Calibration Of U-Tube Manometer Using Frequency Estimation

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Abstract— **U-Tube Manometer is used to measure pressure. It is calibrated using the variation in capacitance. In U-tube manometer, the relation between the level of mercury and the capacitance developed across the copper plates of the manometer is found to be highly non-linear. Due to its non-predictive nature and non-linear relationship, artificial intelligence techniques are used to calibrate the system. The artificial intelligence technique used here is Adaptive Neuro-Fuzzy Inference System (ANFIS). The system is implemented using the microcontroller ARM Cortex-M3. In U-Tube Manometer, the capacitance values obtained from capacitive level sensor are converted into frequency through an astable multivibrator. The counted frequencies are estimated using the Kalman Filter. The Kalman filter is employed to suppress the abnormalities from minute capacitance change of measurements for promoting efficiency in frequency estimation and amplitude estimation of the distorted signal. After frequency estimation, training is done using the ANFIS. The implemented hardware can be used to efficiently calibrate the U-Tube manometer. This system shows that the ANFIS can be implemented in hardware and can be used to calibrate the non-linear systems effectively.**

Keyword- Calibration, U-Tube Manometer, ANFIS, Kalman Filter, Frequency Estimation.

I. INTRODUCTION

A U-Tube Manometer is used to measure pressure. It has a glass tube bend into a U-shape. It is filled with a liquid, typically mercury. The difference in the heights of the columns of mercury is a measure of the pressure of gas in the system. The differential pressure is indicated by the difference in level between the two columns of liquid. U-tube manometer is used to pressure differences in pitot or orifices located in the airflow in air handling or ventilation systems. The units of measurement are commonly inches of mercury(in Hg) when mercury is used as the liquid, or inches of water (in w.c.) when water is used as the liquid. The relationship between the pressure and height of the mercury is as shown below in equation I.

$$P = \frac{mg}{A} = \frac{d_{H_g} V_g}{A} = \frac{d_{H_g} A h_g}{A} = d_{H_g} h_g \qquad \longrightarrow \quad [I]$$

The main objective of this project is to calibrate the U-tube manometer within the range of 0 to 10 cm. The frequency count for different levels from 0 to 10cm is considered. A capacitive sensor is attached to the U-tube manometer. The metal plates, the glass and air column inside the tube act as the dielectric. The sensed capacitance is converted into frequency using an astable multivibrator with 555 timer circuit. The output pulses generated are given as input to the microcontroller. The converted frequency is then counted in frequency counter module. The corresponding frequency count is given to the Kalman Filter for frequency estimation. The estimated frequency values and their corresponding levels are given to ANFIS for training. After training the ANFIS, the corresponding pressure level is displayed on an lcd when pressure is applied on the U-tube manometer. The block diagram of the system is shown in Figure I.

Kalman filter was used here for frequency estimation because of its advantages over other techniques like IQML algorithm [5]. Frequency estimation is the process of estimating the complex frequency components of a signal in the presence of noise. Frequency plays an important role since it is generally used to indicate the system operation state. It can be used as a base for estimating other parameters such as amplitude and phase of the signal[9]. Thus, reliable frequency estimation is necessary for many applications.

ANFIS find their applications in solving the non-linear relations[1]. Training the ANFIS is considered to be the one of the most challenging one. Training involves selection of an appropriate training algorithm, selection of the training patterns and floating point arithmetic for high efficiency.

