INTELLIGENT FLOW SENSOR USING NEURAL NETWORK

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Abstract: The thermal flow measurement is based on the cooling effect of a fluid in a heated transducer. The sensor used suffers a strong influence of the fluid temperature, especially at low rates. In this work, a neural network is trained to learn the errors in the measurements due to the simple thermal model used. The neural network was able to correct the errors and achieve a accuracy bellow 5%.

Key words: Thermal, Flow, Neural Network, Calibration, Fit.

1. INTRODUTION

The fit of a measurement device is the procedure applied on a measurement device to make its performance suitable to a specific application [1]. When the calibration curve is non linear or presents a high drift, the fit procedure may represent an undesired cost. Thus, if the sensor presents an auto-fit capability, it will decrease the need for calibration on site. Auto-fit is also called Auto-Calibration or Self-Calibration. However, this is not in agreement with VIM [1]. The sensor studied suffers a strong influence of the fluid temperature due to its simple thermal model, leading to severe errors, especially at low rates. A neural network is trained to learn these errors and correct the flow values calculated thought the simple model. The achieved results show that the use of the neural network was useful in decreasing the errors in the flow measurements. Without the neural network correction, the error was greater the 20% of the measured value. After the use of the neural network, the maximum error is below 5% of the measured value.

2. THERMAL FLOW MEASUREMENT

The studied sensor is built using a small section of stainless steel tube (AISI304) with heat resistance wrapped around. This sensor is heated and kept in a constant temperature difference from another sensor that does not have the heat resistance and it is used to measure the fluid temperature. Using the temperature and the power in the heat resistance, it is possible to infer the flow value.

3. INTELLIGENT SENSORS

The progress of microelectronics in the last decades has allowed the development and fabrication of intelligent sensors. While a standard sensor is only capable of converting the physical variable input into a signal variable output, an intelligent sensor is an integrated system which comprehends the transducer, the signal conditioning circuit, and a microprocessor module that allows the designer to embed the necessary intelligence.

Honeywell introduced the first intelligent sensor in the market in 1983 [2]. It was a pressure sensor that also presented a temperature sensor. The measured temperature was used to compensate the errors in the pressure measurements due to temperature. The compensation was done by a microcontroller that also converted the compensated signal to 4-20 mA.

From that time on, the continuous evolution of the processing capabilities has allowed the inclusion of new functions in the intelligent sensors such as: filter, self-test and self-adjust.

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4. NEURAL NETWORK

An Artificial neural network (ANN) is a massive parallel system [3] composed of many simple processing elements (neurons) whose function is determined by the network architecture, connection strengths (synaptic weights) and the processing performed at the neurons. Neural networks are capable of acquiring knowledge through a learning process and to store that knowledge in the synaptic weights. One of the most successful neural network architecture is the multilayer perceptron (MLP). It has been successfully applied to a variety of pattern recognition problems in industry, business and science [4]. This ANN is a feed-forward network and is organized in layers: an input layer, hidden layers and an output layer. Only the hidden and the output layers present neurons (Figure 1).

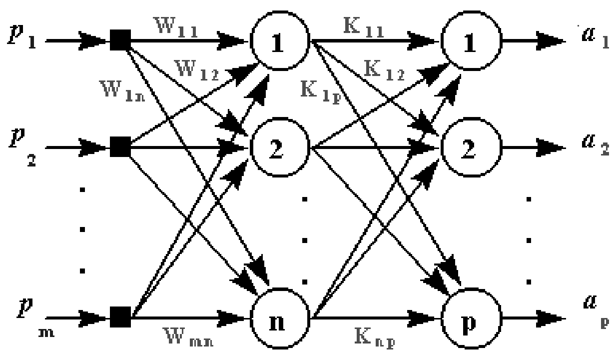

Figure 1 – Multilayer Perceptron Architecture.

It is possible to have an arbitrary number of hidden layers, but the majority of application only needs one hidden layer. Typically, MLPs are trained using an algorithm called backpropagation [3]. This is a supervised training procedure that is divided in two phases: forward and backward. In the forward phase, the data presented in the input layer are processed by the hidden layers up to the output layer, where the generated outputs are compared with the desired outputs and an error signal is calculated. In the backward phase this error is passed backward to update the synaptic weights in order to decrease the output error. This procedure is repeated through several cycles (also called epochs) until a stopping criterion is achieved.

