

# Intelligent Cylindrical Capacitive Level Sensor

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**Abstract**—The capacitive level sensors are most commonly used sensors for the measurement of liquid level in the industries. It is because of their high sensitivity, less power dissipation and ruggedness in design. However, in a capacitance sensor, the problem of high nonlinear response characteristics as well as dependence on the permittivity of liquid have imposed some restriction on the optimal use of such sensors. This paper compares different soft-computing algorithms and their performances.

## I. INTRODUCTION

There can be many direct and indirect methods for increasing the linearity of sensor response. ANN applies one such method. The advantages of using ANN for increasing the linearity range are ease of programming and software portability. It uses the synaptic weights for the training to minimize the error between the desired output and the actual output. After training the hardwired version of neural network (with fixed synaptic weights) can be cascaded with the sensor in order to cancel the sensors nonlinear characteristics. [1] Jagdish Chandra Patra et al. propose Neural networks based scheme, when there is a change in ambient temperature, the ANN automatically compensates for this change based on the learning which it undergoes and on the information stored in its weights. The effect of change in environmental conditions on the capacitive sensors and subsequently upon the output is nonlinear in nature. Especially, change in ambient temperature causes response characteristics of the sensor to become highly nonlinear, and complex signal processing may be required to obtain correct readout. The purpose of direct modeling is to obtain an ANN model of the sensor in such a way that the outputs of the sensor and the ANN match closely. ANN model has been found to be capable of accurately estimating at any ambient temperature from 20°C to 70°C. This fact is the novel characteristic of the proposed ANN model. [2] Artificial neural networks have emerged as a powerful learning technique to perform complex tasks nonlinear dynamic environments. An intelligent pressure sensor based on artificial neural networks to realize auto-calibration and nonlinear compensation of a CPS has been proposed with quite satisfactory performance. This technique can also be applied for other parameters such level etc. There are also some drawbacks of neural networks, such as neural networks cant tell the redundant information from a huge amount of data, which will easily lead to some problems such as long training time and much computation. [3]

As explained in the paper [4], the nonlinear operation of a Multi layer perceptron (MLP) neural network compensates the nonlinear characteristics of a sensor. Sensor linearization can be considered a function estimation (modeling) task, where the non-linear sensor output can be used as input data and the desired linearized response as target data. The capability of a trained network can be measured to some extent by the errors on the training, validation and test sets. This can be done by applying unseen input to network and trace the output and compare with the sensor output. It has been proved successful in representing any measurable function within any desired degree of accuracy, with the correct values of pressures and sufficient number of hidden neurons. [5]

## II. HARDWARE DESCRIPTION

Power supply	24V DC (2wire system)
Probe size	1/4 inch dia probe with high temperature standoff
Type of probe	Dual Probe
output	4-20mA DC
Capacitance range	0pF(min) to 5nF(max)

TABLE I  
HARDWARE DESCRIPTION

Switzer manufacturers capacitive level transmitter is used for the experimentation, whose specifications are shown in the Table 1.

## III. METHODOLOGY

### A. Back Propagation Neural Network

The back propagation NN is trained using gradient descent algorithm, which updates the weights to minimize the error, in each epoch as shown in equation 1 and the error is shown in equation 2

$$W_{n+1} = W_n - \eta \frac{dE}{dW_n} \quad (1)$$

$$E = 0.5 ||target - output||^2 \quad (2)$$

Where,  
 $\eta$  is the learning rate  $0 < \eta < 1$ ,  
 $W_i$  is value of weights at  $i_{th}$  epoch

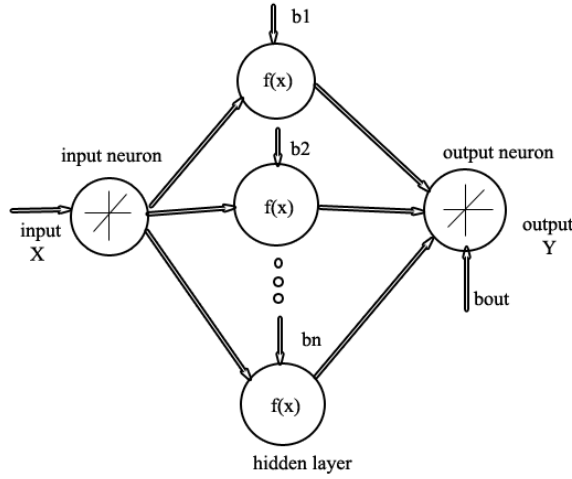


Fig. 1. Single Hidden Layer Neural Network Structure

It is a generalization of the delta rule to multi-layered feedforward networks, made possible by using the chain rule to iteratively compute gradients for each layer. The architecture of the neural network used is shown in Figure 1.

