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Modeling Influence of Tube Material on Vibration Based EMMFS using ANFIS

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Abstract

The modeling of a vibration based electromechanical mass flow sensor using an adaptive neuro-fuzzy inference system (ANFIS) has been presented to study the influence of tube material. The input parameters taken into consideration are tube material, sensor location, drive frequency, height of tube. The results show that a well trained and well tested ANFIS model has the capability to predict the performance of mass flow sensor under varying operational conditions 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 performance of the model in regions where deficiency of data exists has been discussed.

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Keywords: mass flow sensor, performance prediction, adaptive neuro-fuzzy inference system

1. Introduction

Cascetta et al. (1991) observed that Li and Lee in 1953 invented the first application of the Coriolis force for mass flow measurement. In the early 1980's the interest in Coriolis mass flow sensors has been widely accepted in many industries as indicated by Anklin et al. (2006). The basic measurement principle of coriolis mass flow meter also known as vibration based electromechanical mass flow sensor according to Henry et al. (2003) is that a flow tube is caused to vibrate sinusoidally at a resonant frequency which is the fundamental natural frequency in most cases observed in study of Raszillier et al. (1991) by one or more drivers while two sensors monitor the vibration. The flow tube geometry and sensor placement are arranged in 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

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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 strong candidates for the next generation mass flow measurement techniques and this is attributed due to sensing of the true mass flow rate directly, unlike some other instruments that measure the volumetric flow rate. However, there are still problems that prevent their widespread commercialization. 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 useful information about the performance prediction of the mass flow sensor for different operational conditions. However, the main problems with the physical models are the difficulties associated with their construction and limited accuracies due 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 (ANN), fuzzy logic (FL), or fuzzy inference systems (FIS), can be an important alternative to the physical models as they are comparatively: a) easy to build, i.e., there is no requirement for the numerical solution of the coupled partial differential equations, and b) computationally less time demanding.

In literature, there is not a single study reported till date on the performance prediction of vibration based Coriolis mass flow sensors using applied soft computing technique like ANFIS.

Jang (1993) observed that ANFIS is a hybrid model which combines the ANNs adaptive capability and the fuzzy logic qualitative approach. By utilizing the mathematical properties of ANNs in tuning rule-based fuzzy systems that approximate the way human process information, ANFIS harnesses the power of the two paradigms: ANNs and fuzzy logics and overcomes their own shortcomings simultaneously as indicated by Lei et al. (2008). The adaptive network based fuzzy inference system (ANFIS) is a useful neural network approach for the solution of function approximation problems by Buragohain et al. (2008). An ANFIS gives the mapping relation between the input and output data by using hybrid learning method to determine the optimal distribution of membership functions indicated by Ying et al. (2008). Both artificial neural network (ANN) and fuzzy logic (FL) are used in ANFIS architecture observed by Avci (2008). Sengur (2008) mentioned that such framework makes the ANFIS modeling more systematic and less reliant on expert knowledge.

In this study, phase shift of a vibration based electromechanical mass flow sensor was modeled using the ANFIS. The design parameters like tube material, length of tube, sensor location and drive frequency were considered input features. All the above mention design parameters have been observed influential in performance evaluation of such type of sensors by Sharma et al. (2010) and Patil et al. (2012) in their previous experimental and modeling study. The model was first trained and tested for the region where the experimental data is available. Then using this model, the prediction of the phase shift under different operational conditions has been performed.

2. *Experimentation scheme*

In order to develop performance prediction model the experimental results were used. The experimental studies were performed on the omega shape 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.