One of the most important features of a neural network is the ability to generalize what it has learned from the training procedure. This allows the network to deal with noise in the input data and to provide the correct outputs to new data patterns, i.e, data that were not used to train the network. To obtain a network with good generalization capabilities, one has to avoid the overfitting. It happens when the network presents an extremely low error in the training set but does not perform well when it is presented to new data patterns. It means that the network has memorized the training examples but did not learn the relation between the input and the output. One procedure that is normally used to avoid overfitting is called Early Stopping [5]. In this procedure, the data is divided in three sets: training, validation and test. The training set is used to update the synaptic weights in order to reduce the training error. The error in the validation set is monitored during the training procedure, if this error starts to grow, this can be an indication that there is overfitting. The third set (test set) is used to evaluate the capacity of generalization of the trained network.

5. SELF-ADJUSTING ALGORITHMS

In the literature, it can be noticed that ANNs are capable to perform different functions that can be easily integrated in a sensor, such as auto-fit [6], [7], [8], [9], [10], drift prediction [11], fault detection [12], calibration monitoring [13], and transducer linearization to compensate the influence of other physical variables [14].

In the proposed method, a multilayer perceptron neural network is used to correct the errors due to the simple model. Similar application can be seen in Barbosa et al [8] and in Patra et al [9]. In the proposed method, the ANN training (Figure 2) was done using the temperature and power as inputs and the error between the flow value calculated in the thermal model and the Venturi device. So, the ANN can learn the error due to the model and correct it when the sensor is in normal operation. The data set for training the ANN was obtained from a calibration procedure with 14 points in the 0,00375 Kg/s - 0,01275 Kg/s range, for each one the following fluid temperatures 35, 40, 45 e 50 ºC. Thus, the training set has 56 points.

An important step in the ANN design is the choice of the model complexity, i.e, the number of neurons in the hidden layer.

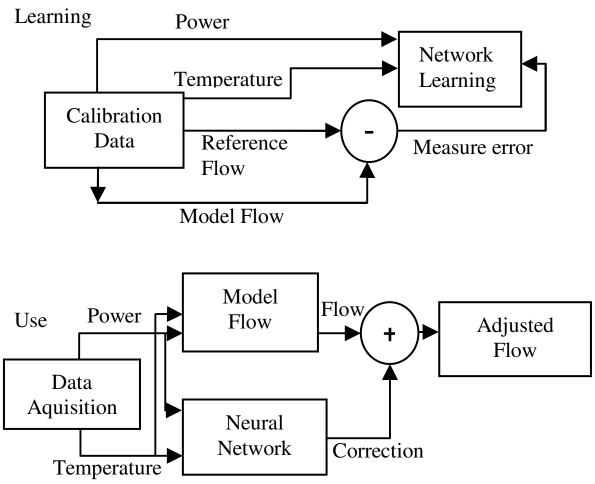

Figure 2 - Network design

It is done with the help of the cross-validation [15]. It is a technique to estimate the performance of a model. The available data set is divided in a fixed number of folds. For each one of the folders, a different network is trained with the remaining folders are used as training and validation sets for Early Stopping. The error estimates (or the output of other performance evaluation function) of the networks in each folder are averaged and used as an estimate the overall performance. After experimenting different number of neurons in the hidden layer, it is chosen the number that gives the best performance, which usually is the smallest error.

Once the number of neurons is chosen, three ANNs are obtained using different training strategies. The first one, NN1, is obtained by keeping the network that presents the smallest error in cross-validation. The second network, NN2, is obtained using the entire dataset. The number of epochs used for training NN2 is given by the average number of the training epochs of all trained networks during cross-validation. Finally, the third network, NN3, was trained with the Bayesian Regularization. This training procedure forces the network to have smaller synaptic weights, which produces smoother outputs, decreasing the possibility of overfitting [16].

