A Review on ANFIS based Linearization of Nonlinear Sensors

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Abstract*: Low cost sensors with high sensitivity, better resolution and linear characteristics are required for industrial applications based on instrumentation and control. Unfortunately, the natural non-linear characteristics of the sensor itself, as well as the dynamic nature of the environment, the aging effect, the inherent noise of the sensor and the data loss due to transients or intermittent faults affects the sensor characteristics non linearly. Since the transfer characteristics of most sensors are non-linear in nature, the processing of data from such a non-linear sensor using an optimized system has always been a design challenge. Linearization of nonlinear sensor characteristic in digital environment, is a vital step in the instrument signal conditioning process. This paper gives a brief review about how to overcome this nonlinear characteristic of the sensor using artificial intelligence such as Hybrid Neuro Fuzzy Logic (HNFL) based on digital linearization technique using VLSI technology such as Field Programmable Gate Array (FPGA).

***Keywords*: Sensor Linearization, ANFIS, VLSI, FPGA.**

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I. INTRODUCTION

Sensors are the fundamental elements which are used in most of the measurement circuits to monitor the physical quantity or to give a feedback signal to the control unit. Sensors generally provide analog output, which may sometimes exhibit non-linear behavior. It is essential to have linear characteristics of the sensor as it improves the performance of the system[1]. Process control systems are often non-linear in nature and tend to change in an unpredictable way[2]. Low cost sensors with high sensitivity, improved resolution and linear characteristics are needed for industrial applications based on instrumentation and process control systems[3]. Due to the dynamic nature of the environment, the inherent noise of the sensor, the aging effect, the data loss due to transients or intermittent faults affects sensor characteristics nonlinearly. Linearization of this non-linear behavior of sensors has always been a design challenge. Linearization of the nonlinear sensor in the digital environment is a vital step in the signal conditioning process of the instrument[4].

Linearization of the characteristics of non-linear sensors is often a complex and computationally intensive task. It is for this reason that Neural Networks and Fuzzy Systems, two branches of artificial intelligence, are gaining widespread acceptance in the field of learning and intelligent control. This is mainly due to their natural parallelism, their ability to learn and adjust and, to some degree, their enhanced tolerance for faults. Apart from the above mentioned benefits, Fuzzy Control has a disadvantage that you need to set new control laws and membership functions every time the system changes. Similarly, the neural network has a drawback that while learning, it can easily fail at a local minimum instead of a global minimum, and it also takes a lot of time to get as many neurons to learn as it makes the system complicated.

In order to make up for the defects, research on integration of neural network and fuzzy logic that is Hybrid Neuro-Fuzzy Logic (HNFL) is under way. The proposed HNFL is an intelligent system that combines the qualitative knowledge of symbolic fuzzy rules with the learning capabilities of neural networks.

Unlike dedicated hardware, the FPGA system is flexible because it can be easily reconfigured by the end user and reused for many different designs. It also enables rapid prototyping by synthesizing the desired system with the appropriate Electronic Design Automation (EDA) tool. In contrast to general purpose processors, the FPGA actually constitutes the logic circuit required to implement the desired algorithm instead of a sequence of instructions on predefined hardware resources. Thus, higher efficiency than general purpose processors can be achieved. The FPGA-based system is also useful because it can significantly reduce development time. Designs are described in a hardware description language such as VHSIC hardware description language (VHDL) and are verified by simulation. Due to these useful features, we have chosen the reconfigurable FPGA systems as the implementation platform for the proposed HNFL. When FPGA-based system is used for implementing the desired HNFL, several alternative designs can be evaluated with the aid of FPGA. Many of the existing EDA modeling, synthesis, verification and implementation tools support the hardware implementation of the FPGA-based system. E.g. Synopsys's FPGA Complier, Xilinx's

F1.3 Project manager, VCC Corporation's Hardware Object Technology.

II. LINEARIZATION TECHNIQUES

Sensors often exhibit nonlinear transfer characteristics, requiring linearization. Typical nonlinear characteristics of sensors are exponential (*e.g.* thermistors [5]), sinusoidal (*e.g.* GMR sensors [6]), or tangential (*e.g.* LMTs [7]). The choice of an ample linearization method is crucial for the overall performance of the system. Several techniques have been proposed to linearize sensor characteristics. They can be classified into four groups: Analog, Software, Mixed Signal and Digital.

