



A Practically Validated Intelligent Calibration Technique using Optimized ANN for Ultrasonic Flow meter

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Abstract: Design of an intelligent flow measurement technique by ultrasonic transducers using an Optimized Artificial Neural Network (OANN) is discussed in this paper. The objectives of the present work are (i) to extend the linearity range of flow measurement to 100% of full scale input range, (ii) to make the flow measurement technique adaptive to variations in (a) pipe diameter, (b) liquid density, (c) liquid temperature, and (iii) to achieve objectives (i) and (ii) by using an optimized artificial neural network. The output of an ultrasonic transducer is frequency. It is converted to voltage by using a suitable data conversion circuit. A suitable optimal ANN is added, in place of conventional calibration circuit, in cascade to data conversion circuit. ANN is trained, and tested with simulated data considering various values of pipe diameter, liquid density, and liquid temperature. The proposed technique is then subjected to practical data for validation. Results show that the proposed technique has fulfilled the desired objectives.

Index Terms: Artificial neural network, Flow measurement, Optimization, Sensor modeling, Ultrasonic transducer

1. Introduction

Flow measurement has evolved over the years in response to measure new products, measure old products with new condition of flow, and for higher accuracy requirement as the value of fluid has gone up. Flow measurement is the quantification of fluid movement. Flow can be measured in a variety of ways, may be by contact type or non-contact type of sensors. Positive-displacement flow meters accumulate a fixed volume of fluid and then count the number of times the volume is filled to measure flow. Other flow measurement methods rely on forces produced by the flowing stream to overcome a known constriction, to indirectly calculate flow. Flow may be measured by measuring the velocity of fluid over a known area. Accurate flow measurement is not only an essential and vital requirement from qualitative view point but also highly essential from economic aspect. Among the non contact type of flow measurement, ultrasonic flow measurement is widely used to measure flow, for its advantages, like high resolution. However, non linear characteristics of Ultrasonic Flow Meter (UFM) have restricted its use.

A review on ultrasonic flow meter reveals that several methods for calibration are available in literature. A look up table is implemented in [1] on a microcontroller for the purpose calibrating the sensor to produce linear output for the variation to flow rate. Calibration of flow meter using several analog circuits is discussed in [2-4, 8, 9, 11]. In [5], a method of flow measurement using a capacitive sensor and its calibration using analog circuit is reported. Linearization of sensors over a certain range using neural network is reported in [6, 15-17]. In [7], calibration of inverted pendulum using the concept of neural network and Digital Signal Processing (DSP) algorithms is discussed. Mathematical modelling and calibration of flow meter is discussed in [10]. A hardwired analog design for linearization of ultrasonic flow meter is carried on in [12-14, 16]. Numerical optimization technique is reported in [19] for linearization of ultrasonic flow meter. These reported works suggests that several techniques are adopted to calibrate UFM but these linearization methods are limited to a certain range of

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input scale. Further, effects of liquid temperature and density on flow measurement are discussed in [20-21], and effect of physical dimensions of flow meter is reported by Zhang Ha et.al [22].

Several techniques, as stated above, have been reported to overcome the restriction faced due to nonlinear response characteristics of the ultrasonic flow meter. But, some of these are tedious and time consuming. Further, linear output for certain range of input flow, and secondly, calibration methods are limited to effect of variations in liquid, temperature, density, and physical dimension of pipe is not considered.

An intelligent flow measurement technique is proposed in this paper. It is made linear for the full scale input range and adaptive of variations in pipe diameter, liquid density, and liquid temperatures. This paper is an extension of earlier reported work [18]. The extended version uses an optimized ANN instead of an arbitrary scheme and algorithm of ANN, and validates the proposed technique with practical data. The optimized ANN is achieved by considering (i) five different algorithms and schemes, and (ii) 10 transfer functions of neuron and comparing their MSE. An ANN having minimum number of hidden layers to achieve best fit of input output data pair is termed as optimized ANN.

The paper is organised as follows: after introduction in Section-I, a brief description on ultrasonic flow meter is given in Section-II. The output of the ultrasonic flow meter is frequency; a brief discussion on data conversion i.e. a Frequency to voltage converter circuit is discussed in Section-III. Section-IV deals with the problem statement followed by proposed solution in Section-V. Result and discussion is given in Section-VI, and the paper is ended with conclusion and future scope of work in Section-VII.

