ПРИБОРЫ И ТЕХНИКА ЭКСПЕРИМЕНТА, 2011, № 3, с. 154–158

## ЛАБОРАТОРНАЯ ТЕХНИКА

# PREDICTION MODELING OF CORIOLIS TYPE MASS FLOW SENSOR USING NEURAL NETWORK


Pravin P. Patil, Satish C. Sharma, S. C. Jain

*Department of Mechanical and Industrial Engineering, Indian Institute of Technology, Roorkee, India 247667, tel.: 91-9760010201, e-mail: pravinppatil2004@gmail.com*

Received November 29, 2010

The neural network (NN) technique has been utilized for prediction of performance of omega-tube type Coriolis mass flow sensor. The results show that a well trained and well tested NN model has the capability to predict the performance of mass flow sensor for varying design parameters depending on the availability of the data and can be used as an alternative to the physical models in the sense that the results can be produced in a fast and cost effective way. The values of correlation coefficient ($R$) for the training, testing and whole datasets indicates that the NN results are in good agreement with the experimental results.

## 1. INTRODUCTION

The Coriolis technology offers high accuracy and reliability in measuring the materials flow in process industry. The mass flow sensor based on this technology is independent of the density or viscosity of the fluid, or the velocity profile or Reynolds number of the flow as compared to conventional volume flow measurement techniques. It is a nonintrusive type of sensor. It has no moving parts (apart from a small-amplitude vibration of the flow tube), thus reducing maintenance problems [1, 2].

The basic measurement principle of Coriolis mass flow meter which is also known as vibration based electromechanical mass flow sensor [3] is that a flow tube is caused to vibrate sinusoidally at a resonant frequency (the fundamental natural frequency in most cases [4]) by one or more drivers while two sensors monitor the vibration. The flow tube geometry and sensor placement are arranged in such a fashion so that the frequency of oscillation can be used to calculate the density of the process fluid, while the phase difference between the two sensor signals provides the mass flow rate.

The flowing fluid passing through the vibrating tube produces Coriolis forces acting asymmetrically on the tube. These forces, which are proportional to the mass flow rate, produce the phase difference as mentioned above. Vibration based electromechanical mass flow sensor are sensing the true mass flow rate directly, unlike some other instruments that measures the volumetric flow rate. In this sense, models play a major role in facilitating the understanding of the various processes for design and optimization of the mass flow sensors.

Alternative to the experiments, which are expensive and in some cases difficult to perform, a well-validated physical model can provide much more useful information about the performance prediction of the mass flow sensor for varying design parameters. However, the main problems with the physical models are the difficulties associated with their construction and limited accuracies owing to the complex nature of the physical processes.

On the other hand, the models that map the relationship between the input and output without any internal knowledge of the system, such as artificial neural networks (NN), fuzzy logic, or fuzzy inference systems, can act as an important alternative to the physical models. They are comparatively: a) easy to formulate as there is no requirement for the numerical solution of the coupled partial differential equations, and b) computationally less time demanding.

An artificial neural network is an information-processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. NN's learn by examples and learning involves adjustments to the synaptic connections that exist between the neurons [5].

The objective of the present research is to develop a neural network based predictive model of the phase shift for performance evaluation of a vibration based electromechanical mass flow sensor. The design parameters like height of tube, sensor location and drive frequency were considered input features.

## 2. EXPERIMENTAL WORK

In order to develop performance prediction model the experimental results were used. The experimental studies were performed on the omega shaped of aluminium vibrating tube mass flow sensor with water as a fluid. The photographic view of the experimental setup is shown in Fig. 1.

