

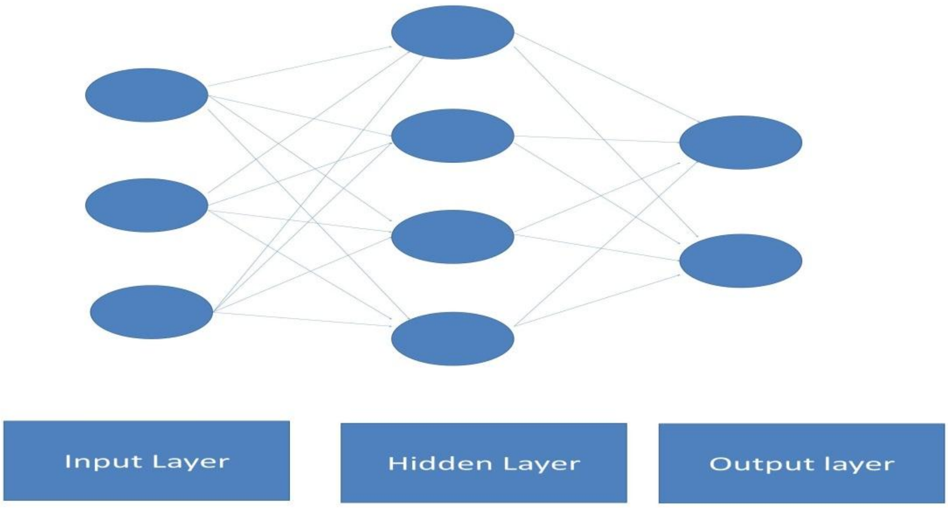


FIg1.1: Basic MLP Structure

Activation Function: In Multilayer Neural Network Activation Function of any node is defined as particular characteristic of a node it defines the output of any node for a particular input or for the set of particular input pattern given to that node. According to the use of System different types of activation functions are used some of these are:

1. Step Function
2. Continuous Log Sigmoid Function
3. Continuous Tan Sigmoid Function

Step Function: Step Function is the function that is basically used by normal perceptron's. Under a particular threshold value the output of this function is low or another standard signal and value greater than a particular threshold the value output of such activation function changes and becomes a particular high value.

$$f(x) = \begin{cases} a_0, & x < 0 \\ a_1, & x \geq 0 \end{cases}$$

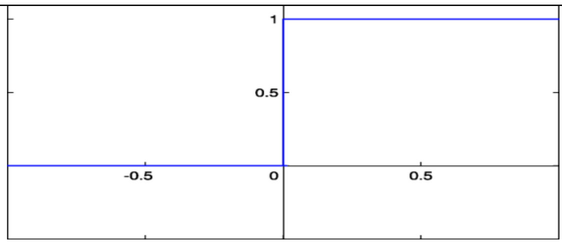


Fig 1.2: Step Function graph

Continuous Log Sigmoid Function: Log Sigmoid function can be abbreviated as Logistic function. The equation of Logistic Function is given as

$$f(t) = \frac{1}{1 + e^{-\beta t}}$$

Slope of the Logistic function can be determined by the value of **β** so it can be said as slope parameter. This function is known as Log-Sigmoid Function because Sigmoid can also be achieved by the hyperbolic function beside of this relationship in such case it would be called as Tan-Sigmoid Function. Log-sigmoid is here referred as sigmoid. The sigmoid is basically similar to the step function but some region is added to the step function which is called as the region of uncertainty.[4] Input- Output characteristic of biological Neurons are very similar to the sigmoid function in many aspects but not the totally. Derivative of Sigmoid function can be easily calculated so they can be referred as simple prized function.

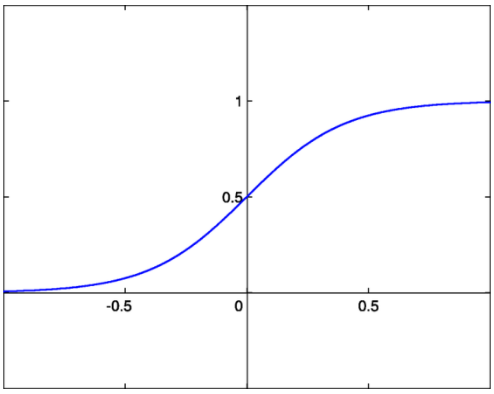


Fig: 1.3 Sigmoid Function Graph

When β =1 then derivative of Sigmoid function cab be calculated as

$$\frac{df(t)}{dt} = f(t)[1 - f(t)]$$

When β ≠1 then

$$\frac{df(\beta, t)}{dt} = \beta[f(\beta, t)[1 - f(\beta, t)]]$$

Continuous Tan Sigmoid Function: Continuous Tan Sigmoid Function's Equation is as follows.

$$f(t) = \tanh(t) = \frac{e^t - e^{-t}}{e^t + e^{-t}}$$

Derivative of Tan-Sigmoid Function is as follows

$$\frac{df(t)}{dt} = 1 - tanh^2(t) = sech^2(t) = 1 - \frac{(e^t - e^{-t})^2}{(e^t + e^{-t})^2}$$

The Functional Link Layer Artificial Neural Network (FLANN) was first suggested by Pao [1]. This Flann Network shows many advantages over the traditional MLP structure. These can be used for functional approximations and classifier for the different pattern with much faster rate of convergence and lesser mathematical computational complexity than a simpler Multilayer perceptron layer network. Flann Structure for the tool for identification of complex nonlinear system is studied. Using trigonometric functional expansion techniques the functional expansion of input layer is done in Flann structure. Comparing Functional Link layer ANN with the MLP structure the better performance of FLANN structure is found in terms of speed of computation as well as in term of computation complexity of the network. Here an option for the MLP structure is discussed which FLANN structure is. Which comes with the more effective and simple identification of complex highly nonlinear dynamic functions. Chebyshev's Polynomials [11] or for the functional expansion of the input patterns the trigonometric functional expansion can be used.

FLANN structure is proposed to reduce the region between the linearity of highly complex multilayered system and simple single layer system. FLANN system consist of a simple single layer feed forward neural network structure. To use it in complex nonlinear system functional expansion techniques are used. In such technique a simple N*1 matrix is converted into a N*P matrix.

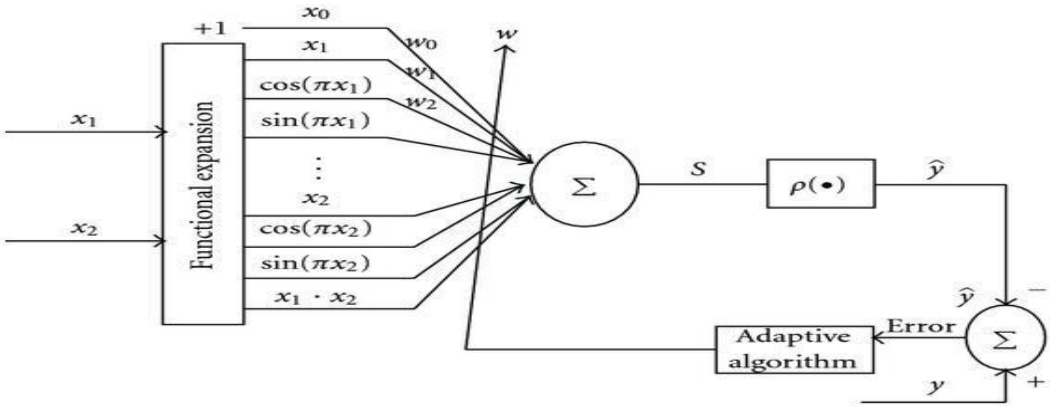


Fig 1.4: Basic FLANN structure

It's a simple single layered neural network structure so mathematical complexity of this network is less compared of a multilayer network.

The FLANN methods are used to identify time domain series complications in discrete time plants as well [8]. The identification process does learning as the same time with functioning feature not the traditional functioning after the learning process. The training processing is dependent on recursive LMS technique.

Motivation: Field of system identification is growing day by day with the rapid speed. In the broad area of Signal and data processing system identification have a major importance. Adaptive Filtering have major importance in the field of nonlinear system identification [3]. Adaptive digital filtering have a major capability of self-adjustment of its transfer characteristics to get an optimal method for a system which is unknown Depended on the output set of the system which is not well known. To achieve an optimal set of model for unknown system, it depends upon structural characteristics of the system as well as the adaptive algorithm and the nature of input signal.

Digital Signal processing based equalizer system has become important in many different application including voice communication, data communication, video communication via different transmission lines. Area of Applications of the system identification is so vast in nature that is acoustic echo controller for the speakerphones which are full duplex for the video purpose.

[6, 7]

1.3 Thesis Layout

System Identification problem are explained and disused in chapter 2 in brief and different models of system identification are given in 2^{nd} chapter. Then the nonlinearity problems in the System Identification explained.

In Chaper3, Non Linearization of different sensors and the methods of linearization of sensors has been discussed in details Some Model of Sensor linearization is discussed in details

In Chapter4, the System Identification process is done with the help of LMS and RLS techniques in time domain and it was shown that RLS (Recursive Least Square) algorithm works with fast rate than the conventional LMS algorithm. Slope of RLS is greater than the LMS so error signal gets die out with faster rate in in the RLS algorithm. So comparison between LMS and RLS techniques are done in chapter 4.

In Chapter5, the MLP and FLANN algorithm for system identification is suggested. The comparison between computation complexity and time requirement for system identification is done.

The basics of Neuron, multilayer Perceptron (MLP) and Functional link Layer ANN (FLANN) were discussed in the chapter number 6. Comparison of the above Methods of system identification is done in the Dynamic and system complex nonlinear systems. Nonlinear system identification problem was solved with help of extensive MATLAB simulation study.

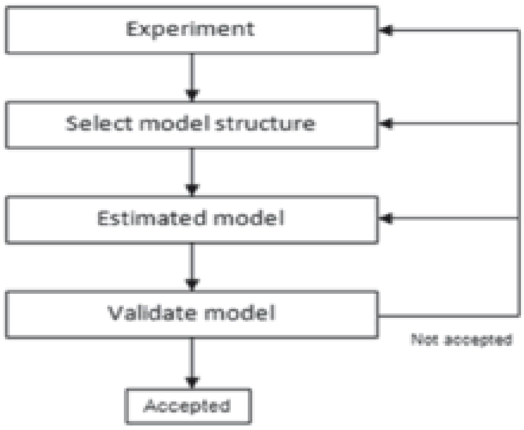
CHAPTER 2

System Identification Techniques

- Introduction and Steps of System Identification
- Introduction of Box Methods
- Theory Behind System Identification
- Derivation of Weight updation

2 Introductions:

System Identification techniques are the experimental technique their accuracy depends upon the hit and trail methods. One can't exactly estimate the result with application of pure theoretical knowledge.[1] There are some steps which have to be follow for the system identification techniques.