2. Ultrasonic flow meter

Ultrasonic flow meters (UFM) have gained a lot of attention over the past years, primarily because of their ability to measure custody transfer of natural gas. They are replacing differential pressure and turbine flow meters in many natural gas applications. UFM's are also widely used to measure liquid flow. This is not limited to clean liquids only. UFM can accurately measure the flow of slurries and liquids with many impurities.

Ultrasonic flow meters are one of the most interesting types of meters used to measure flow in pipes. The most common variety, transit time, has both a sending and a receiving transducer. Figure 1 shows the arrangement of one such UFM. Both sending and receiving transducers are mounted on either side of the pipe wall. The sending transducer sends an ultrasonic signal at an angle from one side of the pipe which is received by the receiving transducer. The flow meter measures the time that the ultrasonic signal takes to travel across the pipe in forward and reverse direction. When the signal travels along the direction of the flow, it travels more quickly compare to the condition of no flow. On the other hand, when the signal travels against the direction of flow, it slows down. The difference between the "transit times" of the two signals is proportional to flow rate [23], [24].

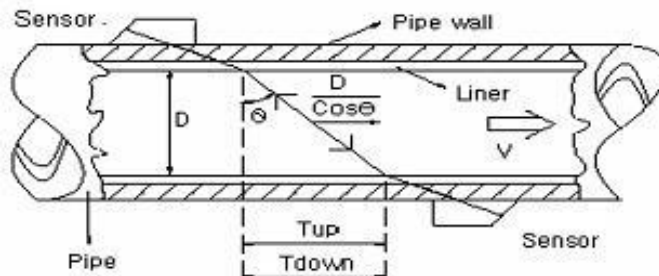


Figure 1. Arrangement of Ultrasonic flow meter

From Figure 1,

$$T_{up} = \frac{M \cdot \frac{D}{\cos\theta}}{C_o + v \sin\theta} \tag{1}$$

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$$T_{\text{down}} = \frac{M \cdot \frac{D}{\cos \theta}}{C_o - v \sin \theta} \quad (2)$$

$$\Delta T = T_{\text{up}} - T_{\text{down}} \quad (3)$$

Frequency, $f_{\text{IN}} = 1/\Delta T$

Where;

M – No of times ultrasonic signal travels in forward/ backward direction

C_o – Velocity of ultrasonic signal in static fluid

D – Pipe diameter

v – Velocity of fluid

The velocity of ultrasonic signal depends on density of liquid [18], [21], [24], [25] as,

$$C_o = \sqrt{k/\rho} \quad (4)$$

with

k – bulk modulus and

ρ – Density of liquid

Effect of temperature on density of [18], [20], [24], [26] is given by

$$\rho_1 = \left[\frac{\rho_0}{1 + \alpha(t_1 - t_0)} \right] / \left[1 - \frac{(P_{t1} - P_{t0})}{E} \right] \quad (5)$$

Where;

ρ_1 – specific density of liquid at temperature t_1

ρ_0 – specific density of liquid at temperature t_0

P_{t1} – pressure at temperature t_1

P_{t0} – pressure at temperature t_0

E – Modulus of elasticity of the liquid

α – temperature coefficient of liquid

The output of UFM is frequency. A frequency to voltage converter is used here as data conversion circuit briefly described in the next section.

3. Data conversion unit

The block diagram representation of the available flow measurement technique using ultrasonic flow meter is given in Figure.2. Ultrasonic flow meter is used to sense the flow rate, as from Eq. 3 it is clear that output of ultrasonic flow meter is frequency to convert this frequency to active signal voltage and f-V converter is used. Output of f-V circuit is calibrated using an analog circuit to display the actual flow

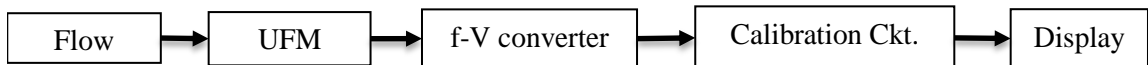


Figure 2. Block diagram of available flow measurement technique

LM2917 series are monolithic frequency to voltage (f-V) converters with a high gain op amp/comparator designed to operate a relay, lamp, or other load when the input frequency reaches or exceeds a selected rate [27]. Frequency to voltage converter circuit using LM2917 is shown in Figure 3.