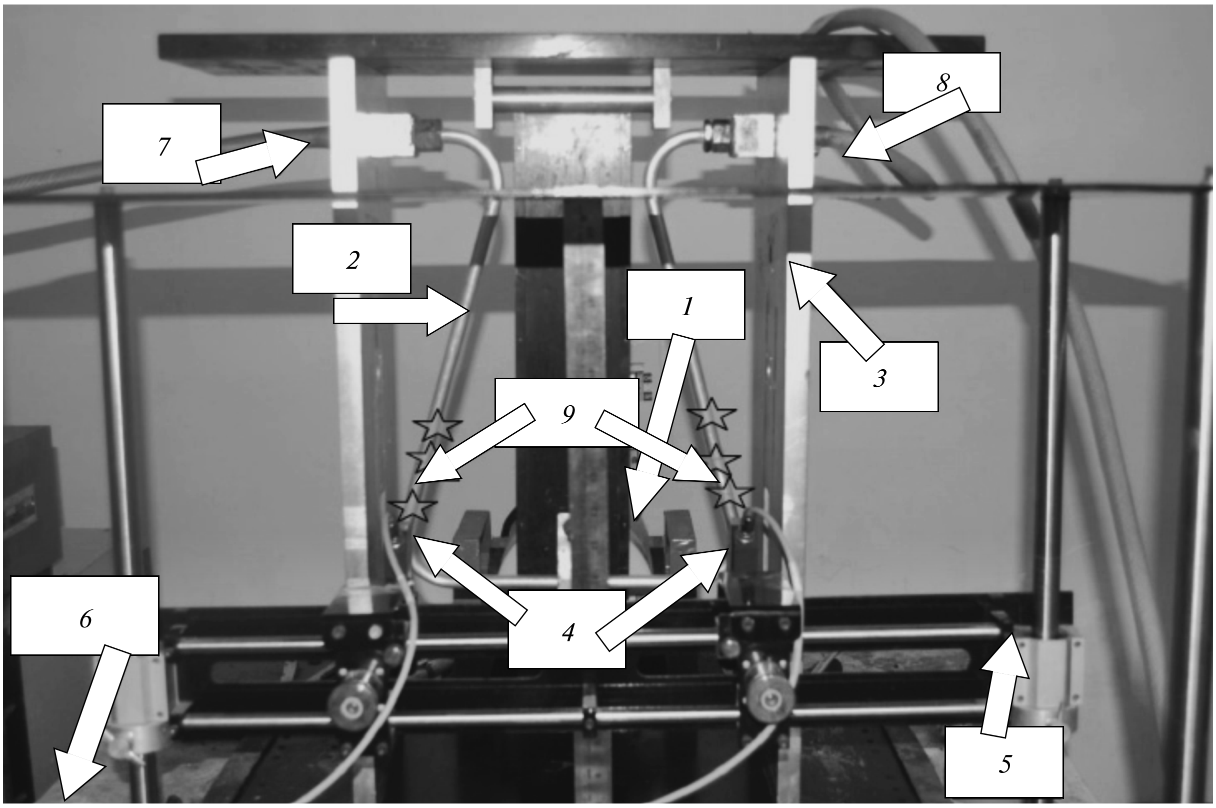


**Fig. 1.** Photographic view of experimental setup. *1* – Vibration driver; *2* – Omega tube; *3* – Test Bench; *4* – Laser sensors; *5* – Sensor holding stand; *6* – Foundation; *7* – Inlet pipe; *8* – Outlet pipe; *9* – Sensor locations.

Optical displacement sensors have been used for motion sensing, as these are sensitive to metal objects, they are helpful in eliminating any unwanted noise generated from the surroundings and inherently resistant to dust, humidity and oil in industrial environment.

The vibration shaker used in the present study delivers amplitude of 5 mm peak to peak and an excitation frequency in the range of 1Hz to 1 kHz. In order to make a contact a mild steel rod of 5 mm diameter is used as a stinger to transfer the motion to the knife-edge support. As the exciter uses a lot of power and generates a lot amount of vibrations, a strong isolated base was provided to damp the vibration and thus avoid movement of exciter or transfer of stray vibrations to the sensor stand or the testing bench [3, 6].