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6. EXPERIMENTAL EVALUATION

The fluid in the experimental evaluation was air and calibration procedure was done using a Venturi device as reference. In the test bench, the two flow meters are in series, which allows simultaneous readings of both meters by control software. There were acquired 14 points in 0,00375 kg/s - 0,01275 kg/s range, for each one the following fluid temperatures 35, 40, 45 e 50 ºC. The calibration results can be seen in Figure 3. It can be seen that without correction, the thermal flow meters presents was greater the 20% of the measured value.

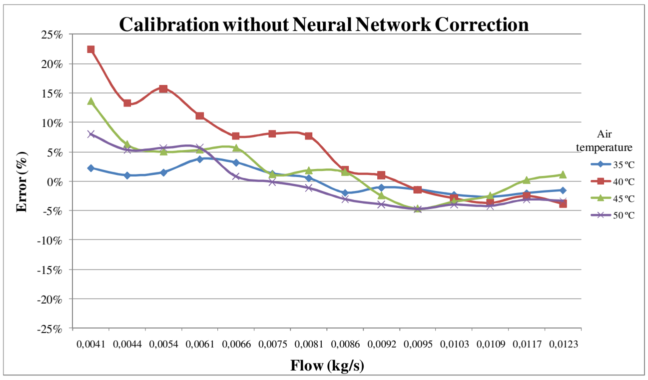

Figure 3 - Calibration without Neural Network Correction

Therefore, it is necessary to perform a correction procedure, which will be performed by the neural network.

6.1. ANN Design

The following procedure was executed to design an ANN that will perform the correction:

- Choice of the training algorithm: The "Levenberg-Marquardt" algorithm was chosen because it presents a faster convergence time and also the lowest error. Besides, this method works extremely well in practice, and is considered the most efficient algorithm for training median sized ANNs [6], [17].
- Choice of the differential temperature: Without correction, the smallest errors occur at de 25 ºC, so this is the value chosen.
- Definition of K folds for cross-validation. The usual choices are K = 5 or K = 10. Since the available dataset is small, it was chosen K = 5.
- Definition of the number of repetitions. In order to reduce the variance in the cross-validation, it has to be repeated several times. The usual choice of the number of repetitions is 10 [15].
- Choice of the number of neurons in the hidden layer. There were performed several experiments varying the number of neurons form 1 to 20. The choice of number of neurons was based on the smallest error in the cross-validation.
- After the definition of the parameters ("K", number of repetitions, number of neurons, differential temperature), three networks NN1, NN2 and NN3 were trained using different strategies (see Section 5) and the errors were compared.

In all experiments, the procedure was repeated three times to access its repeatability. In Figure 4, one can see the results of experiment used to choose the number of neurons in the hidden layer. In this figure, it can be seen the average normalized errors and the standard deviation for three repetitions of the procedure. The average normalized error is defined as average squared error for normalized outputs between -1 and 1.

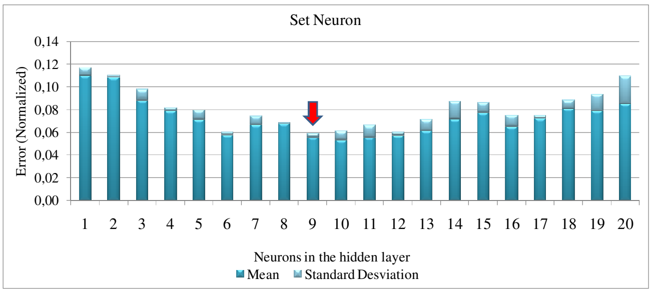

Figure 4 – Choice of the number of neurons

In the figure 5, there is a performance comparison of the ANNs NN1, NN2 and NN3. The best results were obtained with the NN1 network.