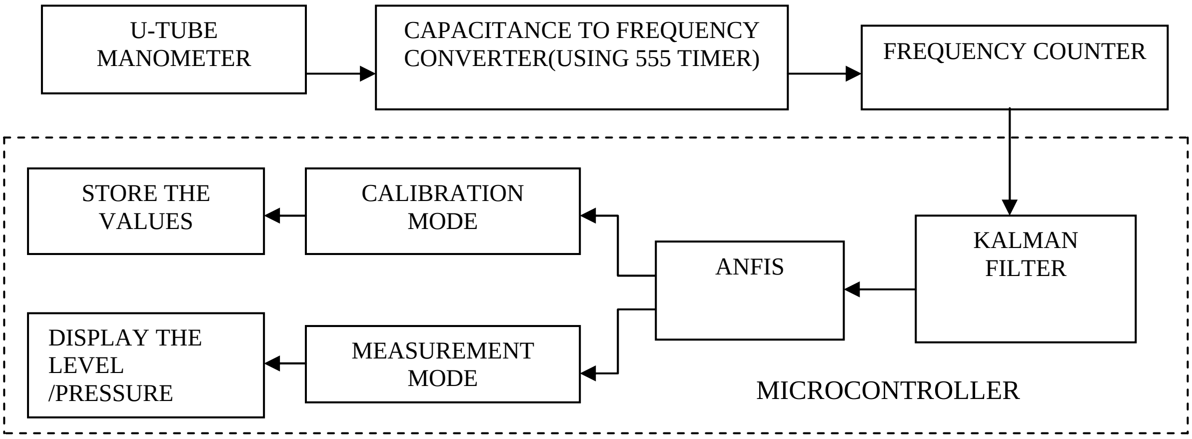

Figure 1. Block Diagram

II. KALMAN FILTER

The Kalman Filter named after Rudolph E. Kalman who proposed a paper describing about a recursive solution to the discrete-data linear filtering problem (Kalman 1960). The Kalman Filter is an algorithm which consists of a set of mathematical equations that can efficiently estimate the state of a process so that it minimizes the mean of the squared error. The main aspect of this filter is that it is very powerful enough that it can estimate past, present and even future states. It can even perform when the precise nature of the modelled system is unknown. The filter mathematically estimates the state of the linear system. The gain, noise covariance and prediction covariance are initialized based on assumptions. The Kalman gain is calculated using these values and predicts the estimated value to update the covariances. The Kalman Filter estimates the true values of the measurements and their associated calculated values by “guessing” a value, estimating the uncertainty of the predicted value, and calculating a weighted average of the predicted value and the measured value. The most weight is given to the value with the least uncertainty. The estimates produced by the method would be closer to the true values than the original measurements because the weighted average has a better estimated uncertainty than either of the values that went into the weighted average. The Kalman filter uses a system model, the control inputs to that system, and measurements (such as from sensors) to form an estimate of the system's changing quantities (its state) that is better than the estimate obtained by using any one measurement alone. All measurements and calculations based on models are estimates to some extent. The purpose of the weights is that values with better (i.e., smaller) estimated uncertainty are selected. The weights are calculated from the covariance which is a measure of the estimated uncertainty of the prediction of the system's state. The outcome of the weighted average is a new state estimate that is a value between the predicted and measured state, and has a better estimated uncertainty than taken alone. This process is repeated, with the new estimate and its covariance for updating the values. This means that the Kalman filter works recursively and requires only the last best estimate.

The equations of Kalman Filter are as follows. There are two steps in this algorithm ie., Filtering and Updation. The priori estimate, priori error covariance matrix and Kalman gain are responsible for filtering operation whereas posterior estimate and posterior error covariance matrix are responsible for update operation.

Priori Estimate X_k :

$$X_k = AX_{k+1} + Bu_k$$

Prior Error Covariance Matrix P_k:

$$P_k = AP_{k-1}A^T + Q$$

Kalman Gain K:

$$K = P_{k-1}C^T(CP_{k-1}C^T)^{-1}$$

Posterior Estimate X_k:

$$X_k = X_{k-1} + K(Y_k - CX_{k-1})$$

Posterior Error Covariance Matrix P_k:

$$P_k = (1\text{-}KC)P_k$$

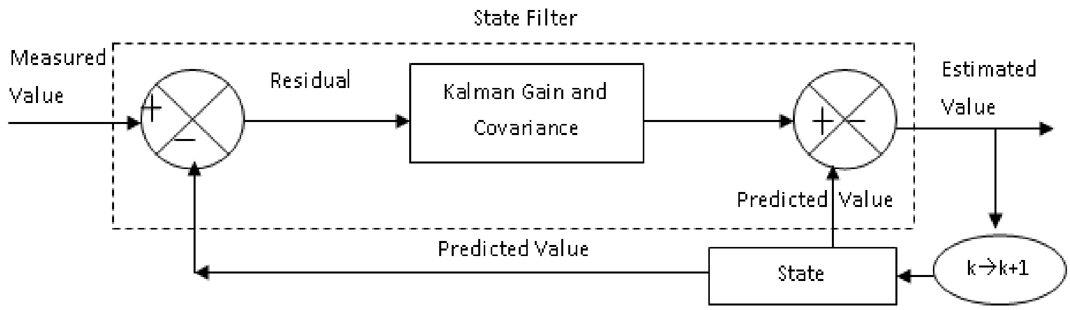

Figure 2. Block Diagram Of Kalman Filter

The Kalman filter algorithm is as follows:

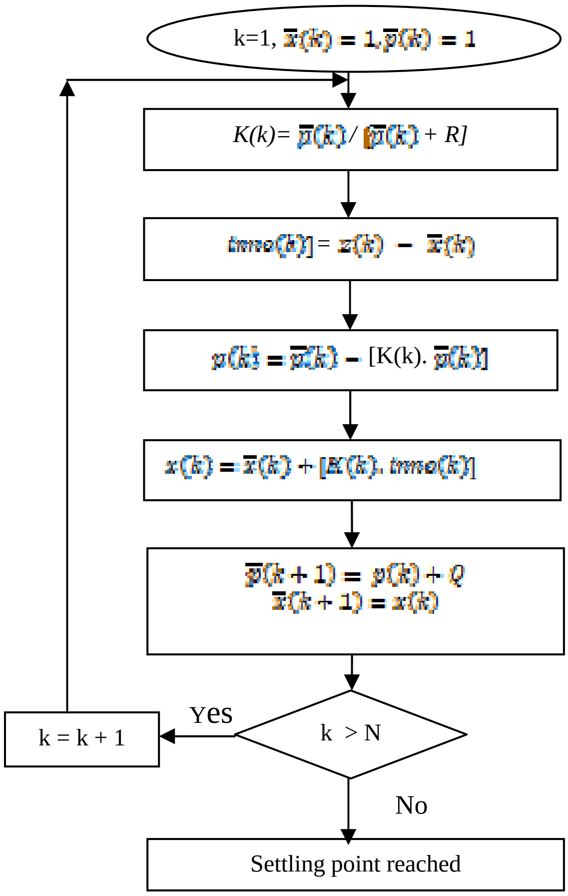

Figure 3. Flowchart

III. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM(ANFIS)

Adaptive Neuro-Fuzzy Inference System is an efficient technique which is used in applications where the system keeps a non-predictive and non-linear relationship. One of the challenges faced is training the ANFIS. The training procedure involves selecting an appropriate training algorithm, selecting the training pattern and floating point arithmetic for high efficiency. Another challenge is implementing the ANFIS in hardware. Most of the implementations till date have been carried out in software. Understanding a nonlinear system is the first step in the implementation. Here, the output maintains a non linear relationship with the input. The major issue faced by nonlinear systems is that traditional methods cannot be used to estimate the output if the nonlinear constant is not known. ANFIS is the solution to this issue. We can integrate this block into the nonlinear system by implementing this block into the hardware. This gives the advantage of flexibility of calibrating the system before its usage. As the hardware can be integrated into the system, we can calibrate it again if some of the dependencies of the system are changed. For example if a non-linear system has a dependency on temperature, the system can be calibrated one more time whenever we feel the temperature is changed. In the U-tube manometer system copper plates are connected in such a way that the air/mercury will act as dielectric in between the copper plates. The capacitance across the copper plate varies whenever the level of mercury varies. The level of the mercury is used in calculation of pressure. The relation between the level of mercury and the capacitance developed is highly non-linear in this case. This makes it difficult for the system designer to calibrate it efficiently. Here, ANFIS based calibration is applied to the U-tube Manometer system, to demonstrate the application of ANFIS to estimate the output of non-linear systems.

Learning is the fundamental form of adaptation. ANFIS has the ability to learn. This is the primary reason for using the ANFISs where the solutions cannot be obtained using traditional methods. ANFIS combines the advantages of both neural network and fuzzy logic which offers good results. Learning duration of ANFIS is very small as the output result depends directly on the firing strength of the fuzzy rule.

