SIMULATION STUDIES ON A NEW INTELLIGENT SCHEME FOR RELATIVE HUMIDITY AND TEMPERATURE MEASUREMENT USING THERMISTORS IN 555 TIMER CIRCUIT

Debangshu Dey and Sugata Munshi*

Department of Electrical Engineering. , Jadavpur University

Kolkata-700032, India.

debangshudey80@gmail.com , smunshi@ee.jdvu.ac.in

*Corresponding autor (Email- smunshi@ee.jdvu.ac.in)

Abstract:

This paper presents a novel and cheap electronic version of wet and dry temperature hygrometer The instrument is centered around a 555 timer, operated in astable multivibrator mode. Two thermistors with negative temperature coefficients (NTC) serve as the two timing resistors of the multivibrator. These thermistors are used to sense the dry and wet temperatures. The durations of the 'HIGH' and 'LOW' levels of the multivibrator output are detected and these values are used to predict the relative humidity and ambient temperature by an appropriately trained Artificial Neural Network (ANN). The performance of the arrangement has been evaluated by numerical simulation studies using thermistor data from manufacturer's table. Significantly good results have been obtained.

Keywords: ANN Linearizer , 555 timer, Relative Humidity, Thermistor.

1. INTRODUCTION:

The sensing of humidity is not only important for weather-related measurements, but it is also required for many industrial as well as few domestic applications. The other application areas range from textile mills, pharmaceutical industries and growing of bacteria to humidity control arrangements for humidifiers, tumble dryers, microwave ovens etc. In many of these applications, simultaneous sensing of humidity and temperature is required. However, humidity is perhaps one of the most difficult environmental parameters to measure.

Earlier, mechanical hygrometers were popularly used for humidity measurement. [1]. After electronic systems took over the reins of instrumentation and as the requirement of humidity sensing spread to newer domains (particularly for humidity control applications), the necessity of having some form of electronic humidity sensors was being felt consistently.

This prompted the development of parametric humidity sensors. Both the capacitive and resistive variety of such sensors are being extensively used. With recent advancements of these sensors, % Relative Humidity (RH) can be measured over its entire with appreciable accuracy [2-7]. Another interesting development is the electronic version of the wet and dry temperature hygrometer (psychrometer). A typical sophisticated electronic psychrometer [8] employs two quartz crystal oscillators to sense the dry and humid temperatures. The relative humidity values are stored in an EPROM, in the form of a look-up table. Frequencies of the oscillators point to the memory location containing the required humidity value, which is subsequently retrieved from this location. This arrangement enables the measurement of humidity as well as temperature of the environment at the same time. Cheaper versions of electronic psychrometers are also available, that employ two identical thermistors [9-12] for sensing the dry and the wet bulb temperatures. A more accurate one, the digital variety [13], is based on the temperature to linear voltage converter, a calculator of the dry and wet bulb temperature ratio, a converter from the ratio to the voltage proportional to RH, and an A/D converter. The maximum error of the arrangement is around 2% of full scale.

The present work is however aimed at achieving a low-cost and compact transducer for simultaneous measurement of relative humidity and temperature of an ambience. The system envisaged, consists of two thermistors with negative temperature coefficient (NTC) placed in a 555 timer circuit working in the astable mode. This forms the core of the measurement system which is without doubt cheap as well as compact. The circuit output, after further conditioning, is processed by an 'Artificial Neural Network' (ANN) which serves as the linearizer. It is worth mentioning that given the present state of the art, the ANN can be easily programmed in a microcontroller and the arrangement is thus within the means of common users.