Diag 2.1: Steps of System identification

1. **Experimental Design**: Purpose of experimental design is to find better experimental data and it also contains of selection of measuring variable and for the character of sets of input data.
2. **Selection for the Model Structure**: With the use of prior knowledge a well suited model structure is chosen in the step of selection of model structure.
3. **Choice of Criteria to fit**: An appropriate function of cost is chosen in this step which shows how well the model approximates the experimental data.
4. **Parameter Estimation**: The parameters explain a physical setting in this way that that measure of the data. An approximate technique attempts by the estimator the pro-

cess which is not known using the measurement. The parameter approximation problem is solved to find the mathematical quantity of the model parameter.

5. **Model Validation**: The module goes under the testing in this step to reveal any inadequacies

The most important aspect of system approximation is to find the proper and suitable model structure. Hence a better model can be found within such suitable model structure. To incorporate a given model in to a given structure (under parameter estimation) is the vital problem in system identification. Thumb rule in system identification is not to estimate such system that you already know.[3]

Use of past knowledge and physical insight should be done while choosing the structure of the model. It is necessary to differentiate between the three levels of previous information which is color coded as follows:

1. White Box Method
2. Black Box Method
3. Gray Box Method

White Box Model: This Technique is used when we have the perfect knowledge of system. White box models can be constructed from the prior information without the help of any observations.

Black Box Model: When no prior model or knowledge of system is available black box technique is used. No physical insight is available in black box model. Most system Identification uses this type of technique. In black box method we do not have the first principles model for the system. It is completely a data driving modeling technique.

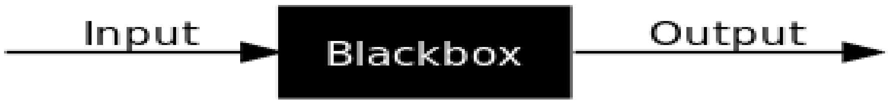


Fig 2.2: Black Box Input- Output Structure

Grey Box Model: In such type of model some amount of insight or information is available but many specifications have to be determined from the observed data.

A black box nonlinear model for a dynamical plant is a module structure which makes to decide almost any nonlinear complex dynamic system. Recently there has been much interest in this black box technique. Black box structure is simply based on the LMS techniques, RLS techniques, Multilayer Perceptron, Functional link Layer ANN, and Radial Basis Function based method. The basics of these algorithms in briefly discussed here.

Fundamental techniques for system identification have two-step process. In first step the useful basis functions are identified using the available data. Then in the second step a linear lest square step to determine the co-ordinates of functional approximation. [5, 6] A particular complexity is to deal with the huge amount of effectively important parameters.

Basics of system identification problems, solutions with the help of various techniques and approaches are introduced. Different basic methods which lead to further complex methods are derived here. The basic overviews of different technique and comparison between the methods of different system identification methods are discussed. Simple Derivation of Least LMS Technique is given further, which is the traditional and mostly used method for adjusting the coefficient of an system identification techniques. Basics of LMS technique is discussed further. Further Recursive Least square (RLS) technique is defined and then comparisons between these two techniques are made. [4] Then new techniques useful for more complex system are discussed, which can be useful for the more nonlinear systems.

Basic Theory behind System identification:

In system identification we have to approximate a method of a system based upon experimental sets of input-output data pattern. Many ways are there to define a system and to approximate or estimate a system.

The procedure of determining a model of a nonlinear dynamic system from experimental observed Input-output pattern consist three basic things:

- The input-output data pattern
- The model structure
- The identification method

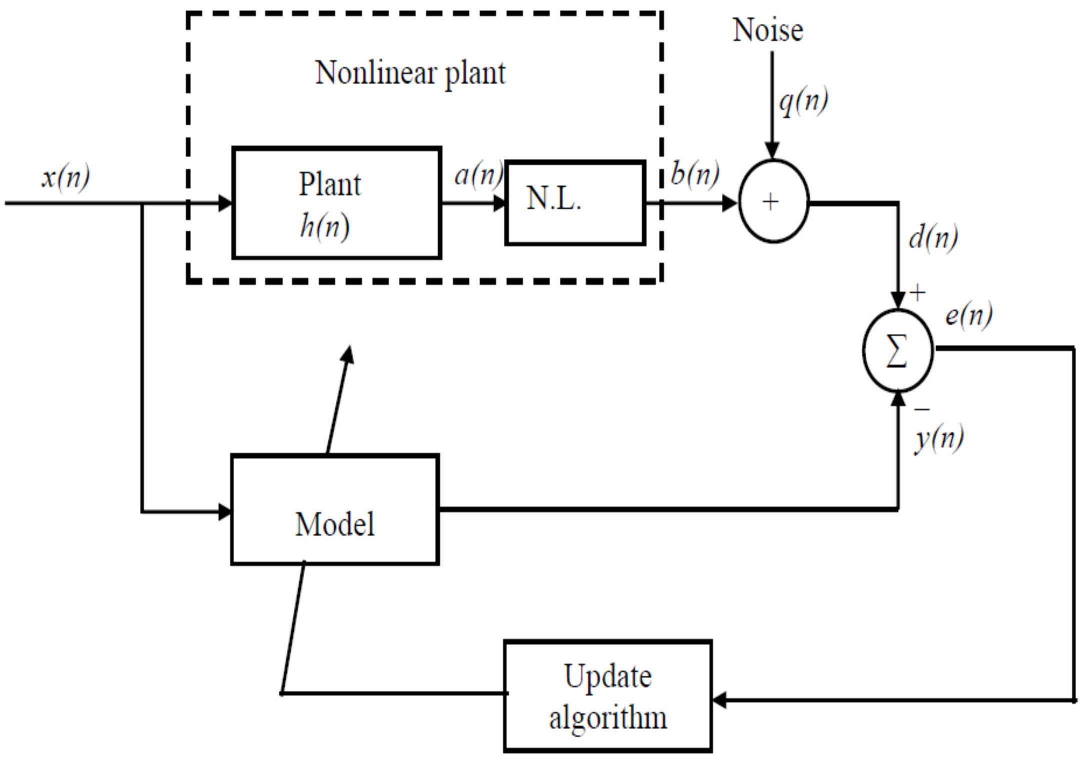


Fig 2.3: Block diagram of system identification technique

The identification process amounts to repeatedly selection of a model structure, finding the best suitable model in the structure and approximate the property of model to check whether they are satisfactory or not.

Basically in system identification techniques we have the set of input-output pattern and we have to build a mathematical model for the system.[7] Here input of any system is denoted by u (t) and the output any time t is denoted by f (t). System is assumed to be a discrete time system. Thus at particular instant of time t we have the input-output data set and the basic relationship in the the input and output data pattern in the form of differential mathematical equations.

$$f(t) + a_1 f(t-1) \ldots \ldots a_n f(t-n) = b_1 u(t-1) \ldots \ldots \ldots \ldots \ldots b_m u(t-m) \qquad (2.1)$$

This system shows the equation of a discrete time system. Data is collected at some particular instant of time interval. A different way to observe above equation is the method of determining the next output value given for the previous values of observations.

Above equation can be written in the form by simple shifting of some terms of equation which will result.

$$f(t) = b_1 u(t-1) \ldots \ldots \ldots \ldots \ldots b_m u(t-m) - a_1 f(t-1) \ldots \ldots - a_n f(t-n) \qquad (2.2)$$

The equation can be simplified further as

$$\Theta = [a_{1,}, a_2, \ldots \ldots \ldots \ldots a_n, b_1,\ b_2, \ldots \ldots \ldots \ldots \ldots b_n]^{T} \qquad (2.3)$$

$$\varphi(t) = [-f(t-1) \ldots \ldots \ldots -f(t-n) u(t-1) \ldots \ldots \ldots u(t-m)]^T \qquad (2.4)$$

With the above two expressions we can state

Output from the Network

y (t)=$\varphi^T(t) * \theta$

Derivation of weight updation:

By selecting a any System Identification architecture, we have to determine the number and different types of parameters which is to be changed or adjusted. An identification technique is use to update the weight parameter values and to minimize the error of the system.

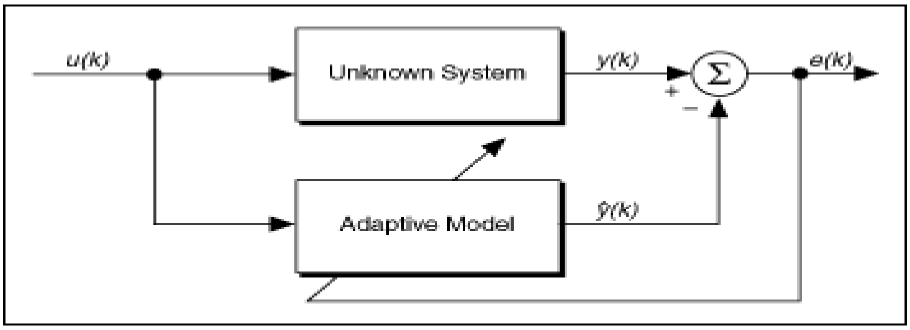


Fig 2.4 Adaptive Filtering problem

Diag 6 presents a basic building block diagram in Digital Input signal is fed to the unknown system, called as adaptive filter that calculate the corresponding output for the particular value of the input. Till the calculating the output for a particular set of input at any instant the structure set of adaptive filter does not have importance but in fact it have the changeable or adjustable parameter whose value affect how it is calculated.[8] The output is now compared with a second signal which can be called as desirable signal. Then after subtracting the output from the desired signal one can find the error signal.

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

Where

d (n)= desired output signal

y (n)=output at the particular time instant 'n'

e (n)= error signal results from subtraction of desired signal from output signal.

After finding the error signal it is fed to the further mechanism which updates or alters the parameters of the system at every instant of time n to n+1.This updating represent in the following diagram. Now the structure of different filters is discussed in brief that are useful in the field of system identification.