ANFIS is five layers architecture. ANFIS uses Sugeno Fuzzy model in which the rule set is given by

Rule 1: If x is A1 and y is B1, then f1 = p1x + q1y + r1

Rule 2: If x is A2 and y is B2, then f2 = p2x + q2y + r2

For a zero order sugeno model, we will consider p1=q1=p2=q2=0. Layer 1 output is the typical membership function with the parameters w1, w2 for A1 and w3, w4 for A2.The membership function can be taken as the difference of two sigmoid functions. Layer2 output is the product of the outputs from the Layer1.If we have only one input, Layer2 output is same as layer1 output. Layer3 output is the normalization output by normalizing the outputs from layer2, which gives the firing strength of the rule. This strength is then multiplied by the sugeno rule, which is the layer 4 output. The output level f_i of each rule is weighted by the firing strength w_i of the rule. The final output of the system is the weighted average of all rule outputs, given by

$$\text{Final output} = \frac{\sum_{i=1}^{n} w_i f_i}{\sum_{i=1}^{n} w_i}$$

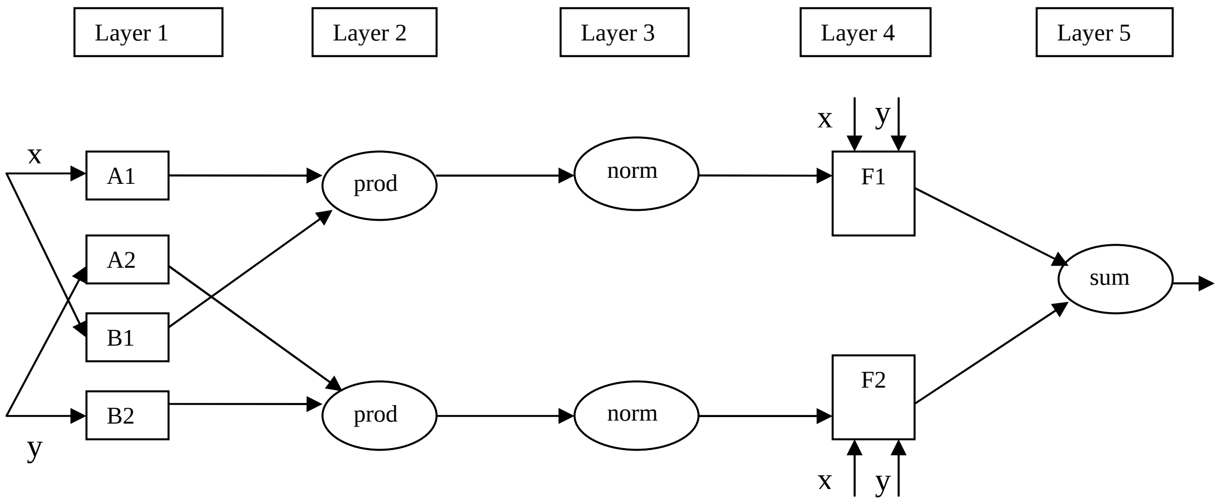

Figure 4. ANFIS Structure

IV. IMPLEMENTATION

The real-time implementation for the calibration purpose has been setup using the required hardware. Firstly, the capacitance sensor is setup which senses the change in level of the manometer. The capacitance is converted to frequency using a stable multivibrator which uses 555 timer. The output of the converter ie frequency is given to GPIO pin P5 of the microcontroller ARM-Cortex MBED LPC 1768. This frequency can be displayed as pulse on the oscilloscope. The voltage is 5 volts. In the programming side, the Kalman algorithm is implemented. The counted frequencies are given to the Kalman filter block which gives one estimated frequency for the corresponding level. This algorithm is used because the frequencies keep changing at one level. So an estimate of the frequencies is taken for efficient calibration. The applied level is then displayed on the hyperterminal using ANFIS technique. The system is trained using this neuro-fuzzy technique. The number of epochs is found out till it gives the accurate results. Then the system is trained to give the corresponding level as applied on the U-Tube Manometer. The ANFIS module takes in the input value and the teacher output as the inputs in training mode and input value as the input in measurement mode. Output value is displayed only in measurement mode in which the training is already done. In the training mode we have to feed the frequency to the microcontroller corresponding to the training levels we have fixed at first. These frequencies are stored in an array for further processing. Once the number of levels we determined is done we will move on to measurement mode. In measurement mode we will use the counted frequency to display its corresponding level.