2. THE PROPOSED SCHEME :

The 555 timer is an extremely versatile but low cost IC which serves as the basic building block of a multitude of circuits. In the present application, the IC is used in the astable multivibrator mode [14,15] and the circuit for such operation is shown in Fig. 1. It is well known that the frequency or the repetition rate of the output pulses from 555 timer circuit in astable mode is determined by the values of the two resistors R_1 and R_2 and by that of the timing capacitor C. The frequency is ,

$$f \approx \frac{1.44}{\left(R_1 + R_2\right)C} \qquad (1)$$

The duration T_1 of the HIGH level (ON time) and duration T_2 of the LOW level (OFF time) of the pulse train as indicated in Fig. 2, can be calculated as,

$$T_1 \approx 0.69\left(R_1 + R_2\right)C \qquad (2)$$

and

$$T_2 \approx 0.69 R_2 C \qquad (3)$$

It is therefore evident that for a fixed C, by measuring the durations of the HIGH and LOW level of the output pulse train, measures of R_1 and R_2 and can be obtained. If two NTC thermistors are used as resistors R_1 and R_2 for sensing the dry temperature (t_d) and wet temperature (t_W), then with the variation of humidity and temperature, R_1, and R_2 and consequently T_1 and T_2 will also change. Thus, on measuring the values of T_1 and T_2 the thermistor resistances R_1 and R_2 can be computed and a prior knowledge of the resistor temperature data of the thermistor will subsequently yield the dry (ambient) and wet temperatures, t_d and t_W respectively. From standard psychometric data, the relative humidity can then be obtained. It is worth mentioning that the value of C should be judiciously chosen so that the timer can operate within its allowed frequency range.

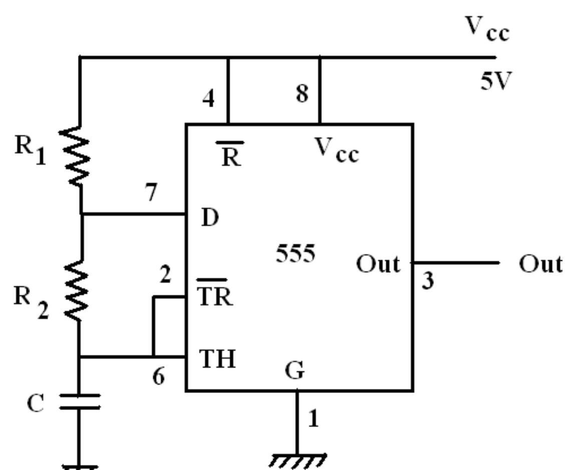

Fig.1 555 Timer in Astable Mode

Here thermistors with negative temperature coefficient have been chosen as temperature sensors since they are cheap, compact and very sensitive. However their highly nonlinear transfer characteristic (as shown in Fig. 3), and nonlinear relations between the humidity and t_d and t_W (as indicated in Fig. 4) make the automated determination of relative humidity a challenging task.

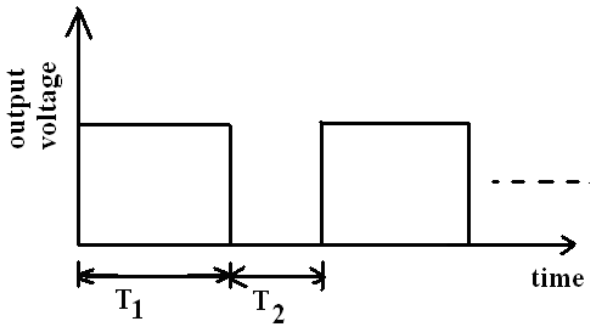

Fig. 2. Output waveform of 555 timer in astable mode

3.THE COMPLETE MEASUREMENT SYSTEM :

Block diagram representations of two possible realizations of the complete measurement setup are shown in Fig. 5.