A. Analog Linearization Techniques

Analog linearization techniques are generally simpler and are often used to improve the linearity of the sensor characteristics. Their main drawbacks are sensitive to temperature drift, gain, offset errors, lack of flexibility when a different kind of sensor is employed, and that accuracy is high only in a small input range. Hence, they are usually the preferred choice in low cost, low performance applications where linearized output is required in analog form [8].

B. Mixed Signal Linearization Techniques

Mixed-signal techniques are especially suited to applications where the sensor signal has to be transformed to digital form and where the signal processing overhead of digital linearization in terms of silicon area, processing time and power consumption needs to be reduced. For example, this may be the case in low-cost integrated sensor interfaces where reasonable performance must be achieved at the minimum silicon cost [8].

C. Software based Linearization Algorithms Techniques

It has been observed that regular mathematical approaches do not provide the acceptable non-linearity prediction results, since an accurate mathematical model, including all sources of error, is rarely known. So, linearization could obviously be implemented either by means of a look up table or software based specific algorithm. However, in many cases, direct computation of the polynomial method is more accurate but requires a longer time for computation, while the look-up table method, though faster, is not very accurate [9].

D. Digital Linearization Techniques

After performing rigorous literature survey, it has been observed that the digital techniques are more flexible, accurate and faster [8]. However, due to the advances in digital VLSI circuits, the digital techniques can be implemented in dedicated FPGA based hardware, which is programmed to achieve the required functionality [10]. Recently, application of hybrid neural networks and fuzzy logic in the field of instrumentation and measurement has emerged as a promising field of research. The modelling capability of hybrid neuro-fuzzy systems has been demonstrated by S. N. Engin et al. [11]. A non-linear system can be modeled very precisely by means of data taken from mathematical model using Adaptive Neuro-Fuzzy Inference System (ANFIS) [12]. The direct modeling technique shown in Fig 1, can be used to estimate the nonlinearity parameters of the sensor, while the inverse modeling technique shown in Fig 2, can be used to estimate the applied input to the sensor, which is used to linearize the sensor, for direct digital readout [13].

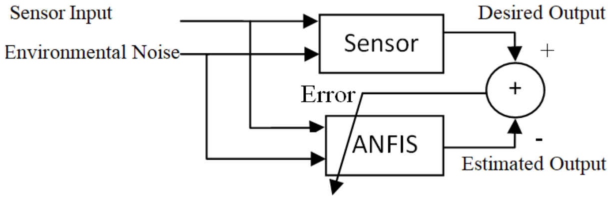

Fig. 1. ANFIS based direct modelling of sensor.

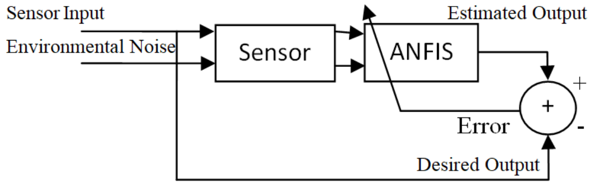

Fig. 2. ANFIS based inverse modelling of sensor.

FPGAs are part of the programmable logic component family, allowing millions of gates to be designed on a single chip, and high-level design techniques have made it possible to create very complex networks [14]. Hybrid Neuro Fuzzy Logic networks can be implemented on a reconfigurable architecture such as FPGA with speed of performance, area of fabrication and precision closer to Application Specific Integrated Circuits [15]. Compensation of several interference and linearization parameters using precise schemes can be achieved by ANNs [16] and Fuzzy Logic networks [10].

III. SENSOR CHARACTERISTICS LINEARIZATION

A. Proposed System

A plan for HNFL based smart sensor is shown in Fig. 3. The nonlinear output of the sensor will be given to the signal conditioning block and then applied to a precise Analog to Digital Converter (ADC) where the analog data will be converted in to an equivalent digital form. The converted digital data will be processed (linearized) by an HNFL. Digital to Analog Converter (DAC) will be used to reconstruct the linearized output [13].