Figure 5. Experimental Setup Of U-Tube Manometer

V. EXPERIMENTAL RESULTS

The capacitance sensor attached to the U-Tube Manometer has the capacitance changing as the level changes when pressure is applied. The capacitance is converted to frequency using 555 timer astable multivibrator. As the capacitance changes, the frequency also changes. The frequency is counted using a frequency counter which is done using the microcontroller. The output pulse can be seen in the oscilloscope. The frequency is displayed in the oscilloscope too. The counted frequency can be seen on the hyperterminal. The counted frequency is then given to the Kalman Filter. The Kalman Filter output is obtained as shown in Table I.

TABLE I
Kalman Filter Output: Teacher Output Values

Level(cm)	Kalman Filter Output Frequency (kHz)
0	27.872967
1	26.967079
2	26.240988
3	25.656218
4	25.183626
5	24.629667
6	24.061539
7	23.552603
8	23.201284
9	22.636694
10	22.435246

The Kalman output frequencies and their corresponding levels were given to the ANFIS block to train the system. The checking datas were given to check if the level was being displayed according to the given frequency. The Kalman output frequencies and their levels are the teacher output values which are used to train the system. The system is trained so that for any random pressure level applied in real-time,the same level can be displayed on the screen. The ANFIS output is as shown in Table II.

TABLE II
Calibration Mode Results

Frequency (kHz)	ANFIS Output Level(cm)
27.43352	0.2
27.05678	0.4
25.94050	2.5
24.90664	4.5

In calibration mode, the system is trained using the teacher output frequencies. In measurement mode, the system displays the level according to the pressure level applied. In measurement mode, training is not required. It directly displays the output. The measurement mode output is displayed on the hyperterminal. It is as shown in the figure below. The screenshot of the hyperterminal shows the corresponding level as applied on the manometer. The pressure level here is moving up from 0.4cm to 0.08cm and the same is displayed on the hyperterminal.

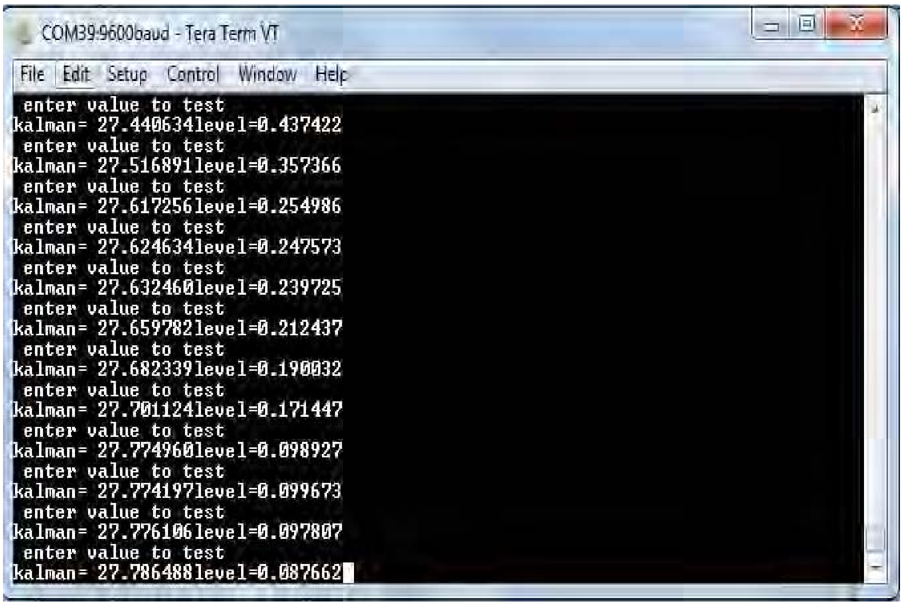

Figure 6. ANFIS Output: Levels Displayed on the Hyperterminal

VI. CONCLUSION

The U-tube manometer was calibrated using ANFIS and accurate results were obtained. Better performance was achieved with ANFIS tuning for non-linear approaches. It is advantageous PID controllers and neural network controllers. ANFIS helps in providing flexibility of calibrating the device. Neuro-fuzzy controllers, like ANFIS, combine the advantages of both neural networks and fuzzy logic controllers.

Till date, the real time implementation of U-tube manometer calibration using embedded C programming have not been realized. The implementation has been done successfully giving accurate results to any pressure level that is applied on the manometer. Also frequency estimation was implemented using Kalman filter. This filter has advantages over other estimation techniques. To conclude, Kalman filter and ANFIS were implemented successfully giving accurate results.

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