Available online at www.sciencedirect.com
ScienceDirect
Procedia Technology 14 (2014) 260 – 265
Procedia Technology
ELSEVIER

2nd International Conference on Innovations in Automation and Mechatronics Engineering, ICIAME 2014

ANN Modelling of Cu Type Omega Vibration Based Mass Flow Sensor

Pravin Patil[a]* ,Satish C. Sharma[b],Vipul Paliwal[a],Ashwani Kumar[a]

[a]*Department of Mechanical Engineering,Graphic Era University , Dehradun, India -248002,* [b]*MIED, IIT Roorkee-247667.*

Abstract

Artificial neural network (ANN) based model has been developed for copper omega type mass flow sensor. The significant phase shift parameter is modeled for various input factors like sensor location, drive frequency, mass flow rate and length of tube. This model is found in good agreement with the experimental results after comparison. The effectiveness of the ANN model was tested with 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 for prediction of phase shift by taking sensor location, mass flow rate, length of tube and frequency excitation as input parameters. A reliable and useful predictor for phase shift for future studies in Cu type mass flow sensor may be developed based on large number of variables used during training the model.

Peer-review under responsibility of the Organizing Committee of ICIAME 2014.

Keywords: soft computing technique, prediction modeling, copper omega shaped tube, instrumentation, mass flow sensor, measurement

1. Introduction

Neural computing is a comparatively new field of artificial intelligence (AI), which tries to imitate the formation and action of biological neural systems, such as the human brain, by creating an Artificial Neural Network (ANN) on a computer. These ANNs are modeling techniques that are in particular valuable to address tribulations where solutions are not evidently formulated [1] or where the interaction between inputs and outputs are not adequately known. Artificial Neural Networks have the ability to learn by example. Patterns in a series of input and output

* Corresponding author. Tel.: +91-9760010201
E-mail address: pravinppatil2004@gmail.com

Peer-review under responsibility of the Organizing Committee of ICIAME 2014.
doi:10.1016/j.protcy.2014.08.034

values of example cases are recognized. This acquired 'knowledge' can then be used by the Artificial Neural Network to predict unknown output values for a given set of input values. A variety of literatures [1, 2] are existing on artificial neural network, and their applications.
However, study on application of ANN to copper omega type Coriolis mass flow sensor lacks in the literature. Hence, this paper describes the prediction modeling of phase shift for copper omega type Coriolis mass flow sensor which 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 [3-6].
Study of this all but constructive experimental data [7] through analytical tools such as 'Artificial Neural Network' will be greatly advantageous both in terms of time and ease of complex data (for example, phase shift prediction can be made for any combination of parameters/variables: SL/DF, DF/L etc) as before did by patil et. al [8, 9] by application of response surface modeling as well as ANFIS modeling. The aim of this paper is therefore, to apply an ANN based model for the phase shift modeling of copper omega type Coriolis mass flow sensor.

2. **Experimental work**

In order to develop performance prediction model the experimental results were used. The experimental studies were performed on the omega shaped vibrating tube mass flow sensor with water as a fluid. The Experimental set up used in the present study has been designed on Pro Engineer Wildfire modeling software and later manufactured at the Instrumentation project laboratory of Mechanical and Industrial Engineering Department, IIT, Roorkee. The photographic view of the experimental setup has been shown in figure 1, which consists of the several functional elements such as: Hydraulic bench for providing regulated water supply to the flow sensor. Test bench for supporting the tubes of the mass flow sensor. Excitation system for providing mechanical excitation to the mass flow sensor, consists of an Electrodynamics shaker, control unit, accelerometer and vibration meter. Virtual instrumentation comprising of non-contact displacement laser sensors, and a signal conditioning unit for extraction of phase shift.
The design parameters varied in this study are flow range between 0 to 0.3 kg/s, the details of these have been shown in Table 1 as below. 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.