The present work utilizes the concept of Virtual instrumentation platform to perform the fast data analysis. Data acquisition and its processing can be conveniently implemented on a digital platform. For ease of coding, a PC platform is chosen as the processing hardware. For acquiring the signal from the sensors to the PC, NI-DAQ card (USB-6211) is used. It consists of two 32-bit counters operating at 80 MHz. It also contains 16-bit A/D converter operating at 250 kS/s, which continuously samples the signal. A visual programming language (Lab View) is used for processing the data in real time. The design parameters varied in this study are the height of tube ($L$) 200–400 mm, tube width 500 mm, sensor location ($SL$) 60–140 mm, drive frequency ($DF$) 15–37 Hz , flow range between 0 to 0.3 kg/s, tube material of aluminium and Omega shaped tube diameter of $d_0$ = 12.7mm, $d_i$ = 10.9 mm, height inclination ($\alpha$) 47–65° and constant widths $b$ = = 120 mm and $a$ = 190 mm and above all these may be visualized from Fig. 2.

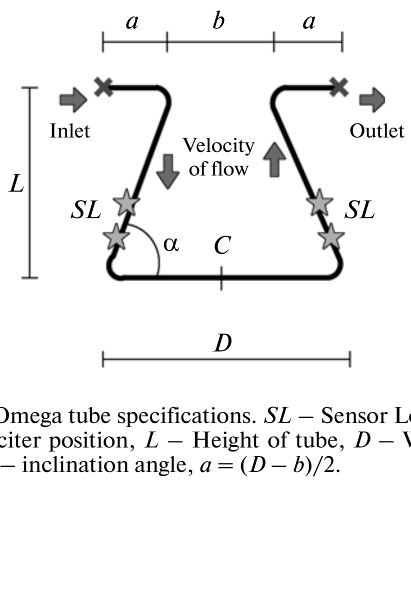


**Fig. 2.** Omega tube specifications. $SL$ – Sensor Location, $C$ – Exciter position, $L$ – Height of tube, $D$ – Width of tube, $\alpha$ – inclination angle, $a = (D - b)/2$.