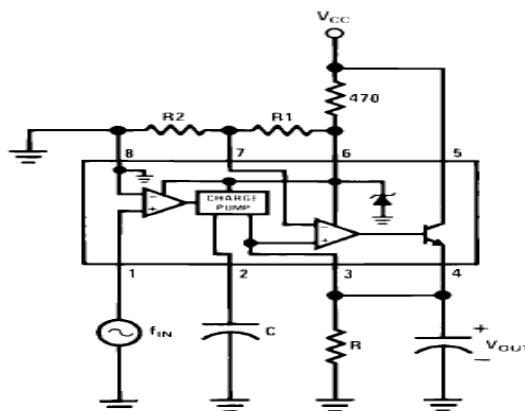


Figure 3. Frequency to voltage converter circuit using LM 2917

The opamp/ comparator is fully compatible with the sensors and has a floating transistor as its output. The collector may be taken above V_{CC} up to a maximum V_{CE} of 28V.

$$V_{OUT} = f_{IN} * R * C * V_{CC} \tag{6}$$

The available calibration circuits is designed to map the flow rate corresponding to voltage output of f-V converter.

4. Problem statement

In this section, characteristics of ultrasonic flow meter are simulated to understand the difficulties associated with the available measurement technique. For this purpose, simulation is carried out with three different pipe diameters. These are $D = 0.1$ m, 0.2 m, and 0.3 m. Three different liquid densities are considered. These are $\rho = 500$ Kg/m^3 , 1000 Kg/m^3 , and 1500 Kg/m^3 . Three different liquid temperatures as $t = 25$ $^{\circ}\text{C}$, 50 $^{\circ}\text{C}$, and 75 $^{\circ}\text{C}$ are considered. The output frequency of UFM is calculated using Eqs. 3, 4, and 5, with respect to various values of input flow considering a particular pipe diameter, liquid density, and temperature. These output frequencies are used as inputs of frequency to voltage converter circuit and by, the output voltages are generated using Eq. 6. MATLAB environment is used for simulation and the following characteristics are found.

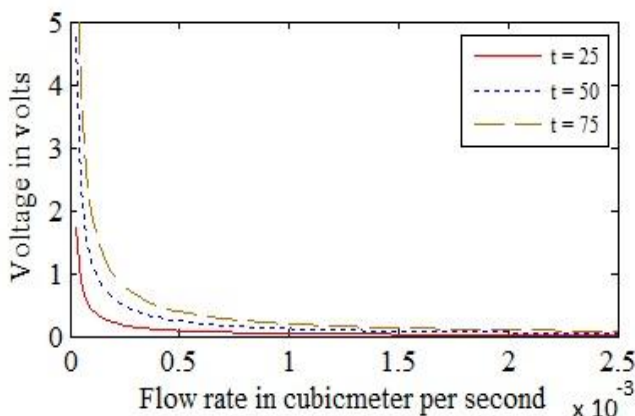


Figure 4. Output of data conversion unit for various flow rates and temperatures when liquid density is 500 Kg/m^3 and pipe diameter is 0.1 m

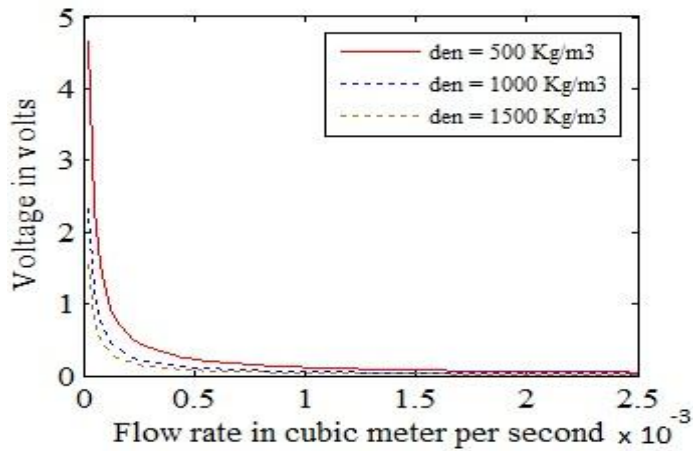


Figure 5. Output of data conversion unit for various flow rates and liquid densities when temperature is 50 °C and pipe diameter is 0.3 m