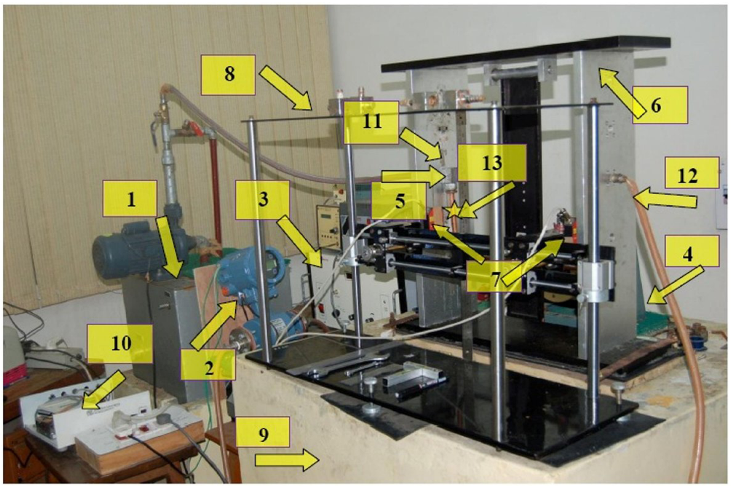

Fig. 1 Actual photographic view of experimental setup
Various design components as follows:

1. Hydraulic bench	5. Omega shape tube	9. Foundation	13. Sensor locations

2. Electromagnetic flowmeter	6. Test Bench	10. Data Acquisition box
3. Vibration Control unit	7. Laser sensors	11. Inlet pipe
4. Vibration driver	8. Sensor holding stand	12. Outlet pipe

The vibration shaker used in the present study which provides the desired excitation to the Coriolis Mass Flow Sensor. This is having amplitude of 5mm 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 so as 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 consists of a 16 bit A/D converter operating at 250 kS/s which continuously samples the signal. A visual programming language (LabView) is used for processing the data in real time.
The various parameters varied in this study are the length of tube (L), sensor location, drive frequency, flow range between 0 to 0.3 kg/sec; the details of these have been shown in Table 1.

Table: 1 Input design parameters

Tube material	Copper
Tube configuration	Omega shaped (Ω)
Tube dimensions	Do=12.7 mm ; Di=10.9mm
Mass Flow range	0 to 0.3 kg/s
Length of tube	200 to 400 mm
Sensor Location	60 to 140 mm
Excitation (drive) frequency	13 to 32 Hz
Fluid	Water

3. Soft computing model development methodology

Back-propagation networks are mainly valuable for examples concerning forecasting and pattern recognition. Back-propagation training is one of the mainly accepted methods for training ANNs with back-up/historical data [1]. Neural network toolbox in MATLAB software [3] was used in the current investigation to execute back-propagation training. In real meaning, back-propagation training adapts a gradient– descent approach of adjusting the ANN weights. During training, an ANN is accessible with the data of thousands of times (called cycles). After each cycle, the error between the ANN outputs and the actual outputs are propagated backward to adjust the weights in a manner that is accurately assured to congregate [2].

3.1 Training soft computing model

The most important property that deems ANNs supremacy to algorithmic and other network based systems is their capability to be trained on historical information as well as real-time data. Training is the act of constantly adjusting their connection weights until they reach unique values that allow the network to produce outputs that are close adequate to the preferred outputs. The precision of the developed model, therefore, depends on these weights. Once optimum weights are reached, the weights and biased values encode the network's state of knowledge. Thereafter, using the network on new cases is merely a matter of simple mathematical management of these values. Training data for the development of the neural network model was obtained from the Experiments conducted and a data set containing 81 sets of input parameters and the corresponding output parameter.

Neural network architecture used

The proposed ANN model was developed using back-propagation architecture with three layers jump connections [10], where every layer (slab) was connected or linked to every previous layer. 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.
The transformed data set was then divided into two parts. One containing 54 data points was used for training the network. Another part containing 18 data points was used for testing the network. The data set used for testing the network was chosen randomly from the experimental data set. A three layer network (Fig.2) 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 (length of tube, mass flow rate, location of sensor and frequency of excitation), 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 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