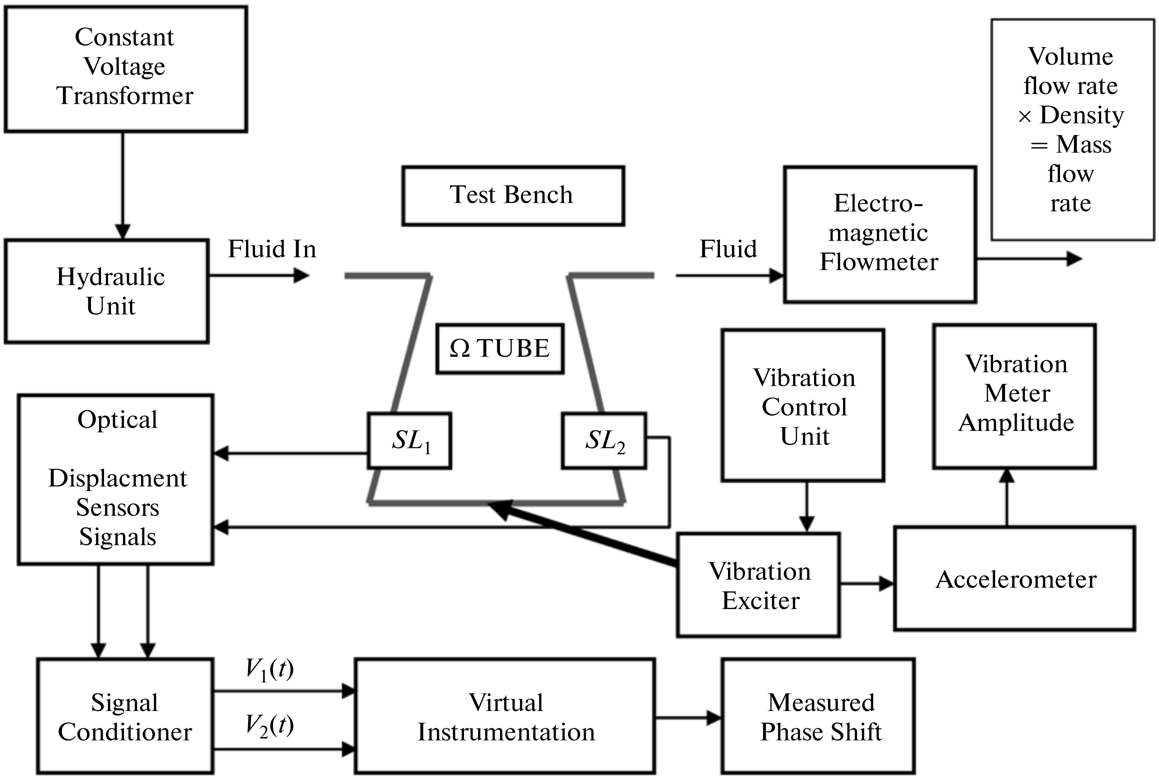


**Fig. 3.** Flow chart describing experimental procedure.

The details of the experimental setup are described in Fig. 3. The hydraulic unit for providing regulated water supply to the mass flow sensor derives its power from the constant voltage transformer (CVT) to maintain constant flow rate. The omega-tube is made to vibrate using an electronic shaker. An accelerometer is attached to the shaker, which measures the velocity, amplitude and acceleration of the vibration induced by the electronic shaker. The accelerometer gives the feedback to the vibration meter, which is observed for maintaining the constant amplitude.

A pair of optical displacement sensors has been placed on the mechanical positioning attachment facing the two limbs of the omega-tube. Their distance from the limbs is adjusted such that they generate square wave. The output terminals of the sensors have been connected to the input of the NI-DAQ through a signal conditioner. NI-DAQ has inbuilt counters which operate at 80 MHz. The processing of the signals, calculation of the phase shift and displaying of the results is processed in Lab view.

Accuracy and repeatability for each experiment was achieved with the same input conditions until stabilized output was achieved.

## 3. NEURAL NETWORK APPROACH

Experiments were conducted and a data set was obtained containing 81 sets of input parameters and the corresponding output parameter. This data set was used for training and testing the neural network model built using the neural network toolbox in MATLAB [7]. The input vectors and target vectors are randomly divided into three sets – 60% are used for training, 20% are used to validate that the network is generalizing and to stop training before over fitting and 20% are used as a completely independent test of network generalization.

A three-layer network as shown in Fig. 4 having one input layer, one hidden layer and one output layer, was formed for the present study. The number of input layer neurons is same as the number of input variables (height of tube, mass flow rate, location of sensor and drive freq.), here it is 4. The output layer consisted of one neuron corresponding to one output variable (the phase shift). The number of hidden neurons depends both on input vector size and on number of input classifications. Too few neurons may lead to under fitting whereas too many neurons can contribute to over-fitting. For the present study, 10 hidden layer neurons were used. The feed-forward back propagation network was employed and tan sigmoid transfer function was used for the hidden layer neurons.

By prolonged training beyond certain epochs, the NN has the tendency to memorize the input-output pattern, which results in poor generalization ability. Thus, in the present investigation the network was trained for 100 epochs.