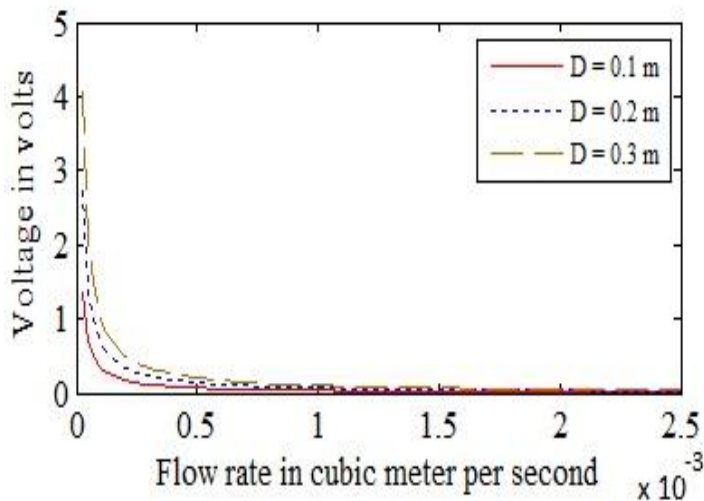


Figure 6. Output of data conversion unit for various flow rates and pipe diameters when liquid density is 1500 Kg/m³ and temperature is 75 °C

Figure 4, Figure 5, and Figure.6 show the variation of voltages with the change in flow rate considering different values of pipe diameter, liquid density, and liquid temperature. It has been observed from the above graphs that the output from the frequency to voltage converter circuit has a nonlinear relation. Datasheet of ultrasonic suggests that 10% to 50% of full scale input range is used in practice for measurement. The output voltage also varies with the change in pipe diameter, liquid density, and temperature. These are the reasons which have made the user to go for repeated calibration. These conventional calibration techniques have drawbacks that these are time consuming and need to be recalibrated whenever pipe diameter, and/or liquid density, and/or liquid temperature is changed in the system. Further, the use is restricted only to a portion of full scale of input range.

To overcome these drawbacks, this paper makes an attempt to design a flow measurement technique using UFM incorporating intelligence to produce linear output for the full range of input scale and to make the system adaptive of variation in pipe diameter, liquid density, and liquid temperature using an optimized artificial neural network model.

Problem statement: given an arrangement for measurement of flow consisting of UFM in cascade with frequency to voltage converter circuit, design an intelligent flow measurement technique using optimized neural network model and having the following properties:

- i. Adaptive to variation in diameter of the pipe.
- ii. Adaptive to variation in liquid density.
- iii. Adaptive to variations in liquid temperature.
- iv. Output bears a linear relation with the input flow rate.
- v. Full scale input range can be measured.

Next section deals with the solution of this problem.

5. Problem solution

The drawbacks discussed in the earlier section are over come by replacing the conventional calibration circuit with an optimized suitable ANN model as shown in Figure.7. The output of the f-V converter is now feed to ANN model, along with the output of temperature sensor which measures the actual temperature of flow under measure. ANN model is also fed with input like the know values of pipe diameter, liquid density. ANN is programmed to produce flow rate and is displayed using a display. The details of ANN model is as given.