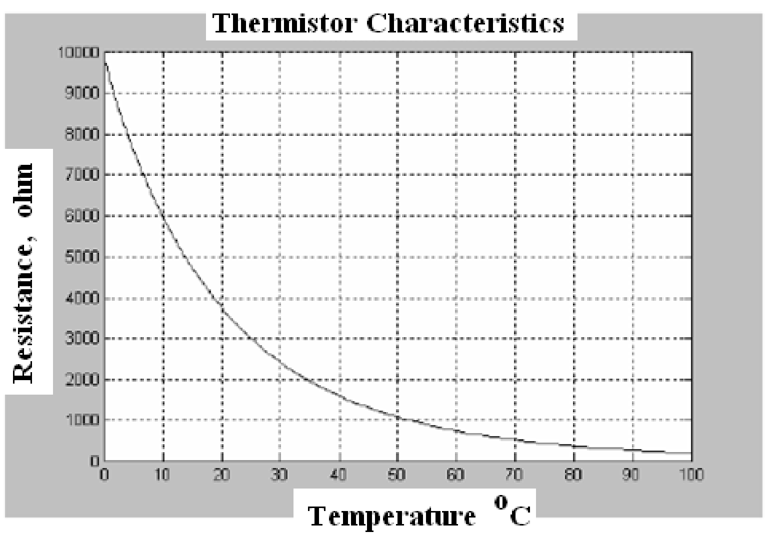

Fig.3. Resistance vs. Temperature characteristics of Thermistor

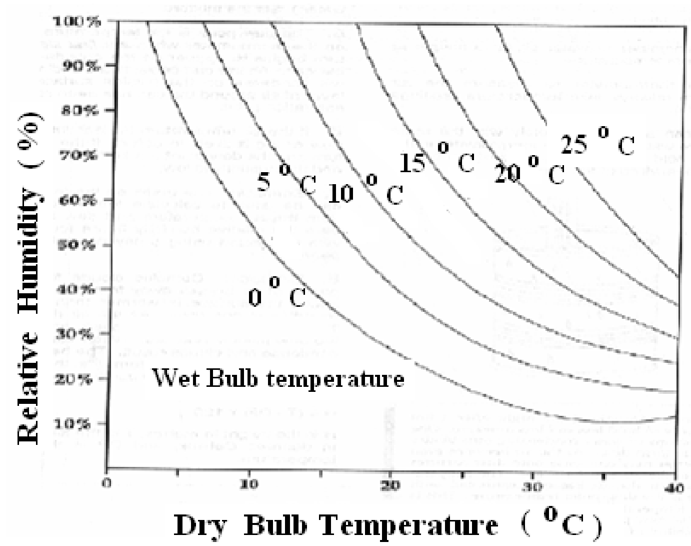

Fig.4. Psychometric Chart

The implementation depicted in Fig. 5(a) assumes that the 'ON' time and 'OFF' time values of the astable multivibrator output are extracted using digital hardware (referred to as the signal conditioning circuit) an these values are processed by ANN linearizer programmed in ANN chip. The circuit for time duration measurement usually utilizes a known high frequency pulse train and calculates the time interval under measurement by counting the number of high frequency pulses accommodated within such interval [16, 17].