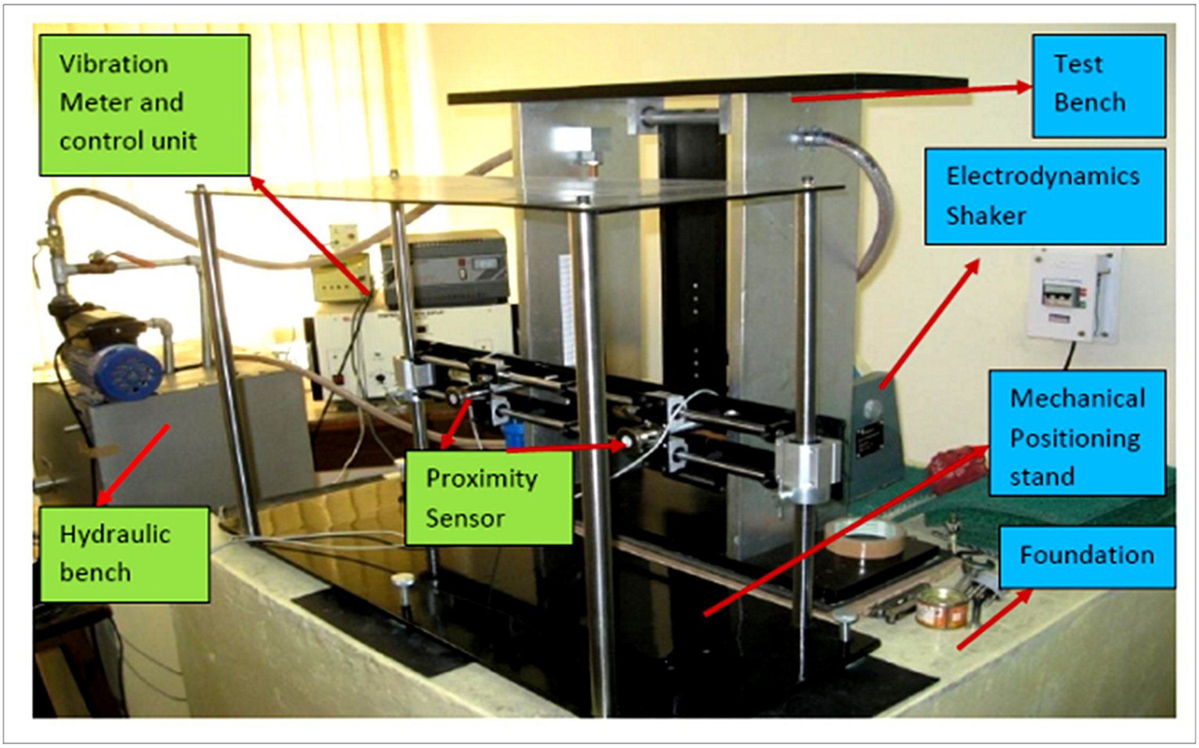

Figure: 1 actual photographic view of experimental setup

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 and material of tube; the details of these have been shown in Table 1.

Table: 1 input design parameters

Tube material	Copper , Aluminium, Mild steel
Tube dimensions	Do=12.7 mm ; Di=10.9mm
Mass Flow range	0 to 0.3 kg/s
Vertical height of tube	200 to 400 mm
Sensor Location	60 to 140 mm
Drive frequency	15 to 50 Hz
Fluid	Water

3. ANFIS:

A total of 243 samples were obtained from experimentation. In order to optimize the parameters of the model it is necessary to divide the available samples into two separated sets: the training set and the testing set. The training set is used to calibrate the model using a supervised learning algorithm, and the validation set is used to validate such