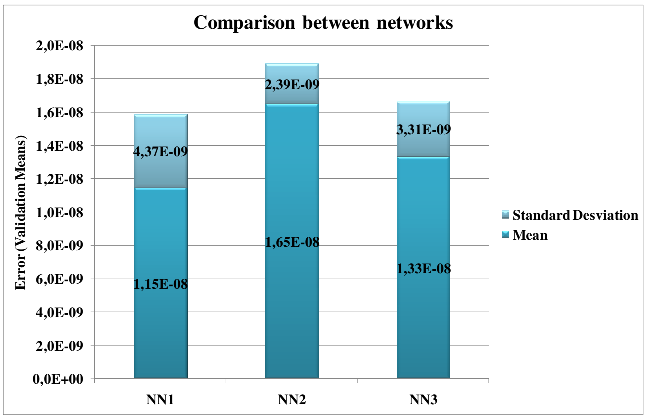

Figure 5 - Comparison between neural networks

The ANNs trained to perform the correction were used to perform the necessary corrections. Figure 6 shows the correction value as a function of the power and the fluid temperature. The figures 7 and 8 show the correction function for NN2 and NN3, respectively. It can be seen that the correction function is smooth, which demonstrates the absence of overfitting. One can also note that the correction function has higher values in the temperature extremes, especially in low power (smaller flow).

In a preliminary analysis in the surface correction plot, it can be seen: NN2 has a very smooth surface, which could be an indication of an under fitted model, that is, the ANN was not able to learn the appropriate correction function. It also presents the higher average error. The surface for NN3 indicates that it presents a slightly better correction capability and the NN1 presented the best results performing the correction as needed and in accordance with the Figure 5.

6.2. Flow Calibration (Intelligent)

Another calibration was performed in thermal flow meter, but at this time it was using the correction performed by the neural network. In the figures 9, 10 and 11, one can see the measurements errors in all temperature and flow to the three networks: NN1, NN2 e NN3.

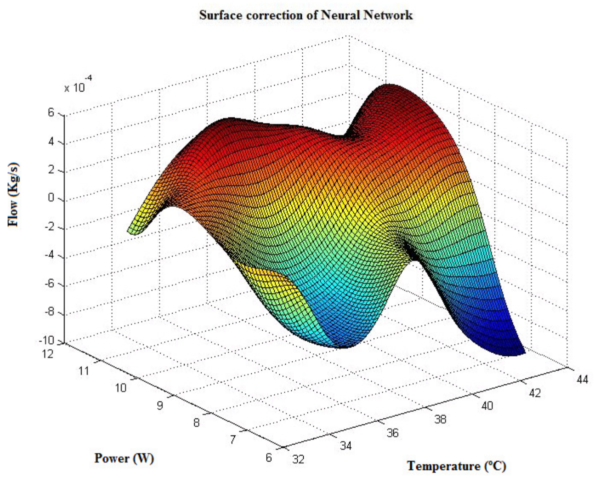

Figure 6 - Surface correction of Neural Network (NN1)

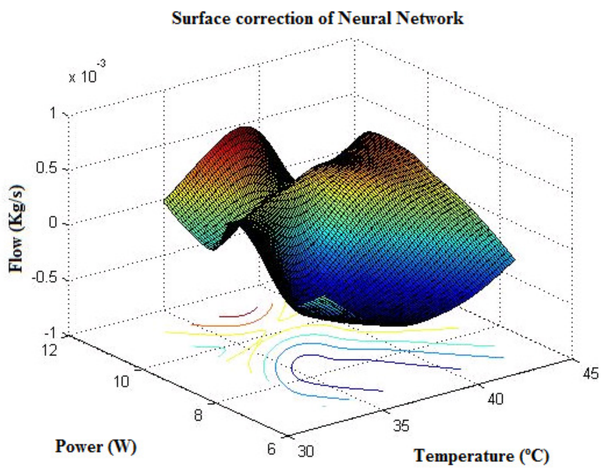

Figure 7 - Surface correction of Neural Network (NN2)

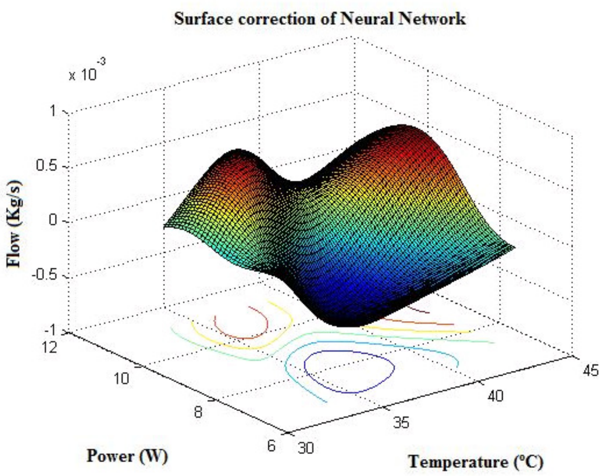

Figure 8 - Surface correction of Neural Network (NN3)