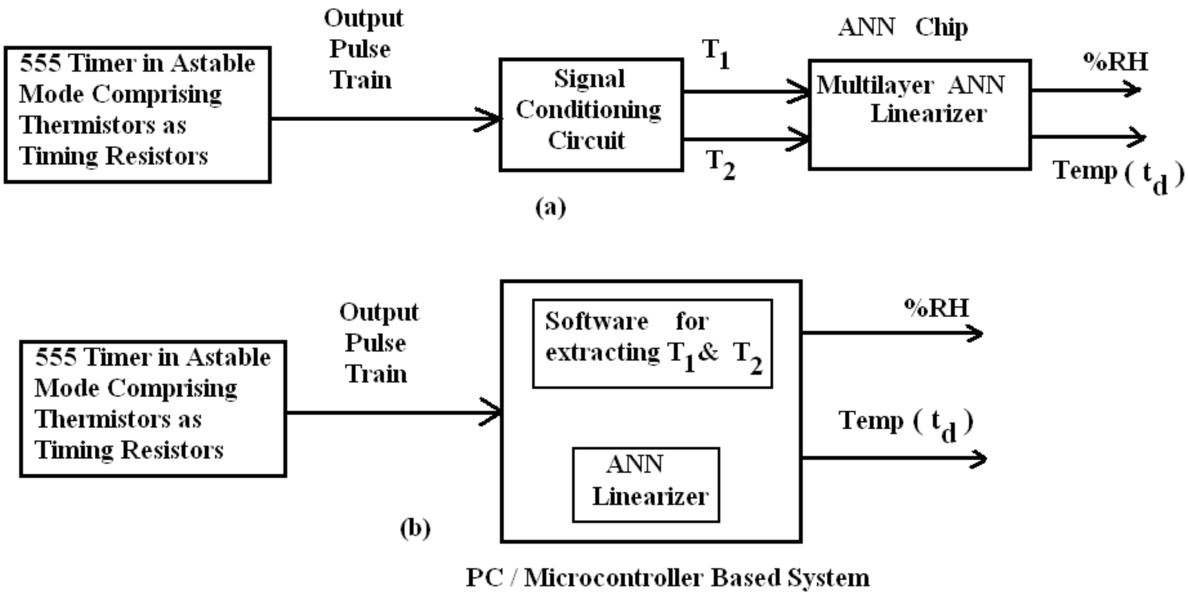

Fig. 5. Block Diagram Representation of the Proposed Scheme

In the other option shown in Fig. 5(b) it is intended that the output of the astable circuit will be taken to microcontroller/PC based system. Here, a software module will determine the values of T_1 and T_2 which will be utilized as before, by an ANN linearizer for further processing. It is worth mentioning that sensor linearization can be considered as a function estimation (modeling) task, where the input data are the outputs of the sensors system , and the target data is the physical variable(s) under measurement, which are the relative humidity and ambient temperature in this case.

In both the cases mentioned above, linearization by artificial neural network utilizes the ability of such networks to learn during the calibration phase, the complex relation between a set of input variables and a set of output variables (measurands) and thereby to predict the unknown values of measurands corresponding to known values of the input variables [18]. Here the measurands are the ambient temperatures (t_d) and the % Relative Humidity, while the input variables are the 'ON' time (T_1) and 'OFF' time (T_2) determined either by hardware or by software method.

Thus one option is to have the astable multivibrator circuit comprising the thrmistors followed by the hardware arrangement for measuring T_1 and T_2 and subsequently by an ANN linearizer programmed in an ANN chip, constituting a complete system. The second option is to combine the multivibrator with the sensors and the preprocessing software (for obtaining T_1 and T_2) and ANN linearizer programmed in a microcontroller, to form a ready-to-use system. The third and simplest alternative is to only have the astable circuit containing the sensors as the hardware unit and relevant software for the neural linearizer. The users of this product may then couple this hardware unit to their own computer or microcontroller, where the program for the neural signal processing should also be loaded.

4. ANN Linearizer

Artificial neural networks (ANN) are processing techniques based on the way the brain works [19, 20]. An ANN consists of a set of neurons (processing elements), and their connections, each connection is modeled by a weight. ANN learns (adjusts its weights) from input-output data (examples); they are model-free estimators, i e., it is not necessary to assume in advance a model function that relates the input-output data pairs. ANN have been useful in a wide range of applications such as signal and image processing, pattern recognition [21], control systems [22] and recently instrumentation [23]. Because of their nonlinear characteristics, they are very useful in solving complex problems more accurately than linear techniques.

In the present case, a multi-layered (2-20-2) feed forward neural network has been considered (as shown in fig.6). It has input layer with two input node, a hidden layer ANN with twenty nodes and output layer with two nodes. Each hidden node multiplies every input by its weight and sums the product and then passes the sum through the sigmoid function. The outputs from the output layer of the neural network are compared to the target value of the training data function to calculate the error. We have used Differential Evolution (DE) algorithm [24-26] for training the ANN. Thus the weights and biases of the network are initialized with DE and thereafter this initialized network is again trained with the help of Levenberg-Marquadt algorithm.