calibration comparing the outputs values of this set with the resulting outputs of the model using the corresponding inputs. Among these samples, 123 were used for training and the remaining 120 were used for testing. The samples were chosen randomly.
The Fuzzy logic Toolbox of MATLAB by The Math Works (2006) is used to generate the fuzzy inference system from the available data. To generate the fuzzy sets, the number of sets for each input variable and their shapes are defined. Large number of sets may produce better fitness in training process but a poor validation due to insufficient samples while few sets may produce a poor fitness but a more adequate generalization. Considering both fitness and generalization, 2 sets for each input variable was selected which was found suitable after some trials. In the present investigation grid partitioning, i.e., uniform distribution within variables' domain was employed. Generalized gauss curve was chosen as the sets' shapes which has the advantage of being smooth and nonzero at all points. In ANFIS, there are certain standard representation shapes, also known as membership functions, such as triangle, trapezoidal, gauss curves, bell curves, etc. Generalized gaussian function was found suitable for the present study as it produced the smallest error during calibration. Thus fuzzy sets were assigned to each kind of input data, but there are only two choices for the output membership function: constant and linear since ANFIS only operates on Sugeno-type systems. For the sake of performance, the constant membership function was chosen.

4. Results and discussion:

By prolonged training beyond certain epochs, the ANFIS has the tendency to memorize the input–output pattern, which results in poor generalization ability. Thus, in the present investigation 300 epochs were set as goal of ANFIS training and the error was found to be asymptotic. The training rms error came out to be 0.57398 degrees. The scatter plots of FIS output against training data and test data are shown in Fig. 2 and Fig. 3 respectively.
The trained ANFIS was initially tested with the 123 input patterns which were employed for the training purpose. For each input pattern, the predicted value of phase shift was compared with the respective experimental value from the database. It was found that the predicted values were very close to the experimental values. Fig. 2 shows the bar graph of the predicted and the actual values of the phase shift for 123 training patterns. The error has been found to be less than 10% for most of the cases.

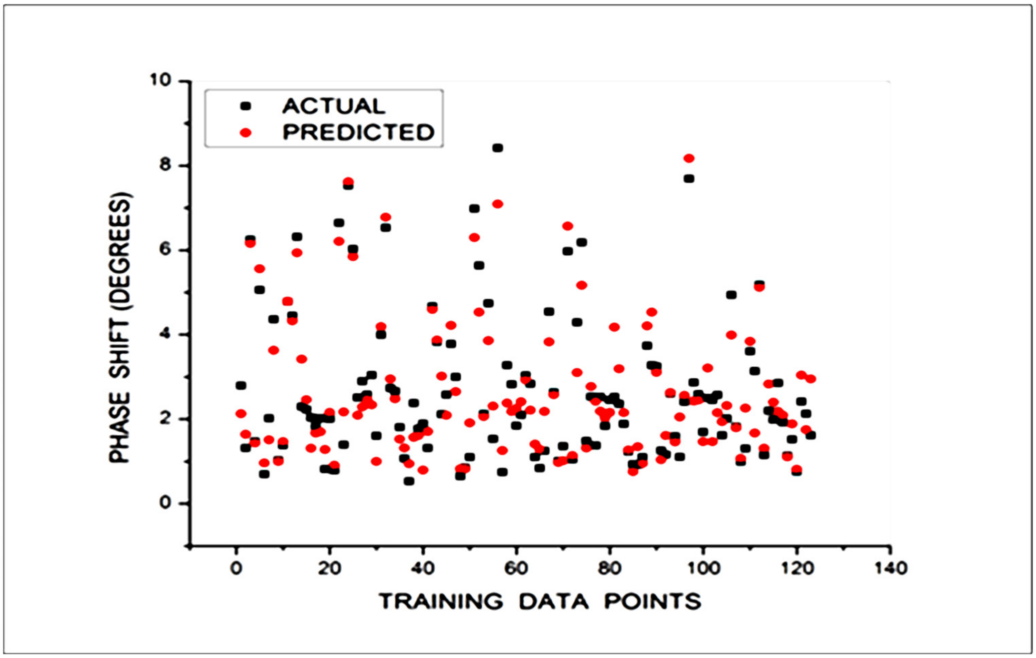

Figure 2 – Scatter of FIS output and target for training data

The trained ANFIS was tested with the 120 test data points which were not used for the training purpose. The comparison of the predicted and the actual output values of the phase shift for the test data set is presented in Fig. 3. From the test results, it may be observed that the predicted values are very close and follow almost the same trend as the actual values.