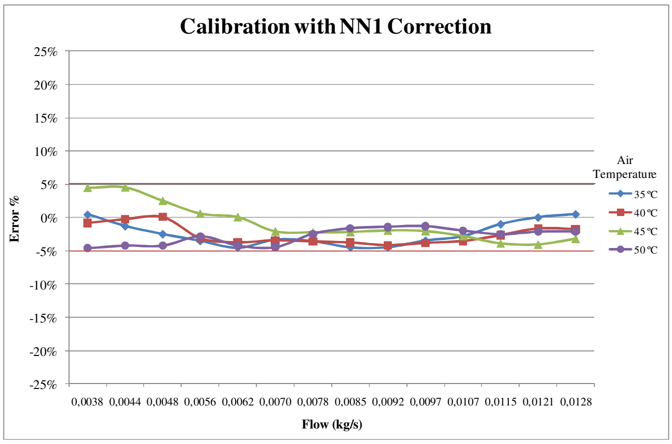

Figure 9 - Calibration with NN1 correction

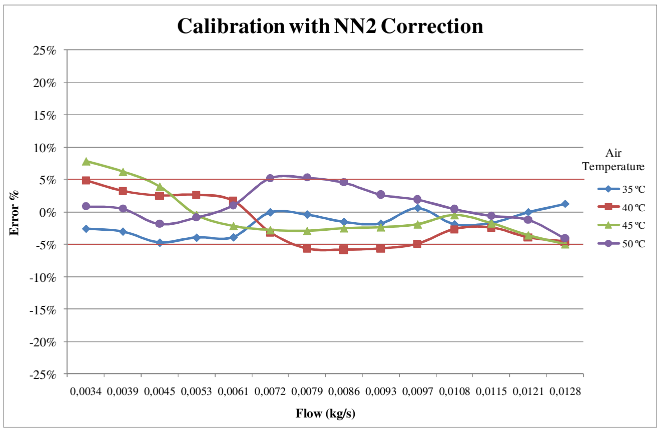

Figure 10 - Calibration with NN2 correction

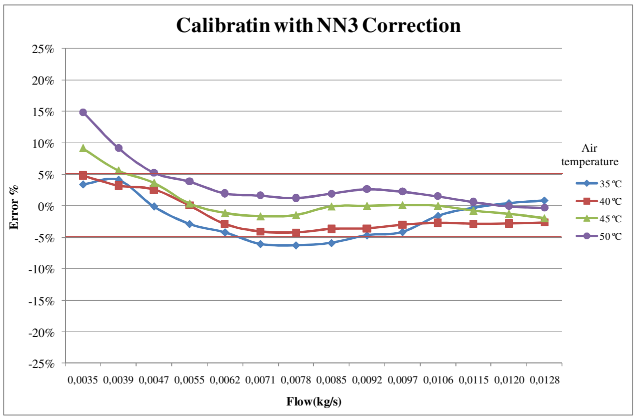

Figure 11 - Calibration with NN3 correction

7. CONCLUSION

A survey in the literature has shown the increasing utilization of neural networks in several applications using intelligent sensor such as: auto-fit [6], [7], [8], [9], [10], drift prediction [11], fault detection [12], calibration monitoring [13], transducer linearization to compensate the influence of other physical variables [14].

It was proposed a framework where a neural network learns the measurement errors in relation to a reference, in order to be able to correct these errors when the meter is in use.

This framework was used to correct errors on PT-100 sensors and the results were published [7] and [10].

In this work, this framework is used to correct the measurement errors in a thermal flow meter. Three different neural networks were evaluated. The first ANN is the one that presents the smallest average squared error in the repetitions of the cross-validation. The second ANN was trained using all available dataset for the average number of epochs found in the cross-validation, and finally the third one was trained using Bayesian Regularization.

Although, not all ANNs were capable of correcting the errors to obtain a reasonable accuracy (5%), all of them were able to improve the accuracy of the proposed flow meter. The next steps in the development of the system will deal with more extensive experimentation with other neural networks architectures and other training strategies.

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