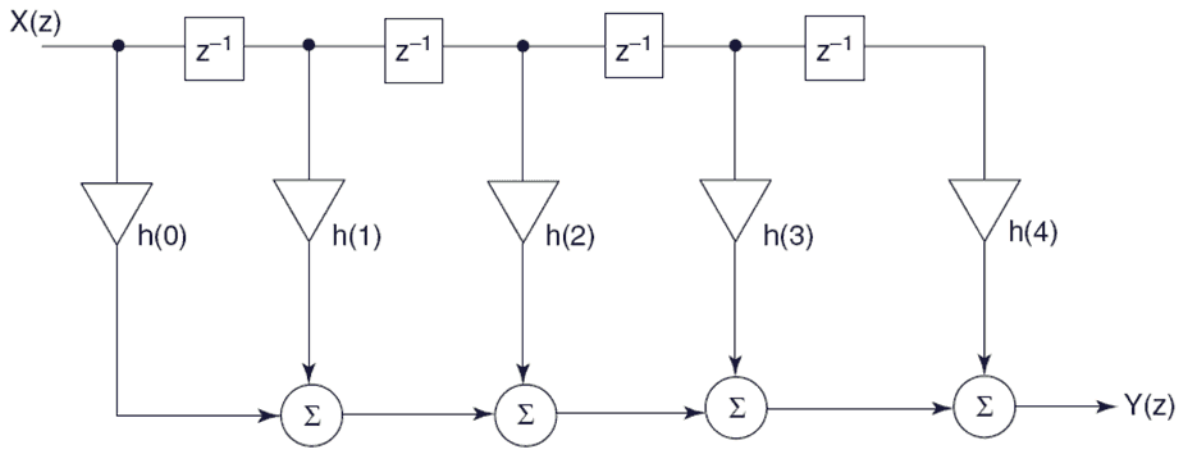


Fig 2.5: Block diagram of FIR Filter

Normally nay system with some number of parameter that will decide that how the output y (n) will be computed from the knowledge of the input x (n).

W (n) = $[w_0(n), w_1(n) \dots \dots \dots . w_{N-1(n)}]^T$

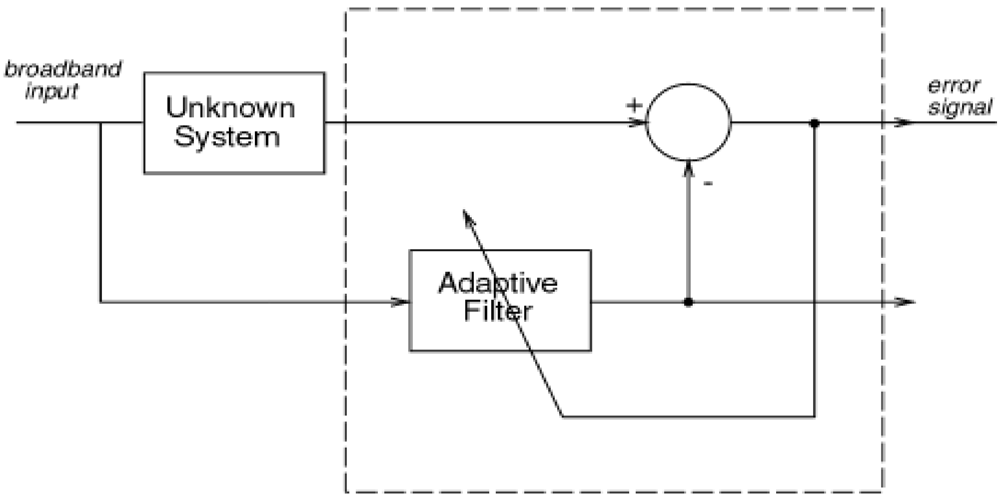


Fig2.6 Weight updation block diagram for Adaptive filter

With the help of such system identification techniques different complex mapping structures can be done like the mapping of most complex structures like brain.

Basic Building block diagram of the System identification technique is given below

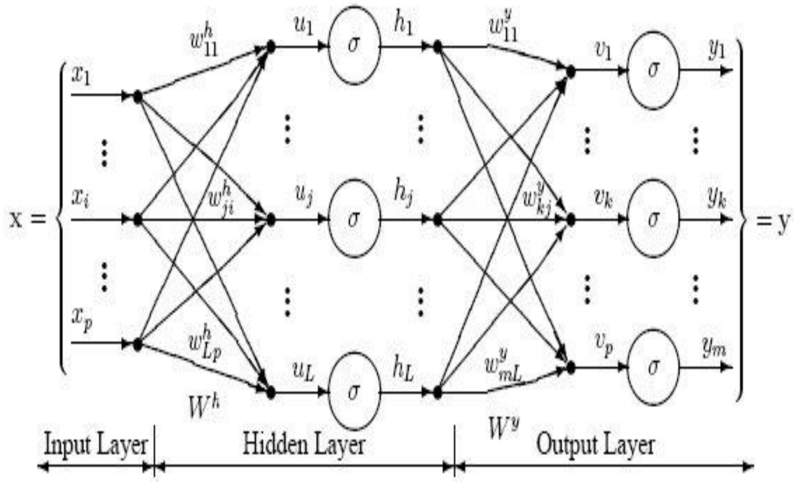


Fig 2.7 Different layers of Neural Network

Output after giving the input to the function will be dependent upon the activation function of layer as well as the weights parameters.

$$\varphi(v) = \tanh(v_i)$$

$$\varphi(v) = (1 + e^{-v_i})^{-1}$$

Error after every iteration may be defined as

$$e_j(n) = y_j(n) - d_j(n)$$

Calculating the mean square value of the error

$$\sigma(n) = \frac{1}{2}\sum_j e_j^2(n)$$

Using gradient descent we find our change in weight will be

$$\Delta w_{ji}(n) = -\eta \frac{\delta\sigma(n)}{\delta v_j(n)} y_i(n)$$

$$\frac{\delta\sigma(n)}{\delta v_j(n)} = -e_{j(n)}\boldsymbol{\varphi}'(\boldsymbol{v_j}(\boldsymbol{n}))$$

Speed of learning is vital factor in the field of system identification and control theory which is determined by the value of constant.

CHAPTER 3

Linearization of Non Linear Sensors

- Sensor Linearization
- Introductions of Nonlinearity
- Introduction of Nonlinear sensor Thermistor
- Thermistor’s Nonlinearity Correction with the help of FLANN

Sensor Lionization:

Historically, the factors of cost spent, size and area of ANN (artificial Neural network) are not the factors of concern for the developers. Such types of issues are many applications some applications of those issues are present in the field of aeronautics department, high volume business product, products having the large size where size limitations needs to be applicable. Some application of artificial neural network in the field of sensor performance improvement has been discussed here. Many a times the linearity is major factor for the sensor performance. Linearity is property of sensor which is highly desirable. Many sensors involves today are nonlinear in nature like thermistor, linear variable differential transformer (LVDT) (after some range of application). Objective of this research is to extend the linearity range of the sensor so that outputs of the sensor can be made more predictive.[1,2]

We want the linearity characteristics for the ideal transducers. But there are many factors which drive transducers toward the nonlinearity. Due to such nonlinearity problem the usable range of transducers gets restricted. Accuracy of the transducers also get effected with the effect of non-linearity problem occurs in transducers. The major effect of nonlinearity comes in order of predictability of sensor get affected and behavior of the sensor becomes unpredictable and working range of the system get affected due to this nonlinearity. Nonlinearity is basically time variant in nature [4] sometimes there are factors in nature which also affect the nonlinearity such temperature and humidity which varies day by day so it makes the working conditions of sensor unpredictable. Then effect of ageing also adds some amount of nonlinearity to the sensor. Many researchers worked in this field but it’s still a very open field for the researchers as much more work is remaining for linearization of nonlinear sensor and one universal technique is still not there. Many algorithm has been came in this field such as in the field of ANN , Functional link layer Artificial Neural Network(FLANN) based ANN, Multilayered Perceptron (MLP), Back propagation network to decrease the nonlinearity range of resistive, inductive and capacitive sensors.[3]

Further it is find that that the MLP and BPN networks are the less efficient as compared to FLANN network as the computation complexity of FLANN network is lower. Hence the FLANN network can be developed with the fewer amounts of complexions.

Introduction: Suppose for a sensor we have particular equation of output for a particular input pattern as

$$\mathrm{F(x)} = a_1 * x + a_2 * x^2 + a_3 * x^3 \ldots\ldots.. = A * x + g(x)$$

Function f(x) decides the linearity deviation of the sensor from the ideal linearity condition. For the case of linearity we want f (x) to be only dependent at the value of x but many a times f(x) becomes dependent at the values of different polynomials of x. Many methods are there to define the linearity or the nonlinearity of the sensor. Each of them can be defined by different methodology. [7] Linearity and the nonlinearity property are conjugate. We can say that the values of nonlinearity can be used for the linearity also i.e. if the sensor is highly nonlinear then it will be a good linear sensor. Measurement of nonlinearity is often done in the form of relative units. It can be measured in term of percentage of maximum full reading of the sensor or transducer or the percentage of the local reading. Ideally we want the nonlinearity to be fully vanish or minimize to a minimum value.

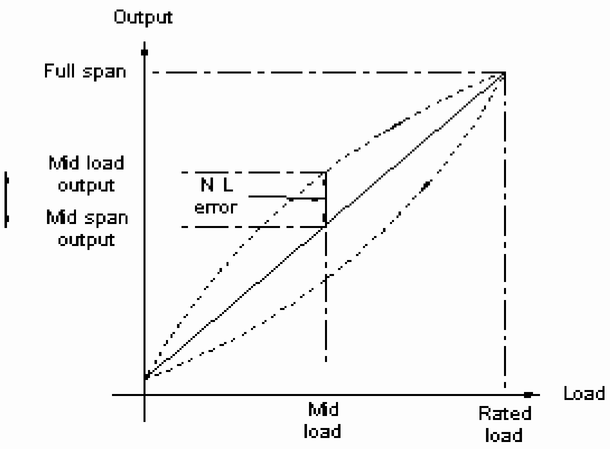


Fig 3.1 Nonlinearity characteristics of Sensor

Above graph shows the nonlinearity measurement method. Nonlinearity (NL) can be measured with help graph. A linear line is drawn and with reference to that line nonlinearity can be measured.

Corrections for Nonlinearity: In this portion of thesis the compensation of nonlinearity will be discussed for the Thermistor will be discussed

Thermistor: A thermistor is the type of resistor, resistance value of it varies significantly with the variation of the value of temperature. Thermistor is made of two words in addition thermal plus resistance which means that the resistance value of thermistor varies with the thermal (temperature) changes. Where we need some control applications we can use the thermistors like in current limiters, on exceeding the particular value of current system will be shut down or flow of current will be stop, Temperature sensors, self-resting exceed current protectors and self-regulating heating transducers.[6]

Thermistor is different from RTD in terms of the material used as sintered mixtures of metal oxides are used in the case of thermistor which is generally Negative temperature coefficient in nature and RTD are the metals like Pt-100 which are positive temperature coefficient metals means with the increase in the temperature the resistance value of metal will increase.