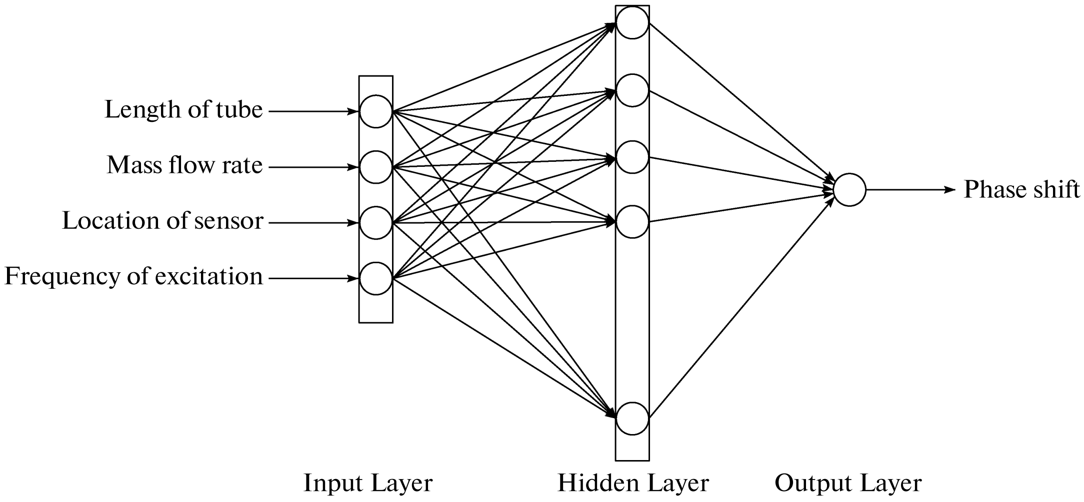


**Fig. 4.** Three layer neural network architecture.

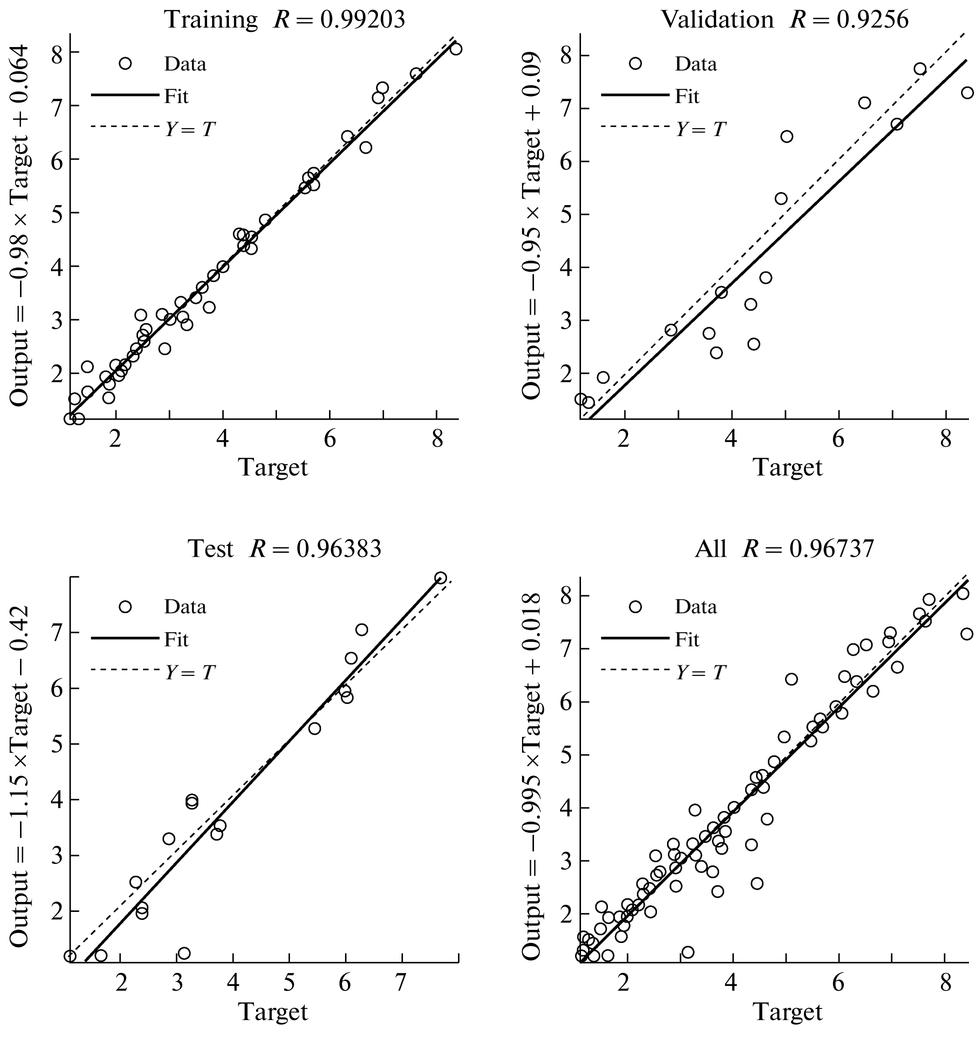


**Fig. 5.** Regression plots for the NN prediction.

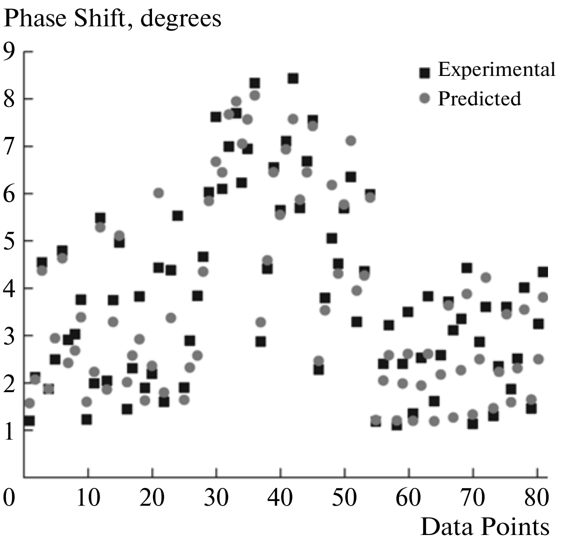


**Fig. 6.** Scatter of predicted and experimental phase shift.

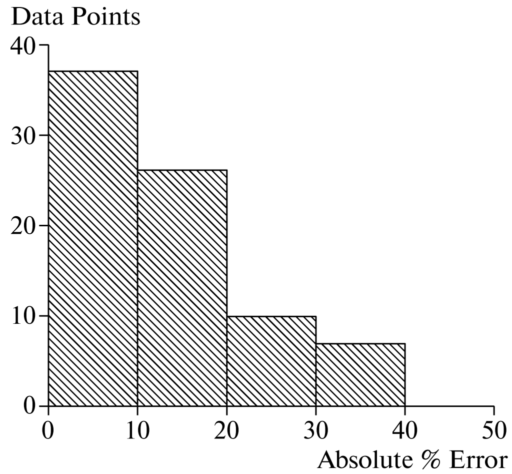


**Fig. 7.** Histogram of error of NN prediction.

## 4. RESULTS AND DISCUSSION

The effectiveness of the NN model was tested with experimental test data. The correlation coefficient $R$ between the predicted phase shift and the experimental phase shift for training, validation and test data was found to be acceptable as indicated in Fig. 5.

The experimental and the predicted values of the phase shift are plotted as shown in Fig. 6.

It is clear from the plot that the predicted values are close to the experimental values and follow the same trend. A histogram of the prediction error in percentage was plotted in Fig. 7 and it was observed that for most cases the error was within 20%.

It is clear from the analysis that NN model can be used as an effective tool for modeling the response of the Coriolis mass flow sensor.

## 5. CONCLUSIONS

In the present investigation, neural network approach has been employed to predict the performance of the omega-tube type Coriolis mass flow sensor. The result indicates that NN has the capability to map the input-output relationship, i.e. predict the performance under different operational conditions