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Neural Network Based Density Measurement

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Abstract. A dedicated microcontroller-based density measurement system is developed to measure density of solids. A strain gauge and a thermocouple sensor are used to measure the mass and temperature of the sample. A three layer neural network is used to train the data for atomic number, temperature and density of sample using back propagation algorithm. After training the neural network, it is used to compute the density at various temperatures.

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1 Introduction

The study of solids is of considerable interest due to their potential applications. No matter in the world is devoid of defects. Most of the physical characteristic quantities, such as pressure, density and temperature, *etc.*, are of analog kind in nature. Among these, density is an important property used to identify elements, compounds and minerals. Non-destructive density measurement is also useful in biological studies for *a priori* sample selection and for growth monitoring. Artificial Neural Networks (ANNs) are becoming recognized as a valid tool for modeling and further they are effective in instrumentation and control application. Research in ANNs has recently been active as a new means of information processing. ANN tries to mimic the biological neural network. Mathematical models and algorithms have been designed to mimic the information processing and knowledge acquisition methods of the human brain. These models are called neural networks. ANN acquires its knowledge through a learning process and stores the knowledge in inter-neuron connection strengths known as synaptic weights. Learning in ANN is a process, by which the free parameters of an ANN are adapted through a continuous process of simulation. Multilayer perception has been applied successfully by training them in a supervised manner with a highly popular algorithm known as back propagation algorithm, which is based on error correction rule. Neural networks can reduce the development time by learning the underlying relationships even if they are difficult to find and describe. They can also tackle problems that lack existing solutions. Second, neural network can generalize: they can correctly process data which broadly resembles the data they were originally trained on. Similarly, they can handle imperfect or incomplete data, while providing a measure of fault tolerance. Generalization has useful practical applications because real world data is noisy. Third, the neural networks are non-linear in that they can capture complex interaction among the input variables in a system.

2 System Description

The decrease of unit cost and increase of on-chip capabilities has made possible the widespread use of single-chip microcontrollers in instrumentation and measurement technology. This development system enabled the use of compensation, calibration and linearization techniques and the application of microcontrollers in system control, data acquisition and processing [1-2]. The block diagram of our density measurement system is presented in Figure 1. The system hardware consists of a strain gauge sensor with cantilever arrangement, instrumentation amplifier, k-type thermocouple and signal conditioning circuits for temperature measurement and PIC16F877 microcontroller. A two-row 16 characters LCD display from Hitachi is interfaced with microcontroller to allow user communications and to display the results. The user enters experimental variables and modes of operation into the system through a keyboard.

2.1 Hardware system

PIC16F877 Microcontroller. The PIC16F877 microcontroller is a low power, high performance RISC CPU 8-bit microcontroller with 8 KW of flash programmable and erasable memory and 368 bytes of RAM. It has three 16-bit timer/counters, two capture, compare and PWM modules, a full duplex serial

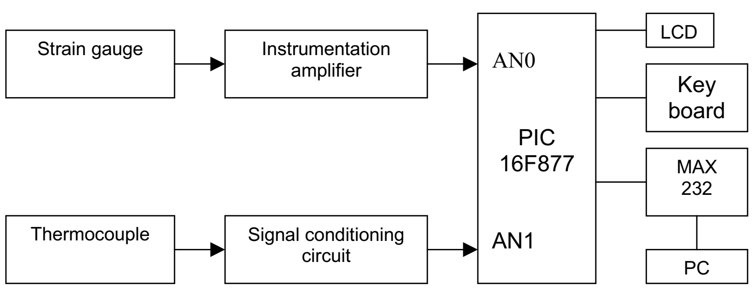

Figure 1. Block diagram of density measurement set up.

port, 5 parallel ports, on-chip oscillator, programmable code protection, 14 interrupt sources, 10-bit 8 channel A/D converter and low power consumption. Pins 2 and 3 (AN0 & AN1) are used to get analog input voltages from the density measurement circuit and the temperature measurement circuit. Port D is connected to LCD display to display the results.

Density measurement. The principle of density measurement is "the weight of a given volume of a solid/fluid is proportional to density". The strain gauge is used as a sensor to measure the mass and hence the density of the substance. The basic principle is that the resistance of a strain gauge changes due to weight of a given mass. In the strain gauge experimental arrangement, the sensor is attached to one end of a rectangular stainless steel metal strip of uniform cross section, which is fixed firmly to a metallic stand. The other end is attached to the sample. Four strain gauges are pasted in strategic positions on the fixed end of the cantilever beam, while the other end is free to move up and down by suspension of weights. The resistance of each strain elements is of 350 ohms. The output of the bridge network is directly proportional to the applied mass. Figure 2 shows the signal conditioning circuit, which consists of the strain gauge sensor and instrumentation amplifier. The instrumentation amplifier amplifies the analog voltage signal form the bridge network is given to the one of the analog input (AN0) of the microcontroller. For various known masses of the substance, the microcontroller reads the data from the microcontroller system