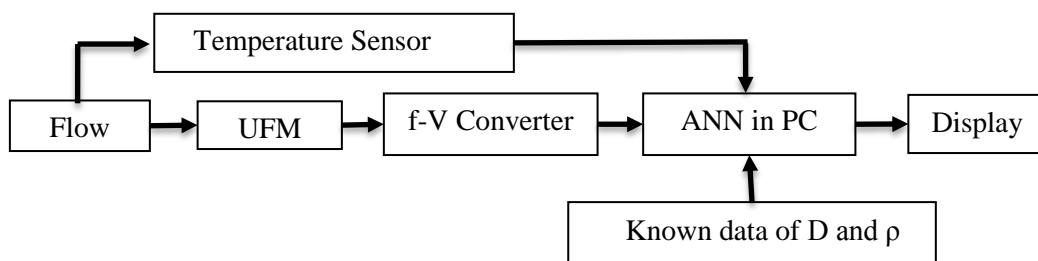


Figure. 7. Block diagram of proposed flow measurement technique

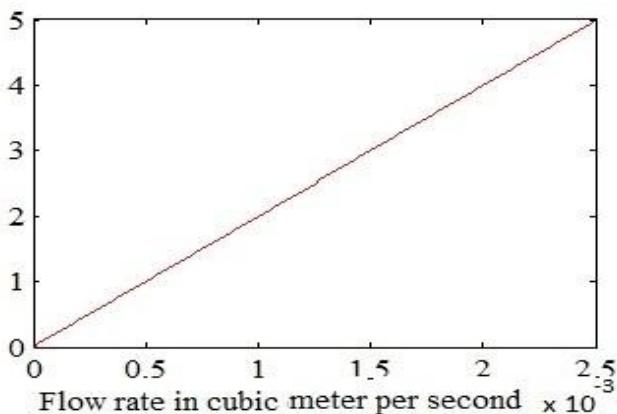


Figure 8. Target graph

This ANN model is designed using the neural network toolbox of MATLAB. The first step in developing a neural network model is to create a database for its training, testing and validation. The output voltage of data conversion circuit for a particular flow rate along with the pipe diameter, liquid density, and liquid temperature are stored as a row of input data matrix. Various such combinations of input flow rate, pipe diameter, liquid density, liquid temperature, and the corresponding voltage at the output of data conversion unit are used to form other rows of input data matrix. The output matrix is the target matrix. Target matrix consists of data having a linear relation with the input flow rate and adaptive of variations in

pipe diameter, liquid density, and liquid temperature as shown in Figure.8. Input data matrix and target matrix are shown in Table-1 and Table-2 respectively.

An ANN model is termed as optimized which gives best fit of input-output data matrix but with minimum number of hidden layers. The optimized ANN (OANN) model is found in two steps. In the first step, five different schemes and algorithms are used to find the optimized ANN. These are linear scheme with Levenberg-Marquardt algorithm (LMA) [28], [30], linear scheme with Gauss Newton Algorithm (GNA) [29], [30], linear scheme with Artificial Bee Colony (ABC) [31], [32], Back Propagation (BP) neural network trained by Ant Colony Optimization (ACO) [33]-[35], and Radial Basis Function (RBF) trained by ACO [36]-[38]. Training of ANN is first done assuming only one hidden layer. Best fit is measured in terms of Mean Square Error (MSE) and Regression (R). MSE is calculated considering the whole database which is subdivided into training, testing, and validation data set. Hidden layer is then increased to 2 and training is repeated. This process is continued up to 6 hidden layers. In all cases MSE and R are noted and are shown in Table-3. Pictorial representation of MSE and R in the form of a mesh corresponding to different algorithms and hidden layers are shown in Figure.9 and Figure.10. From Table-3, Figure.9 and Figure.10, it is very clear that RBF trained by ACO yields most optimized network for a desired MSE as threshold. RBF trained by ACO with 2 hidden layers is considered as semi optimized ANN model for desired accuracy of result. Although there is no direct relationship between accuracy of flow rate and value of MSE, but, lower value of MSE implies higher the accuracy of flow meter.

Table 1. Input data for ANN models

Voltages at the input of ANN with	0.0 m³/s	0.0125 m³/s	0.025 m³/s	...	2.5 x 10⁻³ m³/s
D=0.1, ρ=500, t=25 °C	4.9304	4.9148	4.8991	---	2.3073
D=0.2, ρ=500, t=25 °C	4.5652	4.5507	4.5362	---	2.1364
D=0.3, ρ=500, t=25 °C	4.2503	4.2369	4.2234	---	1.9891
D=0.1, ρ=1000, t=50 °C	3.9761	3.9635	3.9509	---	1.8607
D=0.2, ρ=1000, t=50°C	4.9321	4.9183	4.9043	---	2.9162
.....	---	---	---	---	---
D=0.3, ρ=1500, t=75 °C	3.9833	3.9779	3.9726	3.3813

Table 2. Target data for ANN models

Voltages at the input of ANN with	0.0 m³/s	0.0125 m³/s	0.025 m³/s	...	2.5 x 10⁻³ m³/s
D=0.1, ρ=500, t=25 oC	0	0.025	0.050	5.000
D=0.2, ρ=500, t=25 oC	0	0.025	0.050	5.000
D=0.3, ρ=500, t=25 oC	0	0.025	0.050	5.000
D=0.1, ρ=1000, t=50 oC	0	0.025	0.050	5.000
D=0.2, ρ=1000, t=50oC	0	0.025	0.050	5.000
.....
D=0.3, ρ=1500, t=75 oC	0	0.025	0.050	5.000