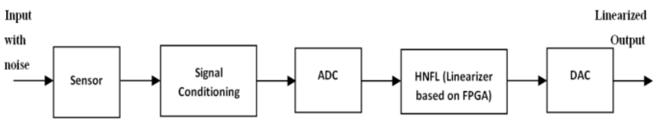

Fig. 3. Proposed System

B. System Implementation

Implementation of this whole sensor linearization process can be divided into three major parts such as Hardware, Training of HNFL and Software.

1) Hardware: The actual system block diagram is shown in Fig. 4 and Fig. 5 shows the actual implemented system. The NTC thermistor, 1K resistor and +5V voltage source are connected in series and this configuration is a voltage divider circuit. The non linear analog voltage across 1K resistor is given to the ADC (MCP 3202). Further the digital output of ADC is given to the digital device named Waxwing Spartan 6 FPGA (XC6SLX45) Development

Board. An ANFIS is implemented in FPGA. The ANFIS takes the digital output (in non linear form) from ADC and processes it and gives a linearize digital signal, which is further given to DAC (MCP 4921) and personal computer. Subroutines were developed in VHDL code and then implemented in Waxwing Spartan 6 FPGA Development Board, so that digital device FPGA can communicate with ADC, DAC and personal computer. In personal computer, graphical programming language such as LabVIEW is used for simulation and real time data acquisition and storage.

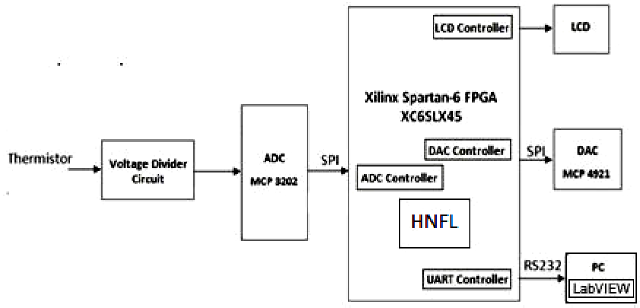

Fig. 4. Actual System Block Diagram

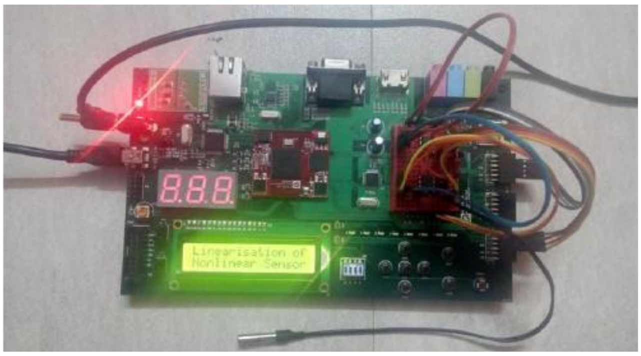

Fig. 5. Actual System

The schematic of voltage divider circuit is shown in Fig 6.

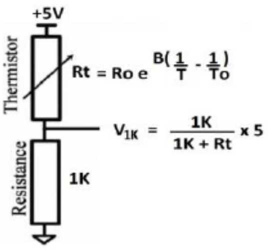

Fig. 6. Schematic of voltage divider circuit

The thermistor used in a voltage divider circuit is a NTC Thermistor whose resistance R_T at temperature T can be modeled by

$$R_T = R_O \, \mathrm{e}\,xp\left[\beta\left(\frac{1}{T} - \frac{1}{T_O}\right)\right] \quad (1)$$

where the NTC thermistor used in this work has R_O = 10,000 ohms, is the resistance at a reference temperature T_O = 298 K (25 °C) and β = 3950, with a tolerance of ±10%.

2) Training of HNFL: Using a given input/output data set, the ANFIS build a Takasi-Sugeno-Kang (TSK) fuzzy inference system (FIS) whose membership functions parameters are adjusted using backpropagation and/or gradient algorithms. This allows the fuzzy system to learn from the data set of the modeled system. The computation of these parameters is assured by gradient vector, which provides a measure of how well the fuzzy inference system is modeling the input/output data for a given set of parameters. Many different methods were analyzed by making changes in the type and number of input membership functions and the type of output membership function. Table-I represents learning phase results for different approaches. The error between the ANFIS output and sensor's inverse characteristic output represents mean square errors (MSE).

Analysis of the learning phase results presented in Table I guide us to choose the method highlighted in gray; two input triangle membership functions and two linear output membership functions with three parameters each one.