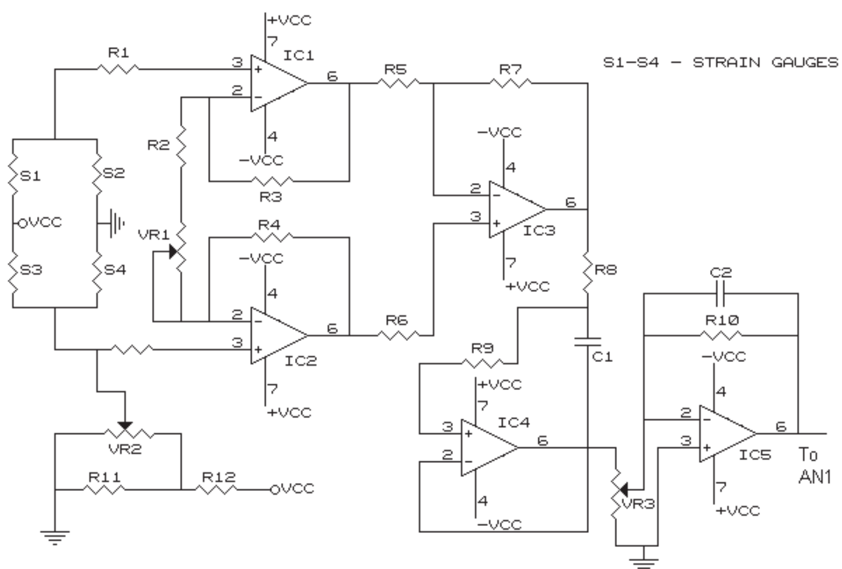

Figure 2. Strain gauge transducers and signal conditioning circuit.

and stores it in memory for calibration. The density of the substance is computed at room temperature by employing Archimedes' principle.

Temperature measurement. To measure temperature of the sample, a chromel alumel thermocouple is used. The signal generated by the junction of the thermocouple due to thermal changes iss fed to an amplifier circuit designed for low signal amplification as shown in Figure 3. The output signal is amplified to a suitable level by using an instrumentation amplifier read by the microcontroller. After amplification, the analog temperature is given to analog input (AN1) of the microcontroller. A semiconductor temperature sensor AD590 is used to simulate a reference junction.

2.2 Software

Software is developed in assembly language and C language to initialize the LCD display and the serial port, to select input channels, to start the ADC conversion, to check for end of conversion, to read the higher and lower bytes of the ADC, to measure the density and temperature of the sample, and then for computation of the acquired data, storage of data, and sending the data to a PC. To transmit data to PC, software is written to select the UART mode, to set 4800 baud rate, and to send data to transmit buffer, so that a PC can read data through its COM1 port. Software is also developed to initialize the COM port of the PC, to receive data from the microcontroller, to store data in a file and to send com-

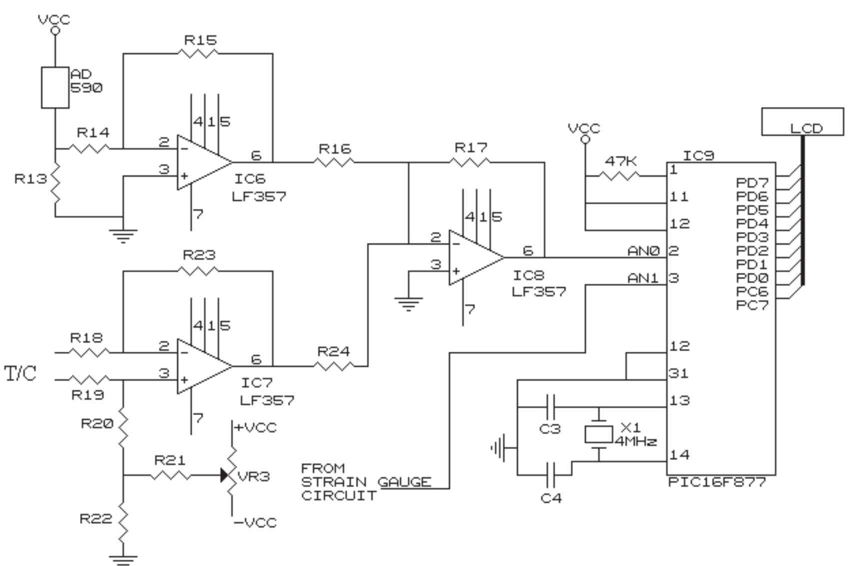

Figure 3. Temperature measurement circuit and PIC16F877 Microcontroller.

mands to the microcontroller, to train the neural network using the data stored in a file and to process the density for a given material at a desired temperature using the trained neural network.