Table 3. Comparison of different ANN models

Layers		Linear GNA	Linear LMA	Linear ABC	BP trained by ACO	RBF trained by ACO
1	MSE	5.85E-3	3.58E-3	2.58E-3	1.00E-4	8.65E-5
	R	0.99325	0.99568	0.99458	0.99985	0.9999
2	MSE	9.98E-5	2.36E-6	2.26E-5	5.84E-7	3.66E-7
	R	0.99921	0.99998	0.999895	0.99992	0.99995
3	MSE	7.95E-7	2.93E-08	2.47E-7	1.852E-9	4.85E-10
	R	0.99996	0.999991	0.999985	0.999991	0.999996
4	MSE	2.85E-9	2.38E-10	1.28E-9	1.11E-11	3.28E-12
	R	0.999999	0.999999	0.999999	0.999999	0.999999
5	MSE	6.85E-11	4.67E-12	3.25E-12	2.58E-13	6.78E-14
	R	0.999999	0.999999	0.999999	0.999999	0.999999
6	MSE	3.12E-13	6.87E-14	4.28E-14	1.01E-15	8.67E-16
	R	0.999999	0.999999	0.999999	0.999999	0.999999

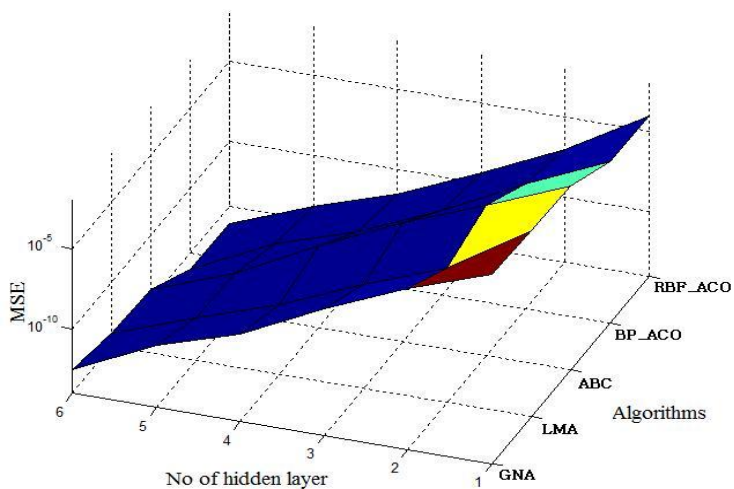


Figure 9. MSE corresponding to different ANN models in the form of a mesh

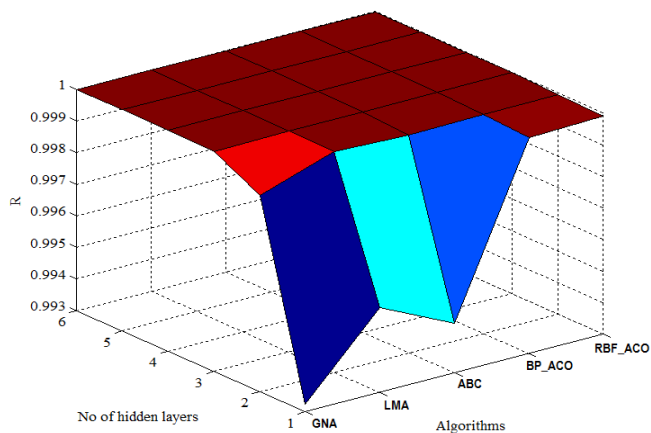


Figure 10. Regression corresponding to different ANN models in the form of a mesh

The second step of optimization is to choose a suitable transfer function of neuron. Literature review suggests that different transfer functions (TF) of neuron are used for ANN model. Training, testing, and validation are repeated with ten different transfer functions of neuron on the semi optimized ANN. The effect of neuron TF in terms of MSE are noted and tabulated in Table-4. Softmax TF is finally used in the optimized ANN based on the outcome, as shown in Table-4.

Table 4. Comparison of different neuron transfer functions

Sl.no	Transfer function	MSE
1.	Tanh	2.62E-7
2.	Sigmoid	2.47E-7
3.	Linear Tanh	2.21E-7
4.	Linear sigmoid	2.54E-7
5.	Softmax	0.99E-7
6.	Bias	2.01E-7
7.	Linear	3.66E-7
8.	Axon	2.22E-7
9.	Tansig	1.01E-7
10.	Logsig	1.23E-7

Table 5. summary of various parameters used in optimized neural network model.

Table 5. Summary of optimized ANN

Parameters of optimized artificial neural networks model					
Database		Training base		90	
		Validation base		30	
		Test base		30	
No of neurons in		1st layer		7	
		2nd layer		8	
Transfer function of		1st layer		softmax	
		2nd layer		softmax	
		Output layer		Linear	
Input		Flow in m ³ /s	D in m	Density in Kg/m ³	Temp
	min	0.000	0.1	500	25° C
	max	0.0025	0.3	1500	75° C

The proposed technique with optimized ANN is tested with simulated data and validated with practical data, results and discussion for the proposed work is reported in next section.