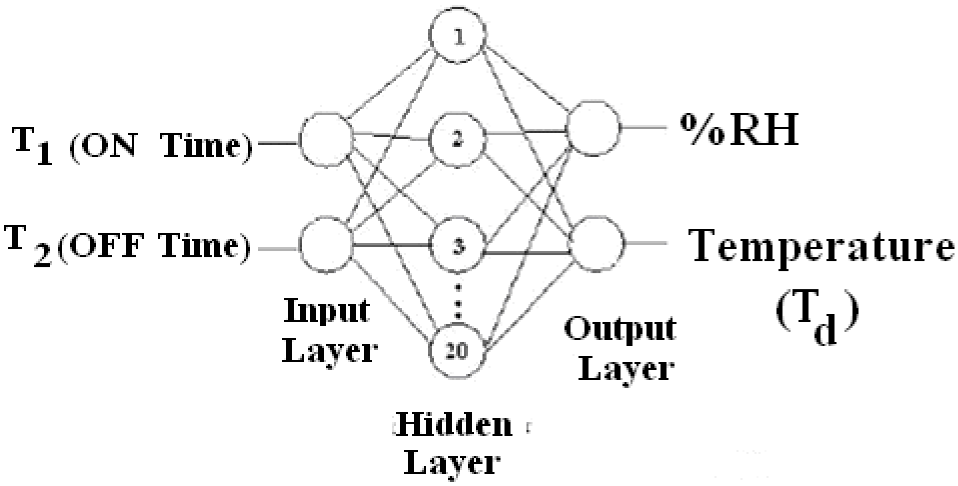

Fig. 6. ANN structure used as Lineariser

5. SIMULATION AND RESULTS :

The simulation and testing of the scheme has been carried out using SIMULINK and Neural Network Toolbox of MATLAB 6.5 in a Pentium 4 processor based PC. *UUA 33J4* thermistors of Omega Engineering have been considered as temperature sensors and their resistance temperature data obtained from the manufacturer [27] have been utilized for simulation. The value of the timing capacitor C has been considered as 1μF. During training of the ANN ,100 epochs (iterations) are used for initialization of the weights and biases of the network by DE algorithm and the initialized network is then trained using 350 epochs (iterations) with Levenberg-Marquadt algorithm. A new program TRAINDE.m is used to implement the DE algorithm for training the ANN, and conventional MATLAB function *trainlm* is used for training the ANN using Levenberg-Marquadt algorithm.

The errors in the measured (i.e. predicted by the ANN) values of ambient temperature and relative humidity have been expressed as percentage of the full scale values of the measurands. The errors are given in Table-1 and the error curves are given in Figs. 7 and 8. The magnitude of maximum error is 0.09 % for relative humidity and 0.08 % for temperature. The error for RH is much below the error (2 %) reported for the prevalent digital variety [13].