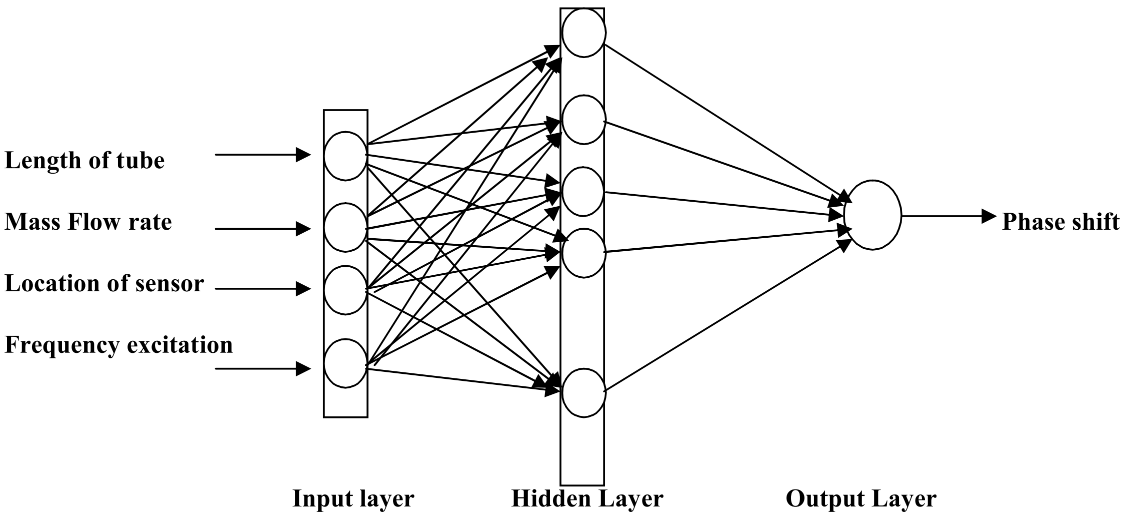

Fig. 2 Three layer neural network architecture

By prolonged training beyond certain epochs, the ANN 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.

4. Evaluation of the trained ANN model

The effectiveness of the ANN model was tested with test data. Fig. 3 illustrates about training plot for the ANN prediction of phase shift. The correlation coefficient(R) between the predicted phase shift and the experimental phase shift for training was found to be 0.91 which is acceptable for prediction of phase shift.

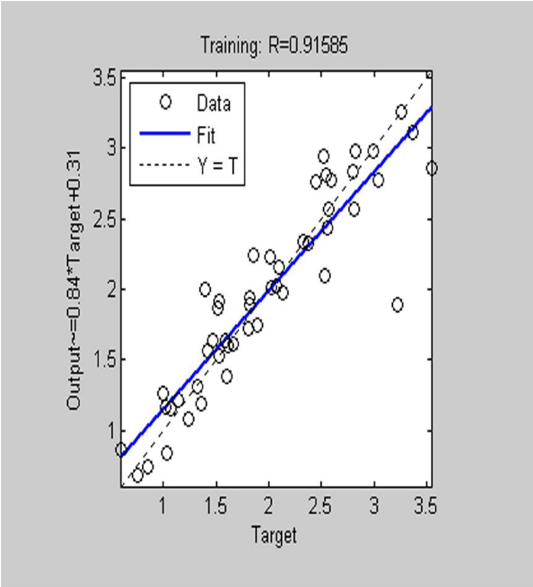

Fig. 3.Training plot for the ANN prediction

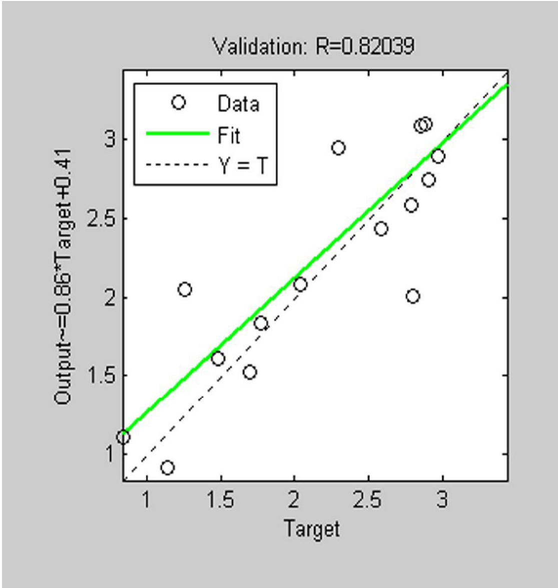

Fig. 4.Validation plot for the ANN prediction

Fig. 4 indicates regarding validation plot for the ANN prediction of phase shift. The correlation coefficient(R) was found to be 0.82 between the predicted phase shift and the experimental phase shift for validation which is acceptable for prediction of phase shift. Fig. 5 describes about testing plot for the ANN prediction of phase shift. The correlation coefficient(R) between the predicted phase shift and the experimental phase shift for testing was found to be 0.92 which is excellent fit for prediction of phase shift.