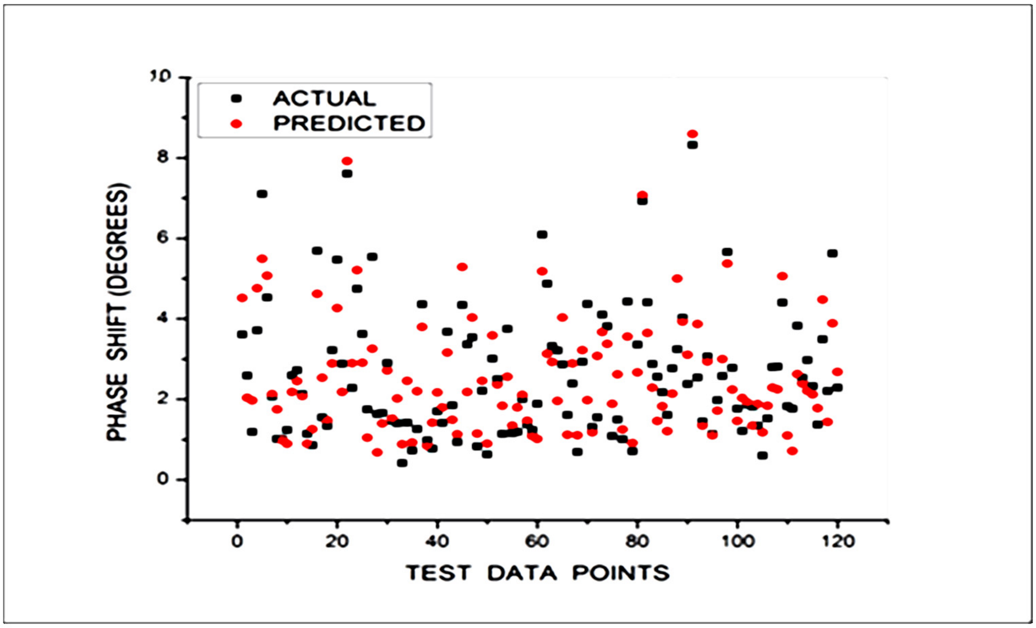

Figure 3- Scatter of FIS output and target for test data

Further, analysis of the performance accuracy was carried out in the form of linear regression analysis between the network output (predictions) and the corresponding targets for the training, testing and whole dataset as shown in Fig. 4 (a),(b) and (c). The ANFIS predicted the values to a high degree of accuracy. The correlation coefficient (R) values for the datasets were found to be satisfactory and show a good degree of agreement between the output and the target values of the phase shift.

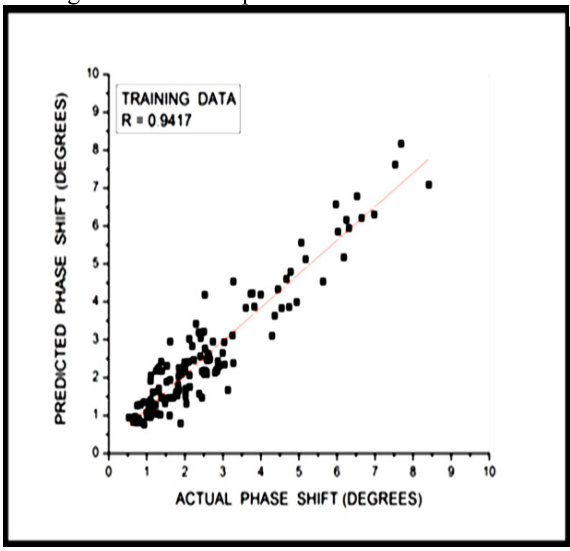

Fig. 4(a)