TABLE I. LEARNING PHASE RESULTS

Input Membership		Training Method	Output Membership Type	Error	Epoch
Type	Number				
Triangle	2	Hybrid	Constant	0.089562	500
			Linear	0.042277	200
		Back Propagation	Constant	0.10639	500
			Linear	0.20319	500
	3	Hybrid	Constant	0.065469	250
			Linear	0.069862	50
		Back Propagation	Constant	0.073769	500
			Linear	0.066717	500
	4	Hybrid	Constant	0.028184	100
			Linear	0.039662	20
		Back Propagation	Constant	0.035134	500
			Linear	0.031191	500
Trapeze	2	Hybrid	Constant	0.052064	300
			Linear	0.043712	200
		Back Propagation	Constant	0.051347	500
			Linear	0.14182	500
	3	Hybrid	Constant	0.043692	200
			Linear	0.018114	200
		Back Propagation	Constant	0.044042	500
			Linear	0.040508	500
	4	Hybrid	Constant	0.032136	200
			Linear	0.0081451	220
		Back Propagation	Constant	0.034315	500
			Linear	0.029078	500
Bell Shape	2	Hybrid	Constant	0.068148	500
			Linear	0.029257	500
		Back Propagation	Constant	0.11602	500
			Linear	0.17479	500
	3	Hybrid	Constant	0.014575	500
			Linear	0.0094959	230
		Back Propagation	Constant	0.066668	500
			Linear	0.032527	500
	4	Hybrid	Constant	0.0080987	500
			Linear	0.0068352	120
		Back	Constant	0.063041	500

		Propagation	Linear	0.026443	500
Gauss	2	Hybrid	Constant	0.21132	500
			Linear	0.044937	500
		Back Propagation	Constant	0.23609	500
			Linear	0.2041	500
	3	Hybrid	Constant	0.059039	500
			Linear	0.017174	420
		Back Propagation	Constant	0.12191	500
			Linear	0.041409	500
	4	Hybrid	Constant	0.018454	500
			Linear	0.010377	250
		Back Propagation	Constant	0.12445	500
			Linear	0.036323	500
Gauss2	2	Hybrid	Constant	0.074492	500
			Linear	0.027118	500
		Back Propagation	Constant	0.11443	500
			Linear	0.17679	500
	3	Hybrid	Constant	0.03082	500
			Linear	0.016948	100
		Back Propagation	Constant	0.083049	500
			Linear	0.055935	500
	4	Hybrid	Constant	0.0150537	500
			Linear	0.0089628	400
		Back Propagation	Constant	0.062011	500
			Linear	0.030194	500

Table II illustrate the parameters obtained in the learning phase of the ANFIS.

TABLE II. PARAMETERS FOR ANFIS ARCHITECTURE

Input Membership			Output Membership		
Tri_1	a	-3.13	f_1	p	0
	b	-35		q	4.5
	c	5.169		r	-0.03
Tri_2	a	0.21	f_2	p	0
	b	3		q	1.225
	c	6.305		r	0.5

3) Software : Software such as LabView, Matlab, Xilinx, etc., will be used to develop an HNFL based intelligent and robust linearizer.

C. Linearization ANFIS Architecture

ANFIS architecture for linearization of nonlinear sensor's characteristic is illustrated by Fig. 7.

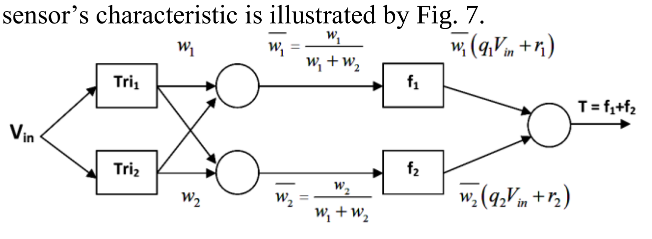

Fig. 7. ANFIS Architecture for Linearization

As is shown in Fig. 7, the final output of the ANFIS linearizer is given by (2) and the expression of the $Tri_i(x)$ function is given by (3).