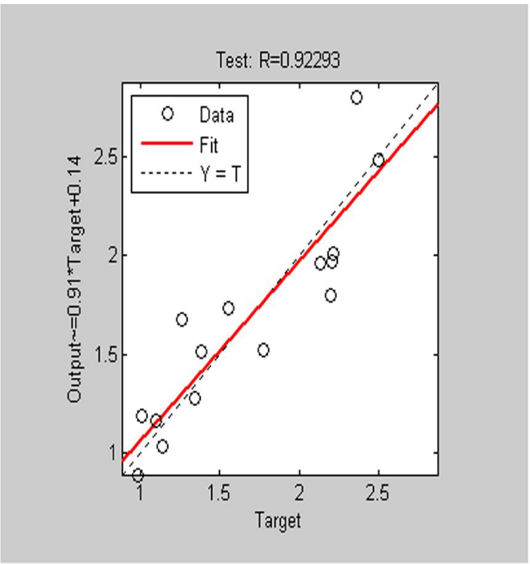

Fig. 5.Testing plot for the ANN prediction

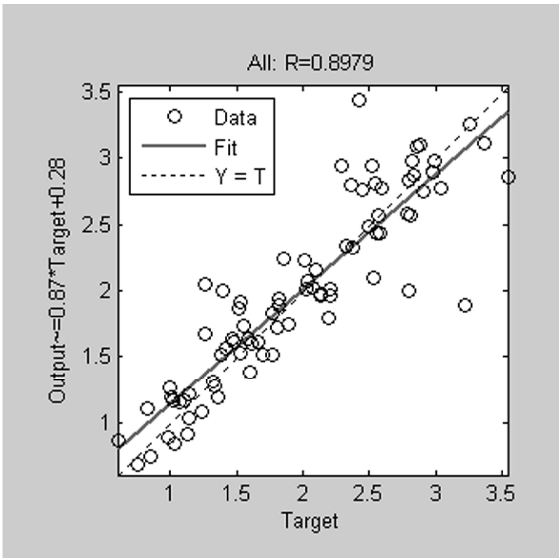

Fig. 6.Regression plot for all data the ANN prediction

Fig. 6 illustrates about regression plot for all data of ANN prediction of phase shift. The correlation coefficient(R) between the predicted phase shift and the experimental phase shift for regression was found to be 0.89 which is acceptable for prediction of phase shift.

5. Conclusions

Soft computing modeling of copper omega type Coriolis mass flow sensor through artificial neural network provided an exceptional matching with the experimental result. The efficiency of the ANN model was tested with 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 for prediction of phase shift by taking sensor location, mass flow rate, length of tube and frequency excitation as input parameters. ANN based model can be used with a high degree of accuracy and reliability, since a large number of variables was used during training the ANN model for predicting the phase shift in Coriolis mass flow sensor. The practical benefits of this model can be extensive to any proportion/combination of design parameters for their prospective applications in mass flow sensing.

References

1) Chester M. Neural networks—a tutorial. Englewood Cliffs, NJ: Prentice Hall, 1993.
2) Rumelhart D, Hinton G, Williams R. Parallel distributed processing. Cambridge, MA: MIT Press, 1986.
3) Anklin M, Drahm W, Rieder A., Coriolis mass flow meters: Overview of the current state of the art and latest research, Flow Measurement and Instrumentation, 17 (6), 2006, pp. 317-23.
4) Plache, K. O. March, Coriolis/gyroscopic flowmeter, Mech. Eng., 1979, pp.36-41.
5) Richard W. Miller, "Flow Measurement Engineering Handbook", third ed., McGraw-Hill International Edition, 1996.
6) R. Cheesewright, A. Belhadj and C. Clark, "Effect of mechanical vibrations on Coriolis mass flow meters", Journal of Dynamic Systems, Measurement, and Control, 125, 2003, pp. 103–113.
7) Sharma Satish C. , Pravin P. Patil , Major Ashish Vasudev, S. C. Jain, Performance Evaluation of an Indigenously Designed Copper (U) tube Coriolis Mass flow sensors, Measurement, 43(9) (2010) 1165-1172.
8) Patil Pravin P, Satish C. Sharma, S.C. Jain, Response surface modelling of vibrating omega tube (Copper) Electromechanical Coriolis mass flow sensor, Expert Systems With Applications , 39 (4) 2012, pp. 4418 – 4426.
9) Patil Pravin P, Satish C. Sharma, S.C. Jain, Performance evaluation of a Copper omega type Coriolis Mass Flow Sensor with an aid of ANFIS tool, Expert Systems with Applications, 39 (5) 2012, pp. 5019-5024.
10) Neural Network Toolbox User's Guide of MATLAB 8.0, The Math Works Company, Natick, MA, 2010.