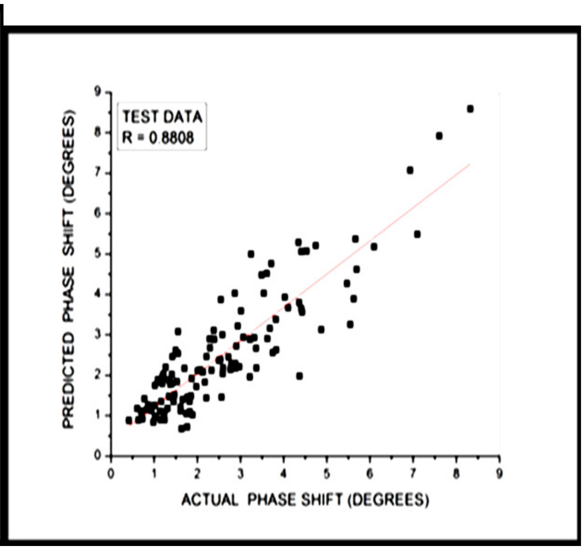

Fig. 4 (b)

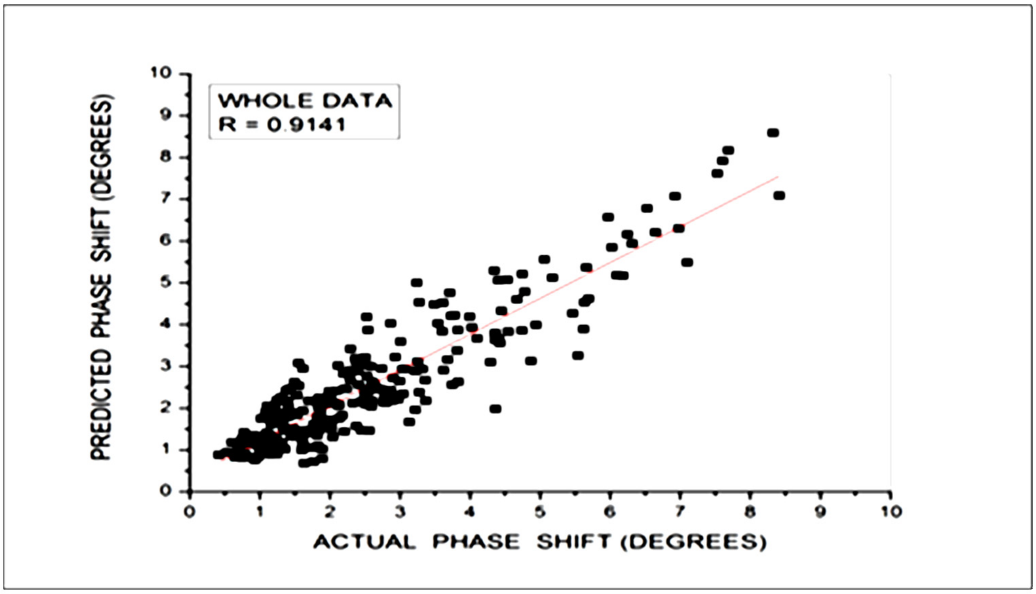

Fig. 4(c)

Figure 4 – The performance of ANFIS model, showing the plots of the predicted vs. target values for the training (a), test (b) and whole dataset (c).

It is quite clear from Fig. 2 through 4 that the phase shift predicted by ANFIS model matches well with the training as well as the test data. The ANFIS model developed can be used as a tool for controlling the response of the Coriolis mass flow sensor.

5. Conclusion:

In this paper, an adaptive neuro-fuzzy inference system has been employed first time in the literature to predict the performance of a vibration based Coriolis mass flow sensor. The result indicates that ANFIS 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 (R) for the training, test and whole datasets show that the ANFIS results are in good agreement with the experimental results. Thus, ANFIS 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 performance of the ANFIS model with more input variables will be investigated in the future. The principal advantage of this model is that the performance curve can be predicted in an accurate, rapid, and cost effective way. Therefore, it can be used as an alternative model to the physical models to predict the performance curve in practice.

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