$$f = \frac{(q_1x+r_1)Tri_1(x)+(q_2x+r_2)Tri_2(x)}{Tri_1(x)+Tri_2(x)} \tag{2}$$

$$Tri_i(x) = \begin{cases} 0 & if\ x \le a_i \\ \frac{x-a_i}{b_i-a_i} = \frac{1}{b_i-a_i}x - \frac{a_i}{b_i-a_i} & if\ a_i \le x \le b_i \\ \frac{c_i-x}{c_i-b_i} = \frac{-1}{c_i-b_i}x + \frac{c_i}{c_i-b_i} & if\ b_i \le x \le c_i \\ 0 & if\ c_i \le x \end{cases} \tag{3}$$

Hence, for the implementation of ANFIS linearizer, two circuits each for the expressions given by (2) ($f_1(x)$ and $f_2(x)$) and (3) ($Tri_1(x)$ and $Tri_2(x)$) are required. Here q, r, a, b and c are the parameters obtained in the learning phase of the ANFIS.

A new optimal neuro-fuzzy architecture is implemented on FPGA, only eight multipliers, six adders, two subtractor, S^{-1} circuit and a small size ROM is required. Fig. 8 and Fig. 9 shows the functional diagram of the digital ANFIS and state machine diagram for the control unit.

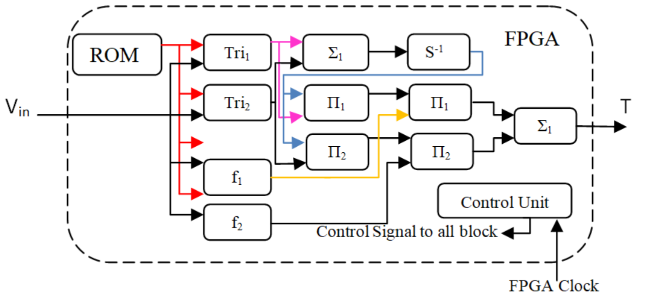

Fig. 8. Functional diagram of the digital ANFIS

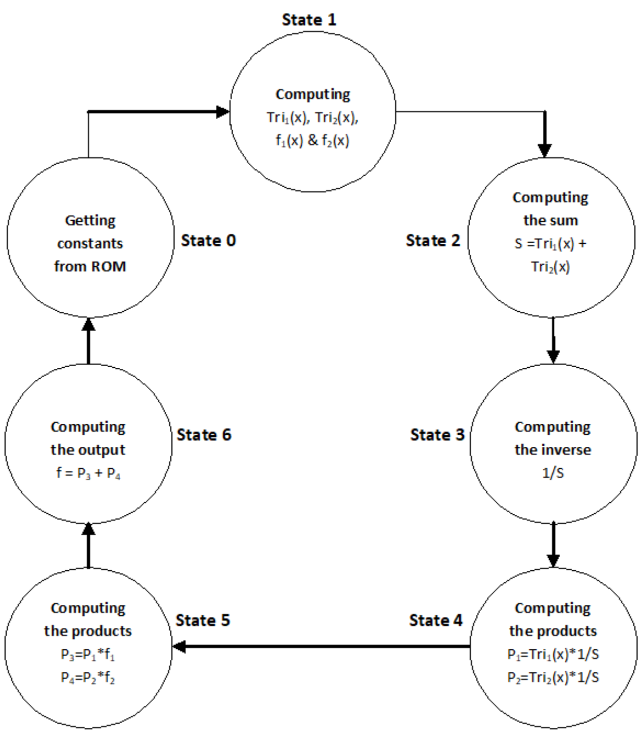

Fig. 9. State Machine Diagram

Table III illustrate Xilinx Synthesis Report summary for ANFIS.

TABLE III. XILINX SYNTHESIS REPORT

Device Utilization Summary			
Slice Logic Utilization	**Used**	**Available**	**Utilization**
Number of Slice Registers	4259	54576	7%
Number of LUTs	251	27,288	19%
Number of occupied Slices	1734	6,822	25%
Number of MUXCYs	2992	13,644	21%
Number of bounded IOBs	26	218	11%
Number of DSP48A1s	0	58	0%

IV. RESULT AND DISCUSSION

FPGA based thermistor signal linearizer has been developed by using HNFL with minimum resources and without much loss in speed. Fig. 10 shows simulation results for one set of input and output membership functions. Fig. 11 shows the real time linearization of thermistor characteristics. The results obtained from the FPGA validate the LabVIEW simulation.