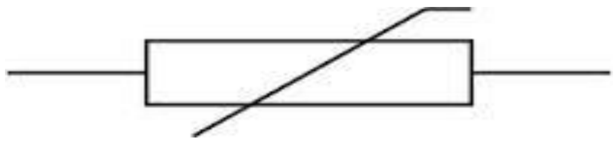


Fig 3.2 Thermistor Symbol

This is symbol of a thermistor rectangular box basically shows the resistance.

Thermistor Equation

$$R = R_{Ref} * e^{\beta(\frac{1}{T} - \frac{1}{T_{Ref}})}$$

Where R_{Ref} = Resistance at reference temperature.

FLANN Based Linearization of Thermistor: FLANN (Functional link layer Neural Network) is the single layer Neural network It does not consist any hidden layer which makes the mathematical computations simple. The functional link works as on an element of the pattern and on the entire pattern itself by creating the group of linearly independent function and calculating these functions with the pattern as argument.[5,8] The differential voltage v at the output of the Thermistor is fed to the FLANN model as the input. In this research trigonometric expansion is used as it provides the better nonlinearity compensation as compared to the other expansions.

Let us consider the FLANN based learning with the flat Net which does not have hidden layers. Let V be the input vector of N elements. Let the net configuration have one output. Each element goes through nonlinear trigonometric expansion to formulate P elements so that the resulting matrixes have the dimension of N*P and the n^{th} input is the v_n 1<n<N the functional expansion is carried out as

Trigonometric Functional Expansion: For the functional expansion of the FLANN network functional expansion block used the functional model consist of a subset of sinusoidal and cosine basis function and the original basic pattern with its outer products. Let's have a example of functional expansion [10, 11] a two dimension input pattern$U = [x_1, x_2]^T$, after functional expansion the enhanced pattern is obtained as $x' = [x_1 \cos(\pi x l)\, sin(\pi x l) \sin(3\pi x l)]$

The LMS technique which is used to train the network thus become simple as no hidden layer is present in the network.

Mathematical analysis of FLANN:

$$x_i = i = \begin{cases} v_n & i=1 \\ \sin(l\pi v_n) & i > 1 \text{ and } i \text{ is even} \\ \cos(l\pi v_n) & i > 1 \text{ and } i \text{ is odd} \end{cases}$$

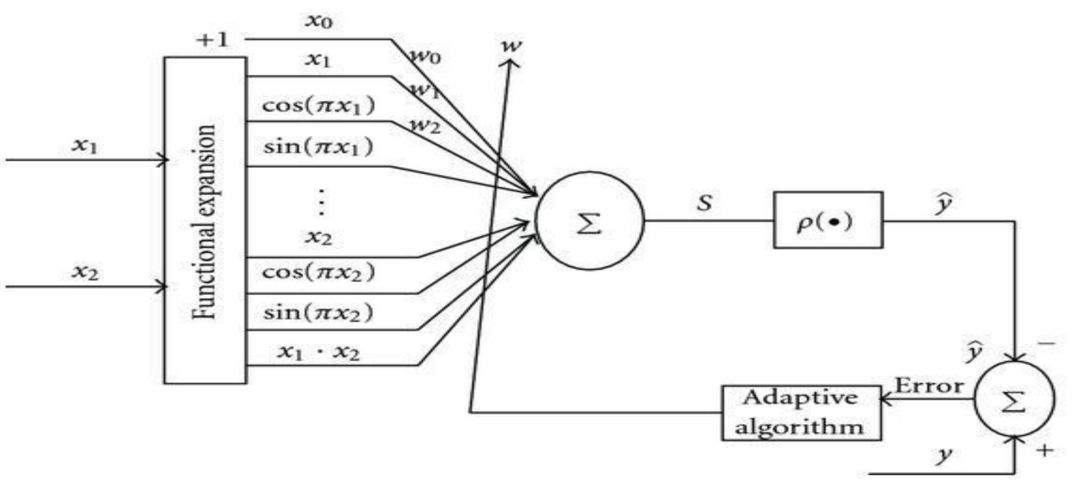


Fig 3.3 : Functional Expansion in FLANN

Let the weight vector is represents as W having Q elements. The y output is then give by

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

The output can be written as

$$Y = S * W^T$$

At the Kth iteration the error signal e (k) is computed as

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

Where d(k) is the desired signal at any instant of time k, which is equal to the control signal given at any instant of time and y(k) is the real output at any instant of time k.

This equation can be written further as

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

With the help of LMS algorithm weight vector can be updated as

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

Here the $\nabla(k)$ is the instantaneous estimate for gradient of ε with respect to weight vector w(k)

$$\nabla(k) = \frac{\partial \epsilon}{\partial w} = 2e(k)\frac{\partial y(k)}{\partial w}$$

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

$$2e(k)s(k)$$

By putting the value of $\nabla(k)$ we get

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

Where μ presents the size of steps ($0 \leq \mu \leq 1$), value of μ controls the speed of Least mean square algorithm.

The results of sensor linearization with help of ANN are shown below. Graph 1 shows the thermistor Resistance vs. Temperature which is highly nonlinear in nature. Graph2 shows the FLANN mirrored graph and the thermistor graph. After compensating the mirrored graph with thermistor original graph 5 shows the final ANN output graph which is approximately similar to the linear approximated graph of thermistor.[9]

Result and Discussion:

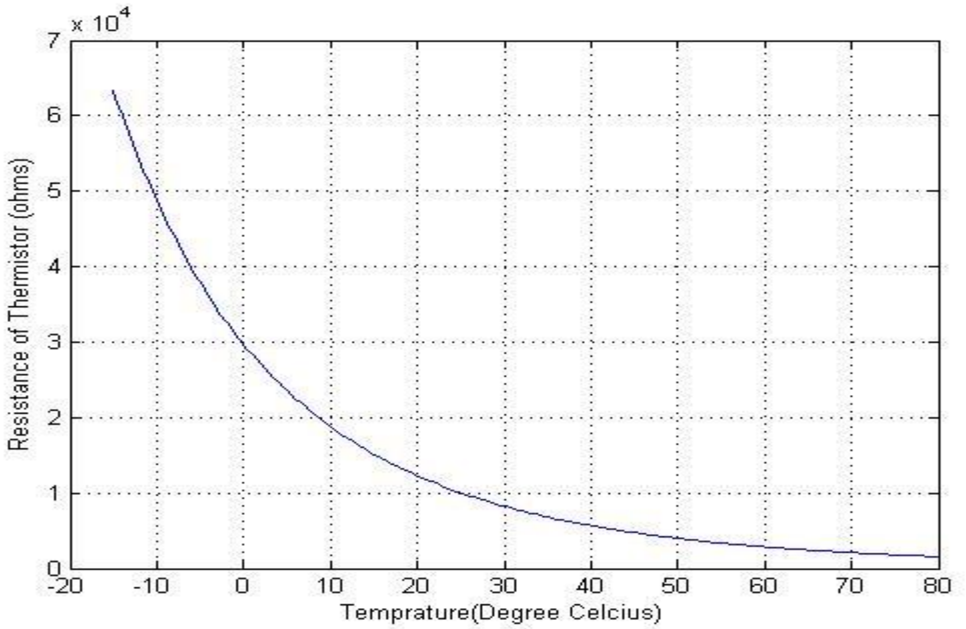


Fig 3.4: Thermistor Resistance vs. Temperature

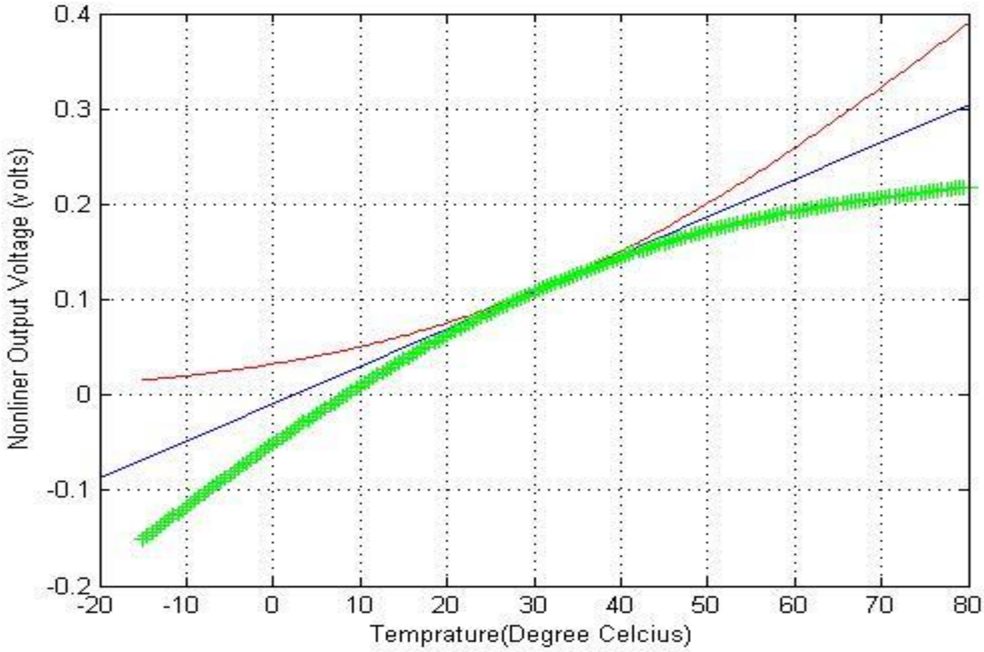


Fig 3.5: Nonlinear output voltage graph of thermistor

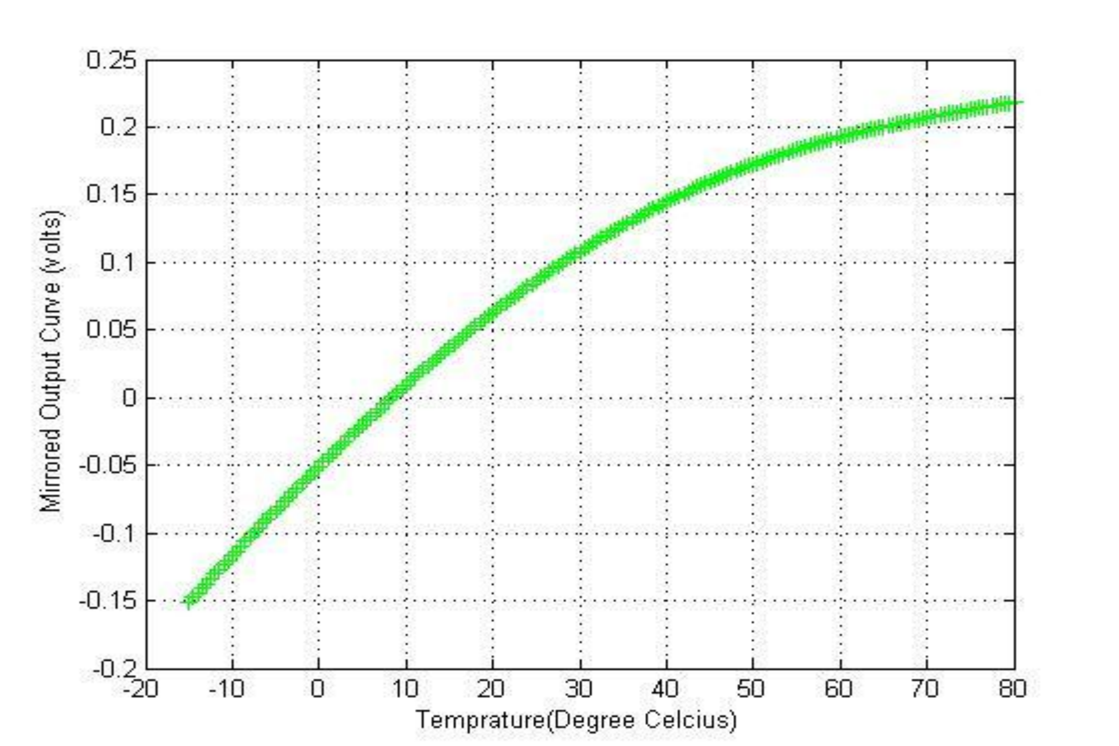


Fig 3.5: Mirrored output voltage for thermistor

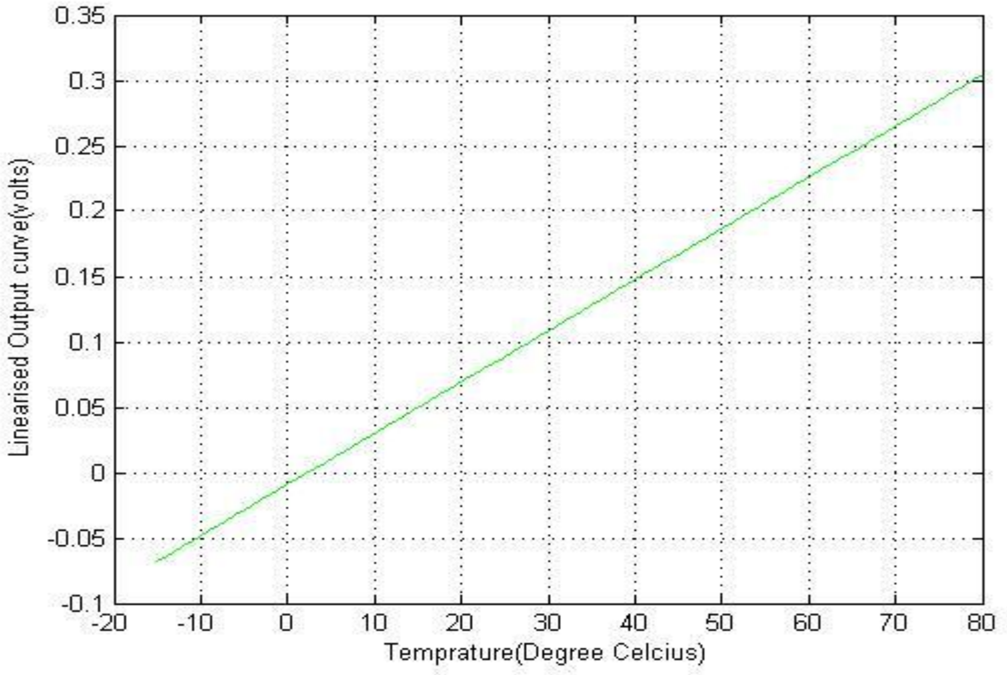


Fig 3.6: linearize output voltage for thermistor

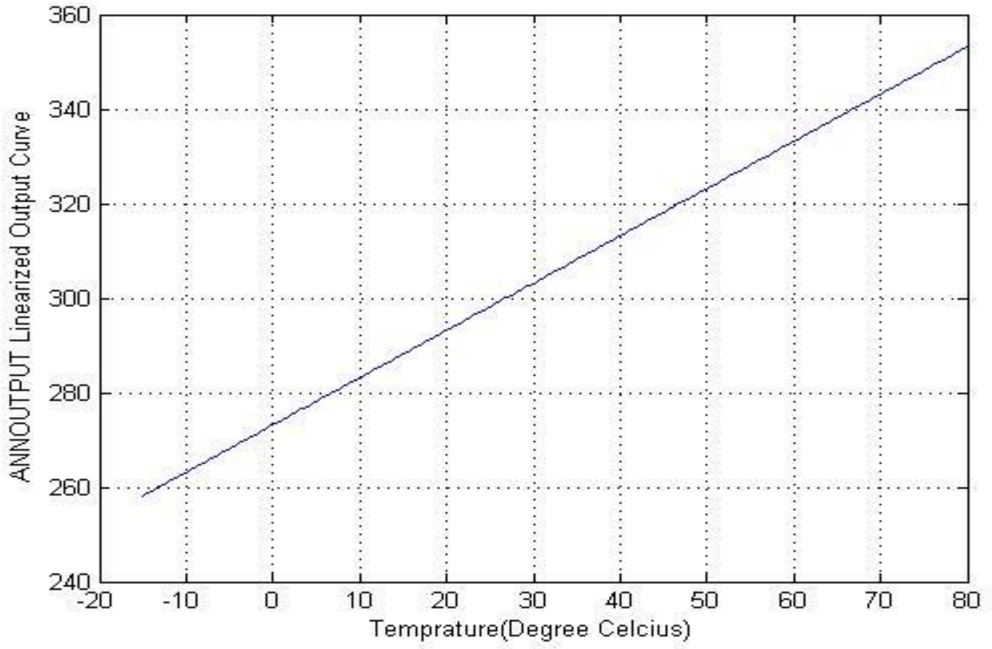


Fig 3.7 LINEAR ANN OUTPUT

As shown in graph the linearized output is presented with the help ANN model. FLANN model is used for the linearization purpose.

CHAPTER 4

System Identification using LMS and RLS

- Introduction
- Least mean Technique for system identification
- Recursive Least Square Technique (RLS) Derivation
- Comparison between RLS and LMS

4. **Introduction:**

Field of the System identification is one of the most interesting f or adaptive filters, especially for the LMS Algorithm (Least mean square algorithm), Robustness and less computation complexity helps the LMS technique in the field of system identification. Depending on the error signal, the coefficients of filters get updated and adjusted. In process of updation the output signal becomes exactly same in the value as the input signal. The advancement in this field is remarkable and opening the door of wide research and making an opportunity for automation and determination.

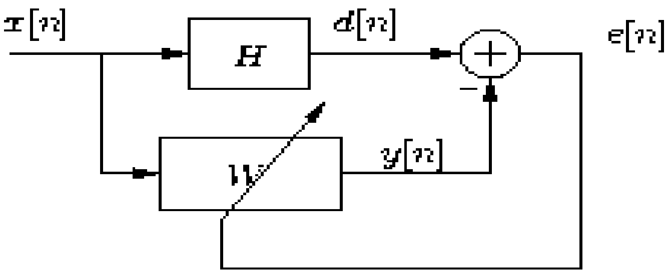


Fig 4.1 Weight updation for Adaptive Filters

Block diagram of LMS technique is shown in figure input x (n) is applied to system S which produce the desirable result d (n) and x (n) is also applicable to the System which have to be realize equivalent to System H which gives the output at the particular time n, y (n) then both the outputs have to applied to subtract which in result gives the error signal after subtracting the y(n) from d(n).[1]

LMS Algorithm Derivation

The error signal can be expressed as

$$E = (d[n] - y[n])^2$$

The cost factor C(n) is the mean square error

$$\nabla_{\hat{\mathbf{h}}^H} C(n) = \nabla_{\hat{\mathbf{h}}^H} E\left\{e(n)\, e^*(n)\right\} = 2E\left\{\nabla_{\hat{\mathbf{h}}^H}(e(n))\, e^*(n)\right\}$$

With the application of chain rule

$$\nabla_{\hat{\mathbf{h}}^H}(e(n)) = \nabla_{\hat{\mathbf{h}}^H}\left(d(n) - \hat{\mathbf{h}}^H \cdot \mathbf{x}(n)\right) = -\mathbf{x}(n)$$

$$\nabla C(n) = -2E\left\{\mathbf{x}(n)\, e^*(n)\right\}$$

Applying the gradient descent algorithm and step size $\mu/2$

$$\hat{\mathbf{h}}(n+1) = \hat{\mathbf{h}}(n) - \frac{\mu}{2}\nabla C(n) = \hat{\mathbf{h}}(n) + \mu\, E\left\{\mathbf{x}(n)\, e^*(n)\right\}$$

The above equation is called as the update equation for LMS.[2]

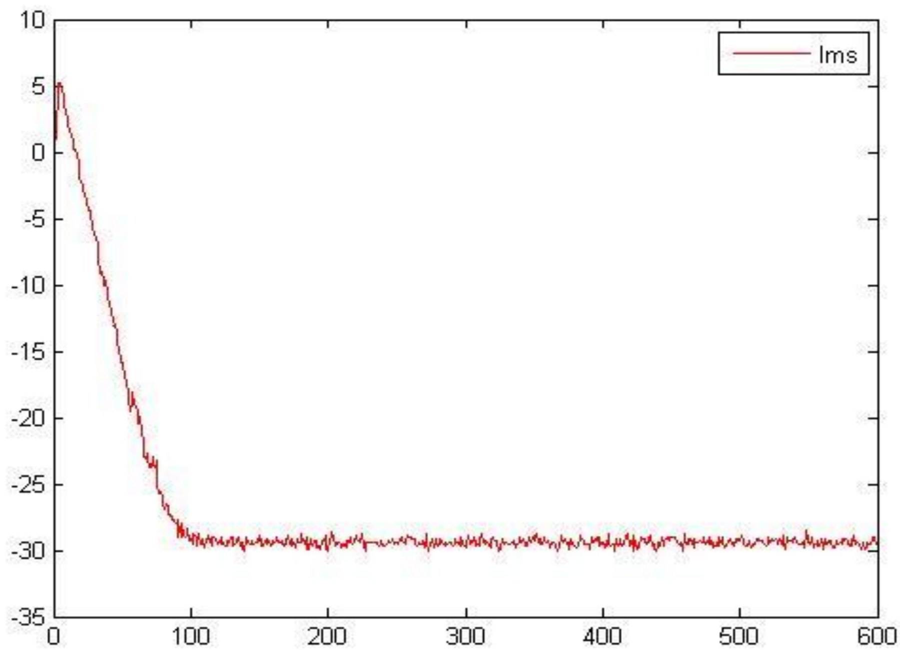


Fig 4.2: LMS error graph

The Least mean square error graph with the number of iteration is shown above graph. As shown in the graph with the increment of iteration the least mean square error is reduced suddenly which depends upon the learning factor μ.