3 Artificial Neural Network Implementation

3.1 Neural network structure

A three-layered neural network (ANN) with seven neurons in the hidden layer, two neurons in the input layer, and one neuron in the output layer is used. The number of hidden neurons is determined empirically. The neurons in the hidden and output layer have sigmoid functions [3]. The weights between the output and the hidden layers are updated using the pseudo impedance control algorithm [4]. It was found that convergence is relatively faster using this rule than using the original generalized delta rule. A large η would initially speed up the convergence, but oscillation tend to alter as the error progressively becomes small and thus η has to be reduced. However, the values of α and β are of 0.8 and -0.15, respectively [5]. A Neural Network is trained to learn the values for the atomic number and temperature as an input vector and the values of density as an output vector by using the back propagation algorithm method. The input and output vectors which are obtained from microcontroller system for copper are used for learning. The density for other temperature is computed using the relation given in [6] by

$$\rho_0 = \rho_t(1 + \gamma t),$$

where γ is the coefficient of cubic expansion; ρ_t – the density at temperature t [$^\circ$C], and ρ_0 – the density at room temperature.

The density for other materials is calculated. During the learning process the weights of the neural network are adjusted so that the calculated output is equal to desired output.

3.2 Learning and testing

The objective of training is to adjust the weights so that an application of a set of inputs would produce the desired set of outputs. Before the training process, the weights are initialized to small random numbers. Under supervised learning, both inputs and output data are given as data for the training. In this process, the weights are modified and the system is trained so that to provide the desired output for a given input.

The process of testing a neural system is like answering a question. In this work, only three samples have been taken for training. The training pattern for the input vectors is the atomic number, temperature and output vector is the density for Copper, Lead, and Aluminium at the temperatures 30, 60, and 90°C as given

Table 1. Training pattern for the input data (Atomic number, Temperature) and Output data (Density)

Atomic number	Temperature [°C]	Density [g/m^3]
Copper		
29	30	8.895
29	60	8.881
29	90	8.868
Lead		
82	30	11.29
82	60	11.26
82	90	11.23
Aluminum		
13	30	2.798
13	60	2.792
13	90	2.786

Table 2. Density calculations for Copper using Neural Network at various temperatures

Input to Neural Network		Output of Neural Network
Atomic number	Temperature [°C]	Density [g/m^3]
Cu 29	35	8.893
29	40	8.892
29	45	8.891
29	50	8.890
29	55	8.888
29	65	8.883
29	70	8.881
29	75	8.878
29	80	8.874
29	85	8.870
29	95	8.861

in Table 1. The density for the temperatures 30, 60, and 90°C is taken as output vectors. The sigmoid function is implemented for both input and output to train the neural network.

4 Results and Discussion

After training of the neural network the weights of the neural network can be saved. They can be reloaded at any time for testing experimental data or computing results. The trained networks for all the input vectors are used to process the densities for a material at a particular temperature. The calculated densities for the materials at different temperatures are compared with outputs obtained from the neural network.

Tables 2, 3, and 4 give the computed densities using ANN for the metals Copper, Lead and Aluminum at temperatures from 35°C to 90°C in steps of 5°C. Table 4 gives the computed densities using neural network for the metals Nickel, Cobalt and Iron, which are not used for training.

From the Tables 2, 3, and 4, we conclude after training the neural network, that it is possible to calculate densities for other temperatures different from the temperatures of 30, 60, and 90°C used for training the neural network for metals Copper, Lead and Aluminum. Similarly, from the Table 5 we find that the neural network is able to process the density at temperatures of 50, 60, 70, 80, and 90°C for the materials Nickel, Cobalt and Iron, which are not used for training. However, it is not possible to process the densities for the other metals. By

Table 3. Density calculations for Lead using Neural Network at various temperatures

Input to Neural Network		Output of Neural Network
Atomic number	Temperature [°C]	Density [g/m^3]
Pb 82	35	11.285
82	40	11.279
82	45	11.273
82	50	11.267
82	55	11.262
82	65	11.252
82	70	11.247
82	75	11.242
82	80	11.238
82	85	11.234
82	95	11.227

Table 4. Density calculations for Aluminium using Neural Network at various temperatures

Input to Neural Network		Output of Neural Network
Atomic number	Temperature [°C]	Density [g/m^3]
Al 13	35	2.797
13	40	2.795
13	45	2.793
13	50	2.791
13	55	2.790
13	65	2.788
13	70	2.787
13	75	2.7869
13	80	2.7868
13	85	2.7862
13	95	2.7855

changing the values of α, β, the number of training cycles, and training pattern it would be also possible to calculate densities for other materials.

The error in the density determination in the neural network with reference to the experimental density measurement is found to be less than 2%. Similarly the error in computing the density using the neural network for the materials cobalt, Nickel and Iron, which are not used for training, is found to be less than 3%.

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