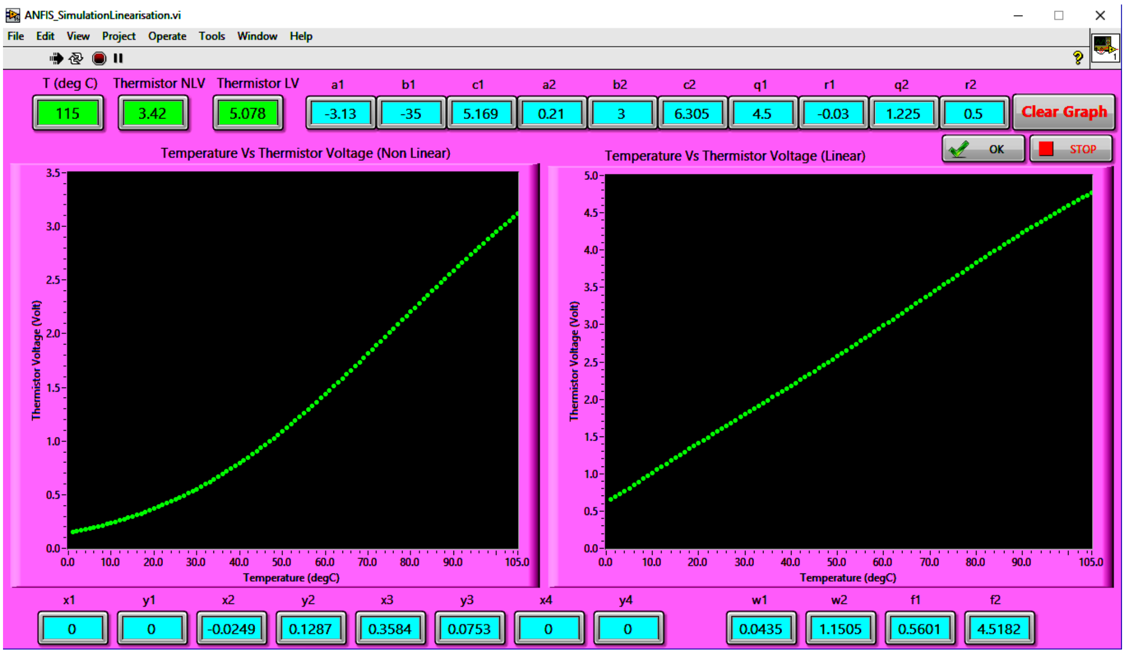

Fig. 10. Front panel of simulation software

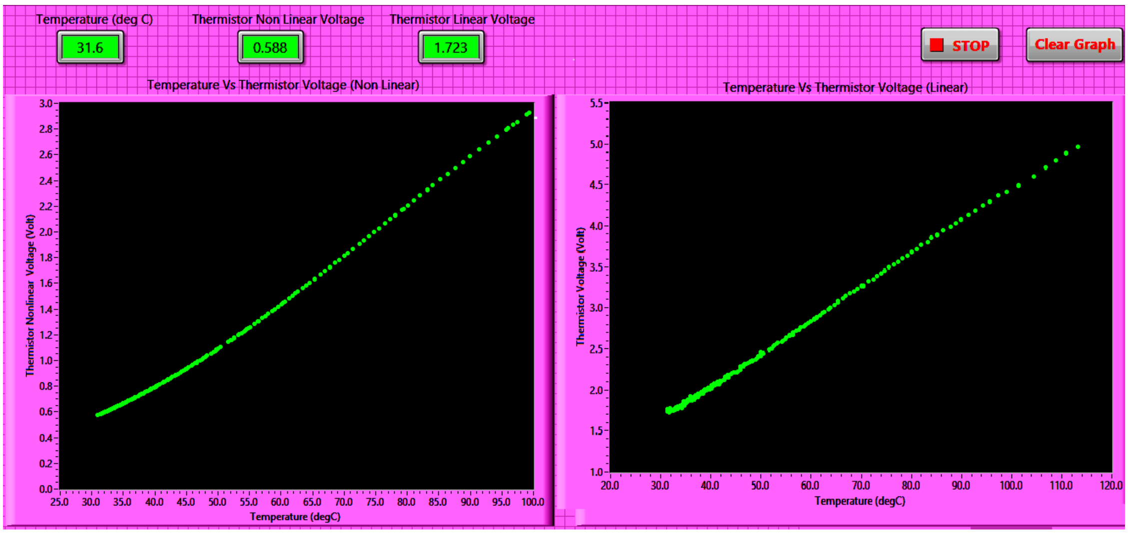

Fig. 11. Front panel of real time data acquisition software

The values extracted from the saved data files are used to trace the graphs of Fig. 12 and Fig. 13. Fig. 12 and 13 shows the simulated and hardware ANFIS model linearized output respectively. Fig. 14 shows the error between the simulated model and hardware ANFIS model. These graphs shows a maximum error in absolute value of 2.8×10^{-2} °C between the simulated model and ANFIS FPGA model.

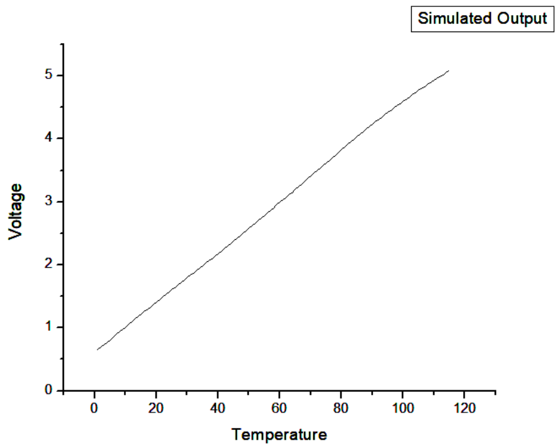

Fig. 12. Simulated Linearized Output

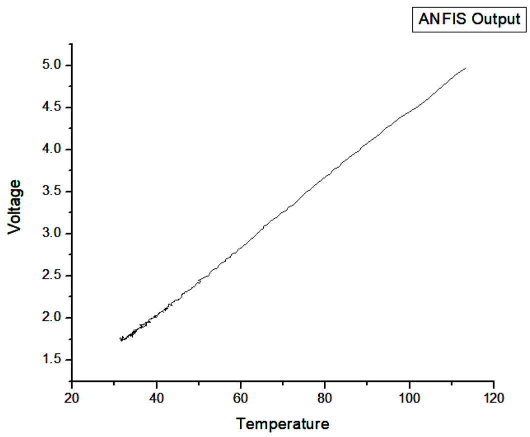

Fig. 13. Hardware ANFIS Linearized Output

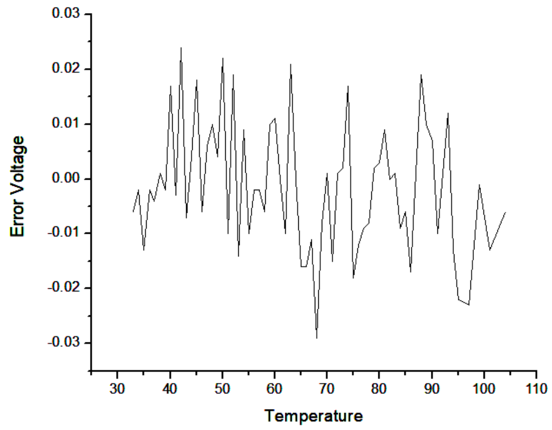

Fig. 14. Error between simulated and designed linearizer

With the same data sets (over than 1800 data values) and for the same precision, the consumption in term of hardware resources using FPGA is reduced to 40% comparing to the technique using the look up table and 55% with using polynomial interpolation technique [9] resulting in significant increase in the speed.

V. CONCLUSION

The proposed system for the ANFIS based linearizer is very much helpful in smart sensor; it will be possible to implement sensors with linearized output digital code. This solution for linearization of nonlinear sensor characteristics appears to be of lower cost and appropriate for VLSI integration, with or without the sensor. This paper may be further extended to realize others nonlinear ANFIS applications such as curve fitting, sensor fault detection and isolation, sensor drift compensation, etc. For many other non-linear sensor applications, a change in ROM values is needed to reconfigure the circuit without altering the basic design architecture.

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