6. Results And Discussion

The proposed optimized ANN is trained, tested, and validated with the simulated data. Once the training is over, the flow measurement system is subjected to various simulated test inputs corresponding to different flow rates at a particular pipe diameter, liquid density, and temperature, all within the specified range. For testing purposes, the range of flow is considered from 0 to 0.0025m³/s, the range of pipe diameter is 0.1 to 0.3 m, the range of liquid density is 500 to 1500 Kg/m³, and temperature ranges from 25°C to 75°C. The outputs of the proposed technique are listed in Table 6.

Table 6. outputs of the proposed technique for various input conditions

Actual flow in m ³ /s	Pipe dia in m	Liquid density in Kg/m ³	Temp in °C	Data conver o/p in V	ANN o/p in V	Measured flow in m ³ /s	Error in %
0.0005	0.15	500	75	3.65	0.9985	0.0004992	0.160
0.0005	0.20	600	70	3.97	1.0025	0.0005012	-0.240
0.0005	0.25	700	65	4.13	0.9992	0.0004986	0.280
0.0010	0.30	800	60	1.09	1.9987	0.0009996	0.040
0.0010	0.10	900	55	1.18	2.0062	0.0010035	-0.350
0.0010	0.125	1000	50	1.43	2.0084	0.0010012	-0.120
0.0015	0.175	1100	45	0.41	2.9967	0.0014991	0.060
0.0015	0.225	1200	40	0.55	2.9986	0.0014988	0.080
0.0015	0.275	1300	35	0.63	3.0081	0.0015022	-0.147
0.0020	0.325	1400	30	0.50	4.0068	0.0020018	-0.090
0.0020	0.075	1500	25	0.88	4.0031	0.0020029	-0.145
0.0020	0.050	550	20	0.51	3.9991	0.0019988	0.060
0.0025	0.20	650	70	0.61	4.9993	0.0024998	0.008
0.0025	0.10	750	33	0.80	5.0029	0.0025003	-0.012
0.0025	0.30	850	48	0.69	5.0051	0.0025008	-0.032

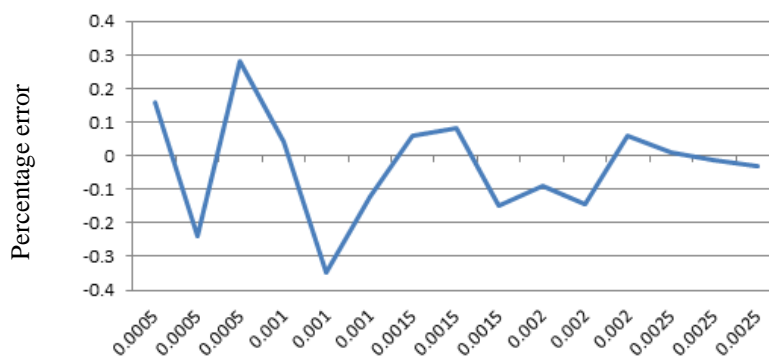


Figure 11. Error graph for simulated results

Table 6 suggests that measured flow rates are almost same as actual flow rate. Root mean square of % error for 15 different simulated test conditions is 0.0403. It may be noted that the test conditions in Table 4 are different from the conditions in the training data set. Simulated results made it clear that objectives of the present works are achieved.

The performance of the proposed intelligent flow measurement technique is validated with real life data generated in a laboratory. The experimental setup used for this purpose is shown in Figure 12. Four different cases are considered. Details of different cases are given in Table 7. Results of the proposed flow measurement using real life data are listed in table 5.