Recursive Least Square Technique(RLS Technique): The RLS (Recursive least square) Algorithm is the algorithm which used to find the filter coefficient that used to minimization of the weights with linear least square cost factor depending upon the input signal with help of recursion. RLS like LMS used to reduce the cost factor or mean square error.[4]

In defining the RLS the input patterns are considered deterministic signal not like the case of LMS technique in which they are considered to be stochastic. On comparing to other similar techniques RLS produce extremely fast convergence speed. But this high convergence speed comes at the cost of a lots of computation complexity. So there is trade off in the speed of convergence and computation complexity of RLS algorithm with some similar cost factor reduction algorithm.

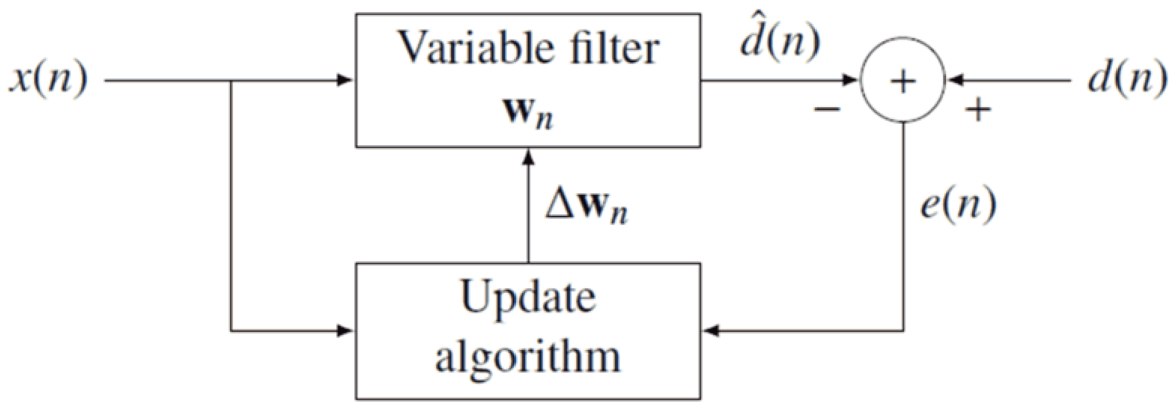


Fig 4.3: Block diagram of RLS algorithm

RLS Algorithm Derivation: Recursive Least square (RLS) algorithm for RLS filter is defined as

Take a zero mean variable randomly d with realization {d (0), d (1)…..}, and a randomly zero mean vector for row u with realization $\{u_{0,}, u_1, ...\}$. The optimal weight factor w^0 that gives

$$\min W|d - uw|^2$$

Can be considered iteratively via the recursion

$$S_i = \lambda^{-1}[S_{i-1} - \frac{\lambda^{-1}S_{i-1}u_i{}^*u_iS_{i-1}}{1 + \lambda^{-1}u_iS_{i-1}u_i{}^*}]$$

$$w_i = w_{i-1} + S_iu_i{}^*[d(i) - u_iw_{i-1}], \ \ i \geq 1$$

With initial condition $S_{-1} = e^{-1}I$ and where $0 \ll \lambda \leq 1$

The mathematical computation cost of RLS is one order greater than computation cost of LMS.

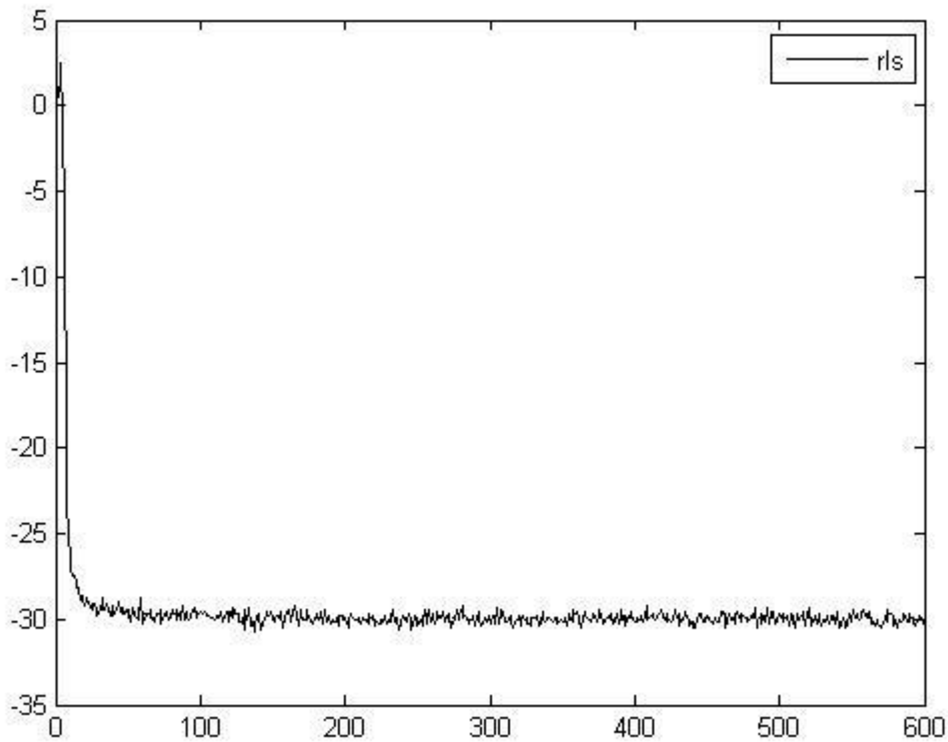


Fig 4.3: Recursive Least Square Error Graph

Comparison between the computation cost of RLS and LMS is shown in following table

Algorithm	Multiplications	Additions	Division
LMS	8N+2	8N	
RLS	$N^2 + 5N + 1$	$N^2 + 3N$	1

Table 4.1: Comparison between RLS and LMS techniques

As shown in the above comparison between RLS and LMS algorithm the computation speed of RLS is much greater then LMS so RLS converges with a very fast rate but in terms of mathematical complexity RLS have some restrictions as mentioned in above table RLS is one more step complex than RLS. So there is a tradeoff between the speed of response and computation complexity of RLS and LMS.[3]

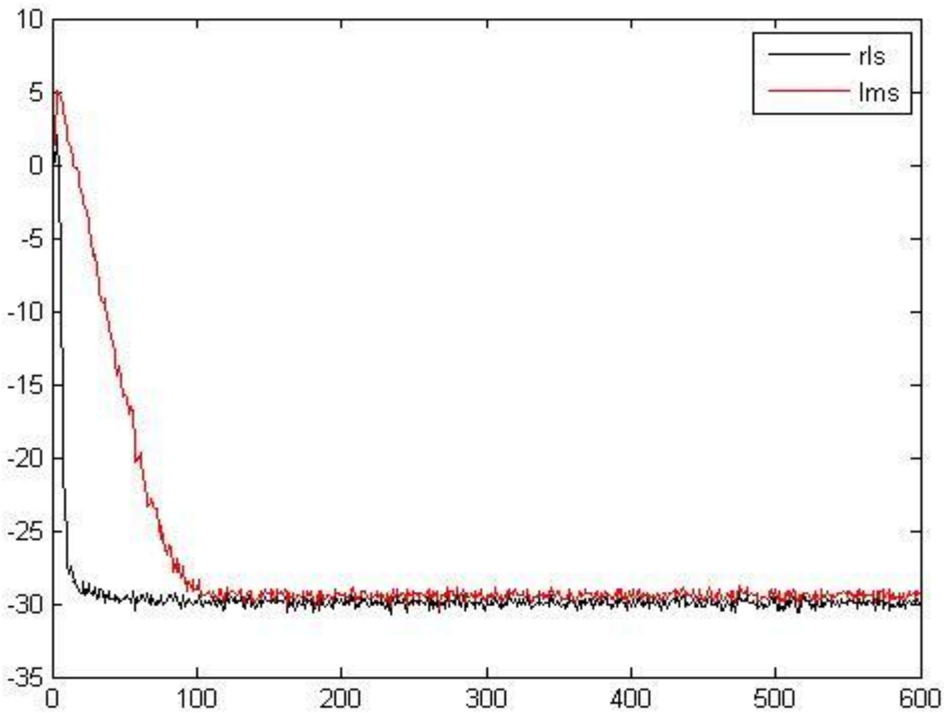


Fig 4.4: Comparison graph of LMS and RLS

For 600 hundred iterations the LMS and RLS algoritm graph is plotted ans as sail earlier graph shows the result that RLS graph (Black) converges with the faster speed and mean square error becomes minimum under the 20 -30 iterations not like the case of LMS (Red) which takes some moe time to minimize the error or in athor word have slow response.

CHAPTER 5

System Identification using FLANN and MLP

- Introduction
- Simulation Study
- Learning Algorithm
- Static System Identification
- Dynamic System identification

Introduction: In industries we have to deal with the many dynamic complex plant. So identification of such very complex nature dynamic plant is area of concern in the control theory because we have to identify the system first then only the controlling operation of the plant can be done. So we need a good and feasible solution for such type of identification problem for automatic control industries. Such as to continue to work with more and more complex environment we need some effective solution for such type of problem.[1,3]

The ability of neural networks to approximate large classes of nonlinear functions sufficiently accurately make them prime candidates for use in dynamic models for the representation of nonlinear plants. The fact that static and dynamic back-propagation methods can be used for the adjustment of their parameters also makes them attractive in identifiers and controllers. In this section four models for the representation of SISO plants are introduced which can also be generalized to the multivariable case.