depending on the availability of the experimental data. The values of correlation coefficient for the training, test and whole datasets show that the NN results are in good agreement with the experimental results. Thus, NN model for predicting the performance of the mass flow sensor is an effective tool for the selection of design parameters in early product development process. The principal advantage of this model is that the performance curve can be predicted in an accurate, rapid, and cost effective way. Hence, to predict the performance of such type mass flow sensors in practice it can be used as an alternative model.

## ACKNOWLEDGEMENT

The authors would like to thank the Department of Science and Technology (DST) Government of India for providing the necessary funding to carry out this research work.

## REFERENCES

1. Plache, K.O., *Mech. Eng.*, 1979, pp. 36–41.
2. Miller, R.W., *Flow Measurement Engineering Handbook*, 1996, McGraw-Hill International Edition.
3. Anklin, M., Drahm, W., Rieder, A., *Flow Measurement and Instrumentation*, 2006, vol. 17(6), pp. 317–323.
4. Raszillier, H., Durst, F., *Archive of Applied Mechanics*, 1991, vol. 61, pp. 192–214.
5. Bishop, C.M., *Review of Scientific Instruments*, 1994, vol. 65, pp. 1803–1832.
6. Cheesewright, R., Belhadj, A., and Clark, C., *J. of Dynamic Systems, Measurement, and Control*, 2003, vol. 125, pp. 103–113.
7. The Math Works Company, Natick, MA, *Neural Network Toolbox User's Guide of MATLAB 7.2.*, 2006.