#### B. RBF Neural Network

Here we use Gaussian function as the radial basis function, shown in equation 3. It can also be interpreted as a rather simple single-layer type of artificial neural network called a radial basis function network, with the radial basis functions taking on the role of the activation functions of the network. The means of the hidden layer are computed using K means clustering using k as number of hidden neurons.

$$\Phi(x) = e^{-\frac{\|x - W\|^2}{\sigma^2}} \quad (3)$$

Where,

$\sigma^2$  is variance,

x is input,  $\Phi(x)$  is output of neuron

W is the mean of the sigmoid function or weight of neuron

#### C. Extreme learning Machine

ELM is one step training algorithm, it uses least squares method to estimate the best fit for the weights of the neural network.

Here output layer weights are computed, where the hidden layer weights are assigned to the random value. The hidden layer output matrix is assigned as H as shown in equation 4. Output weights  $W_{out}$  are calculated as shown in equation 5.

$$H = XW_{hidden}^T + b_{hidden} \quad (4)$$

$$W_{out}^T = H^+(y - b_{out}) \quad (5)$$

Where,

y is the target data,

$H^+$  is the pseudo inverse of H,

$b_{hidden}$  is the hidden layer bias vector,

$b_{out}$  is output layer bias vector.

#### D. Signal conditioning

The frequency output of the 555 timer varies with the input capacitance in accordance with  $(R_1 + 2R_2)$  as shown in equation 6.

$$f = \frac{1}{\ln(2)C(R_1 + 2R_2)} \quad (6)$$

Where,

f is the frequency output and  $R_1=1M$ ,  $R_2=100K$

The circuit diagram of capacitance to frequency is shown in Figure 2.

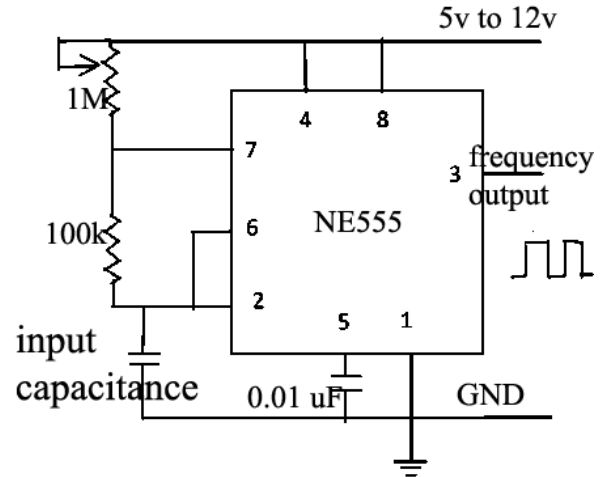


Fig. 2. capacitance to frequency circuit diagram

The high time and the low time in each pulse is given by equation 7 and equation 8 respectively.

$$t_{high} = \ln(2)C(R_1 + R_2) \quad (7)$$

$$t_{low} = \ln(2)CR_2 \quad (8)$$

The frequency to voltage converter uses LM331 IC as shown in Figure 3.  $R_3$  resistance value depends on the supply voltage as shown in equation 9. The output voltage is obtained as shown in equation 10.

$$R_3 = \frac{V_s - 2}{2} 1000 \, \Omega \quad (9)$$

$$V_{out} = 2.09 \frac{R_4}{R_5 + R_6} R_1 C_1 V_{F_{in}} \quad (10)$$

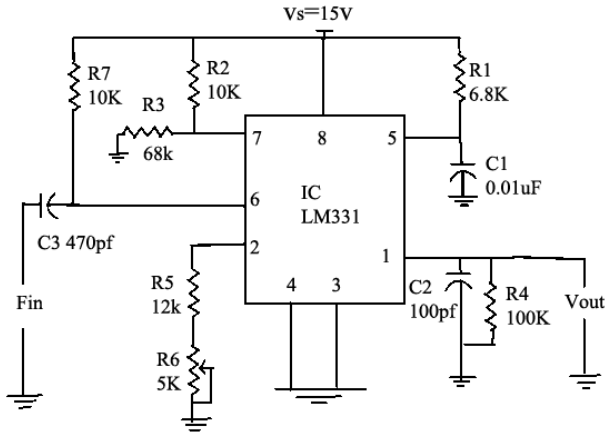


Fig. 3. frequency to voltage circuit diagram

#### IV. IMPLEMENTATION

ATMega328 microcontroller is used to implement the neural network where the input voltage is taken and their respective outputs are obtained and is displayed. Figure 4 shows the systematic flow of the procedure. The input, which is level when changes, the capacitance of the cylindrical capacitive sensor changes results in change in frequency output of the capacitance to frequency converter. This frequency output is fed into f/v converter circuit, results a voltage output, this is given as input to ATMega328 microcontroller where the algorithm gives the final level as the output with the compensated non-linearity. The experimental setup is shown in Figure 5.