Simulation Study: Simulation study for the FLANN and MLP network is given below. The four models of discrete-time plants studied can be described by the following nonlinear difference equations:

Model 1:

$$y_p(\text{k+1})= \sum_{i=0}^{n-1} \alpha_i \, y_p(\text{k-1}) + g\,[u\,(k), u\,(k-1)\ldots,(k-m+1)]$$

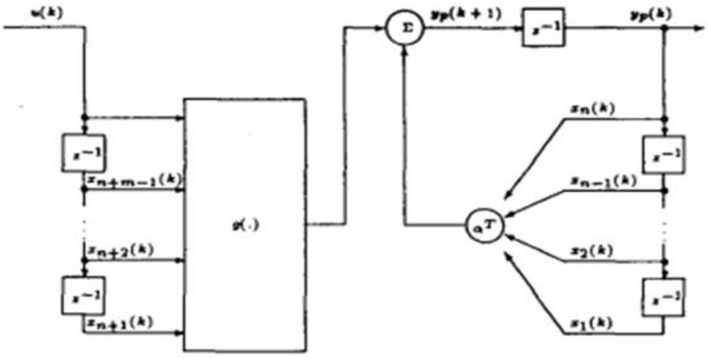


Fig 5.1: Block Diagram for model 1

Model 2

Difference equation for the model 2 is given by

y_p(k+1)=f[$y_p(k)$,$y_p(k-1)$……..y_p(K-n+1)] +$\sum_{i=1}^{m-1} \beta$u (k-i)

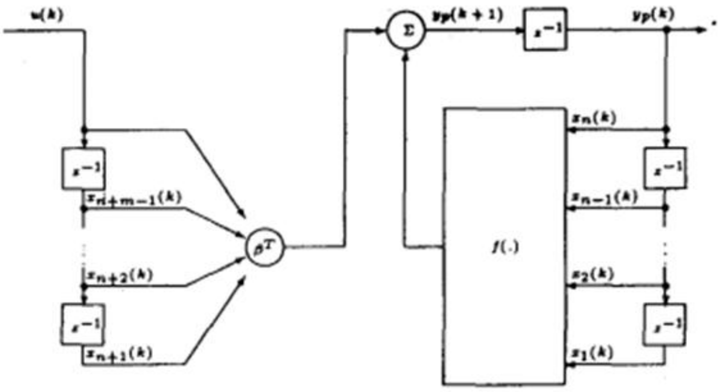


Fig 5.2: Block Diagram for model 2

Model 3:

y_p(k+1)=f $[y_p(k), y_p(k-1) \ldots \ldots.., y_p$(k-n+1)] +$g[u(k), u(k-1), \ldots..u(k-m+1)]$

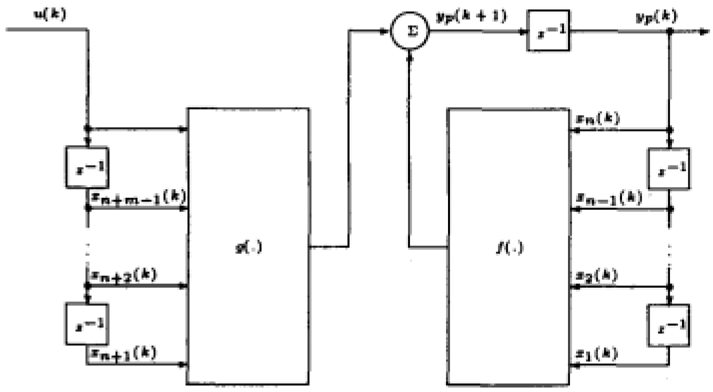


Fig 5.3: Block Diagram for model 3

Model 3:

y_p(k+1)=f [$y_p(k)$,$y_p(k-1)$........y_p(K-n+1)+[$u\ (k)$, $u(k-1)$,…..$u(k-m+1)$]

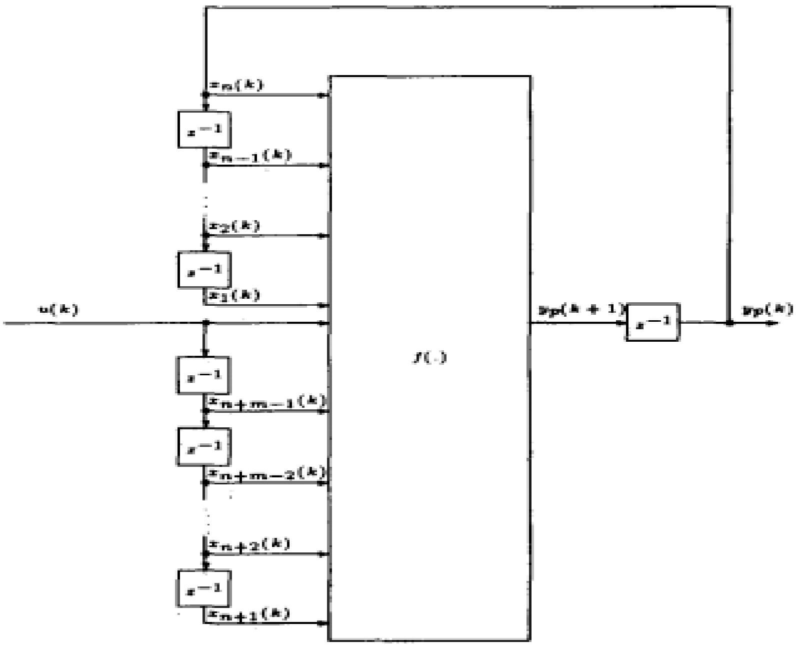


Fig 5.4: Block Diagram for model 4

The Learning Algorithm

Let number of patterns be applied to the network in a sequence repeatedly. Let the training sequence be denoted by $\{X_k, y_k\}$and the weight of the network by W(k); where is the discrete time index given by k=k+αk ;for all α=0,1,2,3 ….; and k=0,1,2,3,…….K:

Weight updates Equation:

W (k+1) =W (k) + $\mu\delta$(k)φX(k)

Where W (k) = $[w_1(k), w_2(k), w_3(k) \ldots . w_m(k)]$'

Static System:

For the 1-20-10-1 MLP structure following four systems is identifies and the nonlinear function used is the sigmoid function.

$$f_1(u) = 1.2u^3 + 0.55u^2 - 0.435u$$

$$f_2(u) = 0.5\sin(\pi u) + 0.3\sin(3\pi u) + 0.1\sin(5\pi u)$$

$$f_3(u) = \frac{6u^3 - 1.4u^2 - 3.2u + 1.5}{0.6u^5 + 0.9u^4 - 1.4u^4 + 1.0u^3 + 0.2u^2 - 2}$$

$$f_4(u) = 0.7sin^3(\pi u) - \frac{3.0}{u^3 + 2.0} - 0.3\cos(4\pi u) + 1.2$$

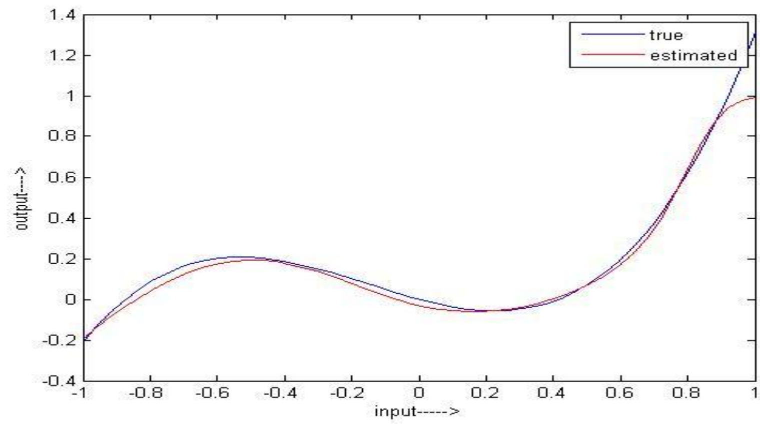


Fig 5.5 Result for f_1 using MLP

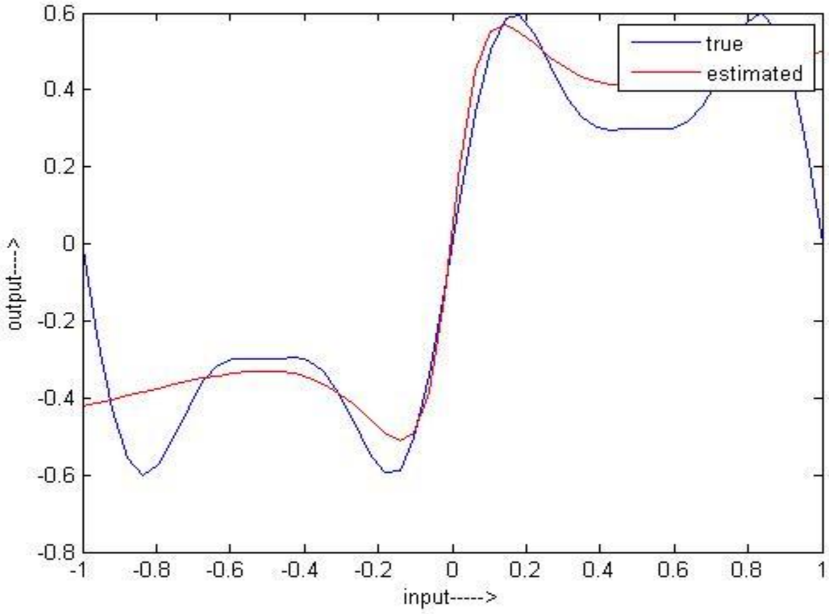


Fig 5.6 Result for f_2 using MLP

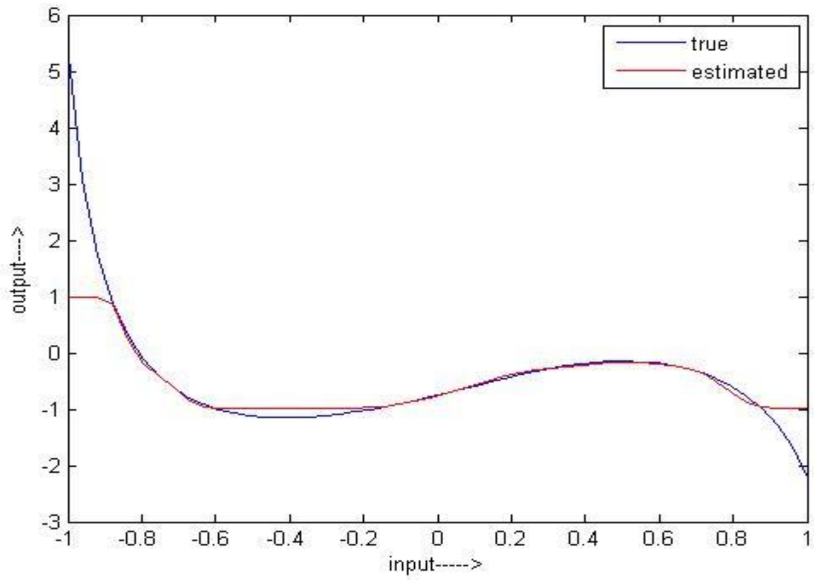


Fig 5.7 Result for f_3 using FLANN

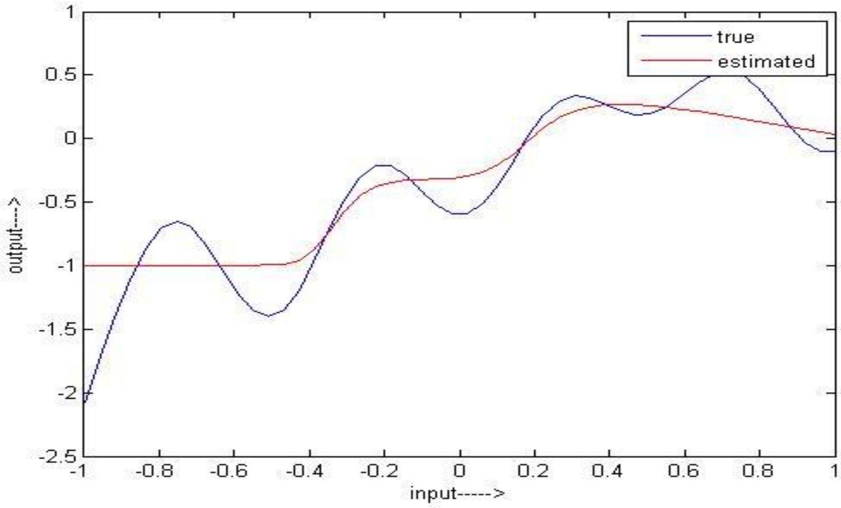


Fig 5.8 Result for f_4 using FLANN

Dynamic System:

In Dynamic System following non Linear functions are used along with the delays. So the past inputs are fed back to the present outputs.[1]

$f_1(u) = u^4 + 0.5u^3 - 0.6u^2$ …………………………………………….. (1)

$f_2(u) = 0.8\sin(\pi u) + 0.7\sin(4\pi u) + 0.2\sin(6\pi u)$ …………(2)

$f_3(u) = \frac{5u^3 - 0.8u^2 - 1.2u + 1.2}{0.9u^5 + 0.6u^4 - 1.4u^3 + 0.6u^2 - 5.0}$ …………………………………………… (3)

$f_4(u) = 0.8sin^3(2\pi u) - \frac{2.0}{u^3 + 2.0} - 0.7\cos(7\pi u) + 3.5$ ……… (4)

For 20000 Iterations the weights of neural networks are updated. Then testing of this network is done with the help of 600 iterations of the following sinusoidal signal.

U (k) =sin ($^{2\pi k}/_{250}$) for k≤ 250 ……………………………………… (5)

U (k) =0.8sin ($^{2\pi k}/_{250}$) +0.2sin ($^{2\pi k}/_{25}$) for k≥ 250 …………. (6)

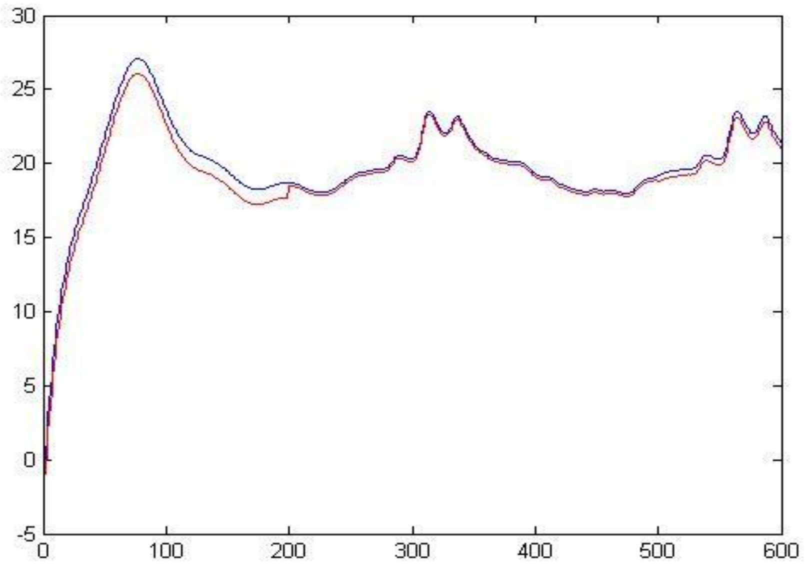


Fig 5.9 Result for f_1 using MLP

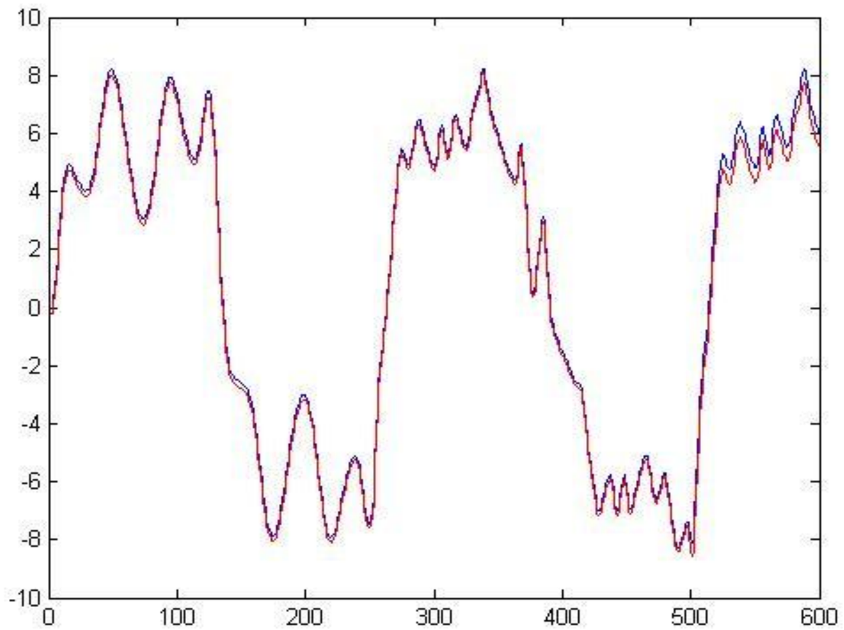


Fig 5.10 Result for f_1 using MLP

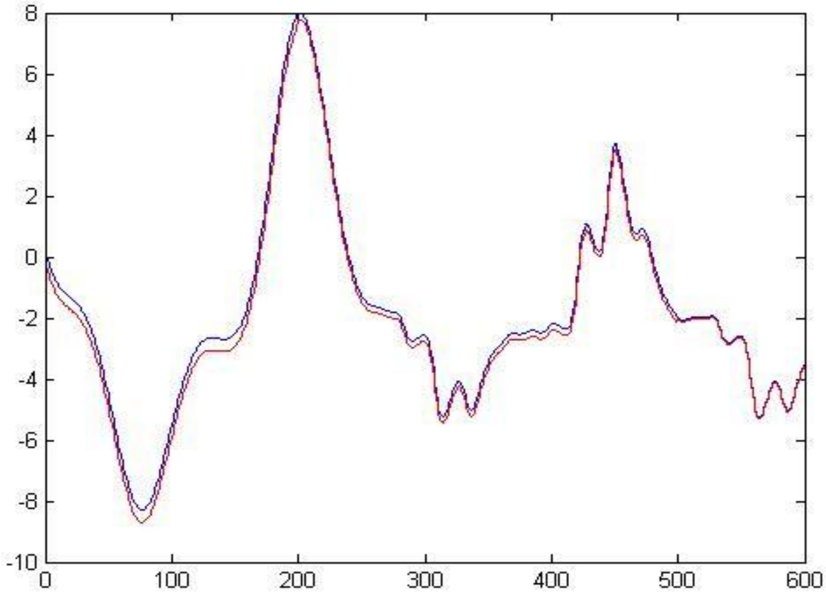


Fig 5.11 Result for f_1 using FLANN

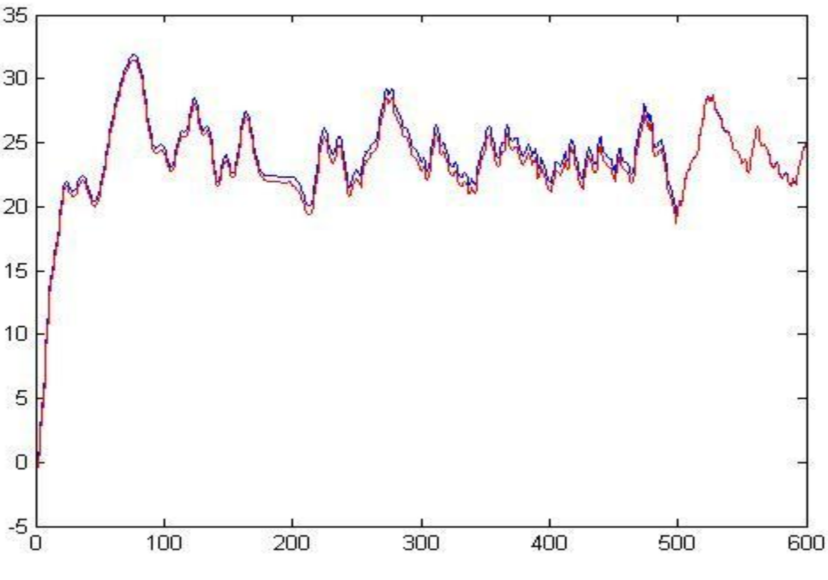


Fig 5.12 Result for f_1 using FLANN

System Identification approximation models have been discussed by the following example and comparison between them is given further.

CHAPTER 6

Conclusion and Future Work

- Conclusion
- Future Work

Conclusion:

A MLP and the FLANN structure is studied with the help of several example. As seen in the table below the computation complexity of the FLANN structure is much less than the MLP structure. Number of addition, multiplications and sinusoidal and cosine function is shown in the table below

OPERATION	MLP	FLANN
Addition	2IJ+3JK+3K	2K(D+1)+K
Multiplication	3IJ+4JK+3J+5K	3K(D+1)+2K
tanh(.)	J+K	K
cos(.),sin(.)	-	I

Table 6.1 Comparison of computation complexity between FLANN and MLP

Future Work:

1. To Simplify the computation complexity of MLP structure with Functional Link layer Artificial Neural Network
2. To reduce the nonlinearity pressure sensors with the help of artificial neural networks.
3. To reduce the nonlinearity of LVDT by using ANN.

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DISSEMINATION OF THE RESEARCH WORK

Prateek Mishra and Avinash Giri, " Review of System Identification Techniques using Neural Network Techniques" proc. of ITR international Conference on electrical electronics and data communication (ICEEDC-2014), April 2014, Bhubaneshwar India