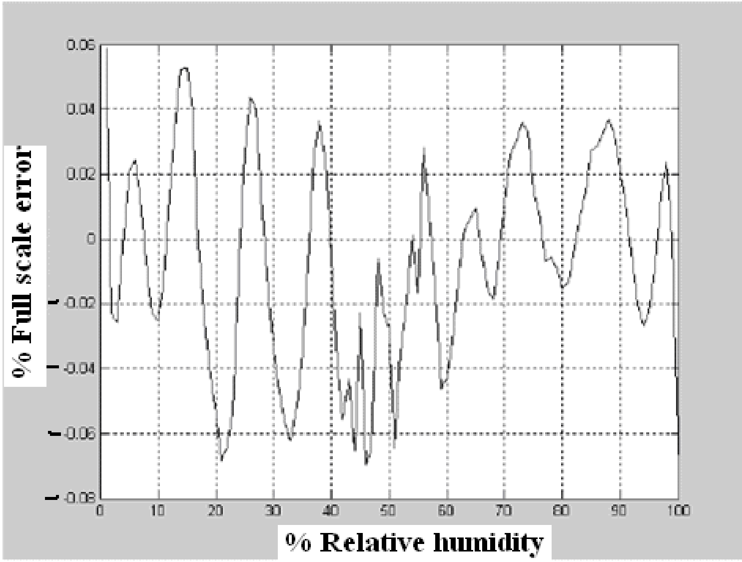

Fig. 7. % Full scale error curve for Relative Humidity

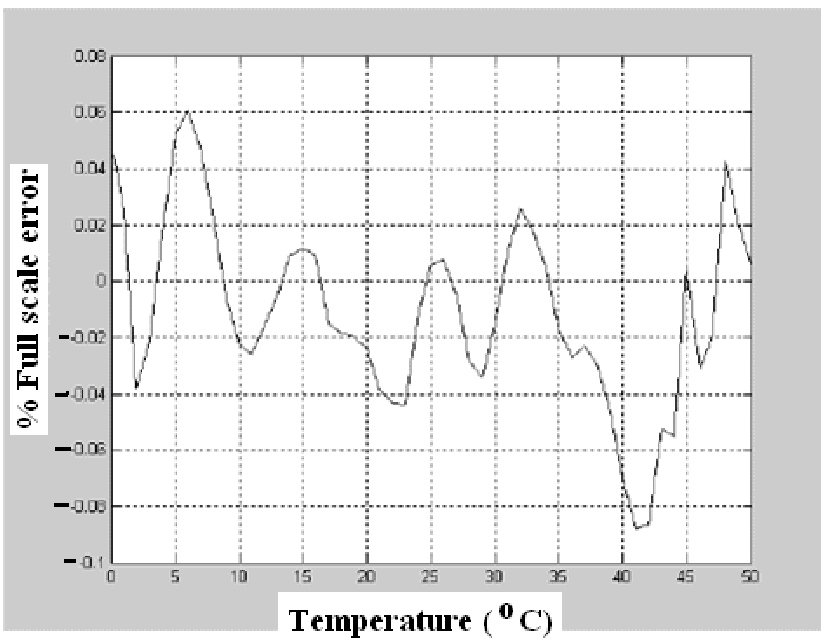

Fig.8. % Full scale error curve for temperature

6. CONCLUSION :

In this work a simple scheme for measurement of relative humidity and temperature has been devised and its performance has been assessed by simulation. Although two identical thermistors have been assumed for simulation studies, in practice it will not be necessary to use matched thermistors. This is because the measurement set up will invariably be calibrated prior to its use. It can be easily appreciated that the scheme is not only practically feasible but can also be expected to be manufactured commercially because of its ease of implementation and low-cost. The assessed measurement errors have been substantially low, much lower than that reported for a typical prevalent digital psychrometer using thermistors, thereby guaranteeing fairly accurate measurements. Although humidity measurement system with lesser measurement error has been reported [8], such a system is much costly than this proposed system.

TABLE -1:

% Full Scale Error of the Measurement System for %RH and Temperature

% Full Scale Error in the Measured Value of		
	%Relative Humidity	**Temperature**
Maximum Error (positive)	**0.07**	**0.063**
Maximum Error (negative)	**0.09**	**0.083**
RMS Error	**0.023**	**0.0198**

7. REFERENCES:

[1] A.E Fribance, Industrial Instrumentation Fundamentals, Tata McGraw Hill Publishing Co.Ltd.,New Delhi,1984.

[2] http://www.humirel.com

[3] http://www.sensorelement.com

[4] U.Tietze and Ch.Schenk , Electronic Circuit Design and Applications, Narosa Publishing House, New Delhi,1992.

[5] Philips, Portable Hygrometer, Application Note #019.

[6] L. H Sherman, Sensor and Conditioning Circuits to Simplify Humidity Measurement, EDN 30,No 12 , pp. 179-188, 1985.