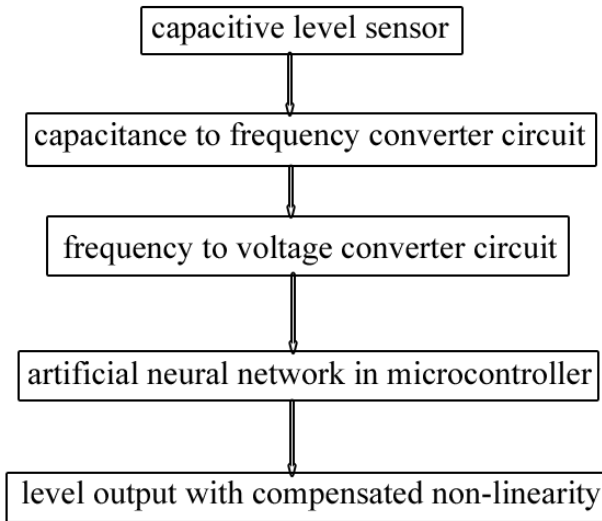


Fig. 4. Block Diagram

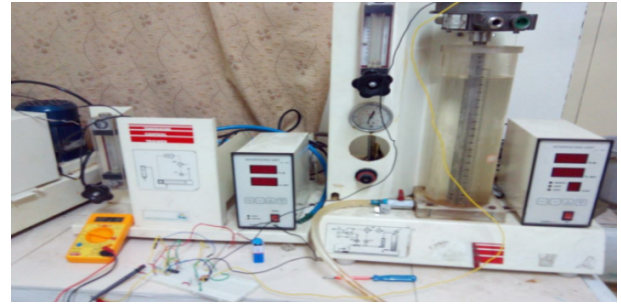


Fig. 5. Experimental Setup

Method	Accuracy	Function used	no of neurons
Back Propagation (Feed forward Single layer ANN)	99.8%	tansig	4
ELM(Feed forward Single layer ANN)	98%	sig	10
RBF(Feed forward Single layer ANN)	99.84%	gaussian	13

TABLE II  
RESULTS

#### V. RESULTS

Sensor output with water is 92.7% linear, where as with soap solution it is 87% linear. After training the single layer neural networks with methods shown in Table 2 with the ideal response of the capacitive sensor without any noise, the results which are obtained is shown in Table 2.

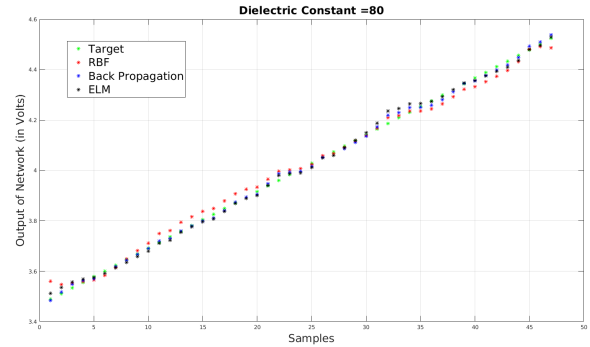


Fig. 6. Response of network with dielectric constant 80

The response of the networks with two different liquids are shown in Figure 6 and Figure 7.

#### VI. CONCLUSION

All the single layer feed forward neural network, were on the same idea of support vector regression where the inputs are mapped to higher dimensions using kernels which we choose in the hidden layer, where classification or regression can be done easily using linear interpreters.

Here the response of the capacitive sensor is almost linear but with very small deviations. Where this noise is best interpolated using the tansig kernel compared to others, with

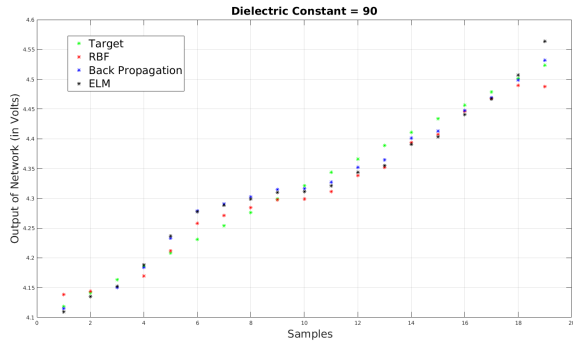


Fig. 7. Response of network with dielectric constant 90

just four neurons.

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