Table 7. Results of validation of proposed technique with real life data

Case-1: D = 2.54 cm, t = 26°C, ρ = 1000				
Actual Flow in m ³ /s	Actual O/p of DCC in V	ANN o/p in V	Measured flow in m ³ /s	% Error
0.0005	3.16	0.99	0.0004969	0.62
0.0010	1.85	2.00	0.0010102	-1.02
0.0015	0.84	3.00	0.0015021	-0.14
0.0020	0.42	4.00	0.0019928	0.36
0.0025	0.12	5.00	0.0025025	-0.10
Case- 2: D = 1.905 cm, t = 26°C, ρ = 1000				
Actual Flow in m ³ /s	Actual O/p of DCC in V	ANN o/p in V	Measured flow in m ³ /s	% Error
0.0005	3.38	1.00	0.0005112	-2.24
0.0010	1.92	1.99	0.0009986	0.14
0.0015	0.86	2.99	0.00149788	0.14
0.0020	0.41	4.01	0.0020189	-0.95
0.0025	0.11	4.98	0.00249857	0.06
Case- 3: D = 2.54 cm, t = 40°C, ρ = 1000				
Actual Flow in m ³ /s	Actual O/p of DCC in V	ANN o/p in V	Measured flow in m ³ /s	% Error
0.0005	3.29	0.99	0.0004962	0.76
0.0010	1.88	1.99	0.0009978	0.22
0.0015	0.85	2.98	0.0014989	0.07
0.0020	0.39	4.00	0.0020247	-1.23
0.0025	0.10	5.02	0.0025338	-1.35
Case- 4: D = 1.905 cm, t = 40°C, ρ = 1000				
Actual Flow in m ³ /s	Actual O/p of DCC in V	ANN o/p in V	Measured flow in m ³ /s	% Error
0.0005	3.56	1.01	0.0005129	-2.58
0.0010	1.99	1.98	0.0009921	0.79
0.0015	0.92	2.98	0.0014989	0.07
0.0020	0.51	4.02	0.0020148	-0.74
0.0025	0.16	4.99	0.0024987	0.05



Figure 12. Experimental setup used for the proposed setup

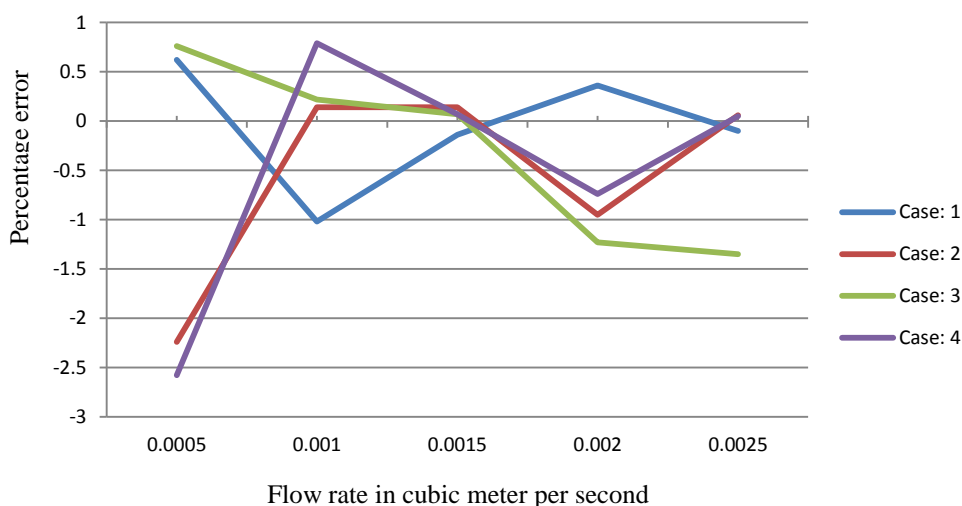


Figure 13. Experimental setup used for the proposed setup

Results in Table-7 show that the propose technique has worked well when validated with real-life data. Root mean square of % error of 20 different real life data is 0.9836. Thus, the proposed technique has fulfilled the objectives with real life data within reasonable accuracy. Table-6 and Table-7 show that the proposed system is made adaptive of variations in pipe diameter, liquid density, and liquid temperature, and made linear for full range of input scale.

7. Conclusion and future works

Available reported works have discussed different techniques for calibration of flow measurement, but these are not adaptive of variations in pipe diameter, liquid densities, and temperatures. Hence, repeated calibration is required for any change of these parameters. Sometime the calibration circuit may itself be replaced. Further, most of the reported works have not utilized the full input scale of measurement. In comparison to these, the proposed flow measurement technique achieves linear input output characteristics for full scale input range and makes the flow measurement adaptive of variations in pipe diameter, liquid density, and temperature. All these have been achieved by using an optimized ANN model. Five different combinations of scheme and algorithm and ten different transfer functions of neuron are considered for this purpose. RBF with ACO algorithm and softmax transfer function is found to have achieved the desired MSE and Regression close to 1 with only two hidden

layers. This is in contrast to an arbitrary ANN used in most of the earlier reported works. The proposed flow measurement technique is validated with 4 set of real-life data. Results show that proposed technique has fulfilled the set objectives.

8. References

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