[7] K. Arshak , K. Twomey and D. Heffernan , Development of a Novel Humidity Sensor with Error-Compensated Measurement System, Proceeding of 23rd International Conference on Microelectronics (MIEL 2002), Vol. 1, NIS, Yugoslavia, pp. 215-217, 2002.

[8] T.T Lang , Computerized Instrumentation, John Wiley & Sons, France, 1991.

[9] H. L. Penman and I. Long, A Portable Thermistor Bridge for Micro-meteorology Among Growing Crops, Vol. 26, pp. 77-80, 1949.

[10] A.P. Brady, H. Huff and J.W McBain, Measurement of Vapour Pressure By Means of Matched Thermistors, Journal of Physical Colloid Chemistry, Vol. 55, pp. 304-311, 1951.

[11] B.G. Richards, Measurement of the Free Energy of Soil Moisture by the Psychrometer Technique Using Thermistors, Moisture Equilibria and Changes in Soils Beneath Covered Areas , A Symposium in Print, Butterworths, Australia, pp. 39-46, 1965.

[12] B.D. Kay and P.F. Low, Measurement of the Total Suction of Soils by a Thermistor Psychrometer, Soil Sciences Society of America, Proceedings, Vol.34, pp. 373-376, 1970.

[13] Y. Nantou, Digital Ventilated Psychrometer, IEEE Transactions on Instrumentation and Measurements, Vol. 28, 1 , pp. 42 – 45, 1979.

[14] R.F Coughlin and F.F Driscoll, Operational Amplifiers and Linear Integrated Circuits, Pearson Education, Inc., New Jersey, 2002.

[15] http://www.doctronics.co.uk.

[16] T.S Rathore, Digital Measurement Techniques, Narosa Publishing House, New Delhi,2003.

[17] G.Mirsky, Microprocessors in Instrumentation, Mir Publishers, Moscow, 1987.

[18] A.Chatterjee, S.Munshi, M.Dutta and A.Rakshit, An Artificial neural Linearizer for Capacitive Humidity Sensors, Proceedings of 17th IEEE Instrumentation and Measurement Conference, Baltimore, 2000.

[19] S. Haykin, Neural Networks, A Comprehensive Foundation. Macmillan, 1994.

[20] B.Martin del Brio and A.Sanz Molina, Neural Networks and Fuzzy Systems, RA-MA, Madrid, 1997.

[21] J A.Freeman, Neural Networks: Algorithms, Applications, and Programming Techniques, Addison-Wesley, Massachusetts, 1992.

[22] M.E Aggoune, F. Boudjema, A. Bensenouci, A. Hellal, S.V Vadari. and M.R El Mesai, Design of an adaptive-structure voltage regulator using artificial neural networks, Proc. of the 2nd IEEE Conference on Control Applications, Vancouver, Canada, pp. 337- 343, 1993.

[23] L.F Pau. and F.S. Johansen, Neural Network Signal Understanding for Instrumentation, IEEE Trans on Inst & Meas, Vol. .39, **4** , pp. 558-564, 1990.

[24] C.Charalambous, Conjugate gradient algorithm for efficient training of artificial neural networks, IEE Proceedings (Circuits, Devices and Systems), pp. 301-310, 1992.

[25] G. D Magoulas, V. P Plagianakos, M. N Vrahatis, Hybrid Methods Using Evolutionary Algorithms for On-Line Training, Proc. of the IEEE International Joint Conference on Neural Networks, IJCNN 2001, Washington DC, USA, **3** , pp. 2218-2223, 2001.

[26] T. Masters, and W.Land, A new training algorithm for the general regression neural network, IEEE International Conference on Systems, Man , and Cybernetics, Computational Cybernetics and Simulation , **3** , pp. 1990-1994, 1997.

[27] Temperature Measurement Handbook, Stanford, Connecticut: Omega Engineering Inc., 1979.