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Gas Flow Metering Using the PSO Optimized Interval Type- 2 Fuzzy Neural Network

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Abstract

Orifice flow meter is one of the most common devices in industry which is used for measuring the gas flow. This system includes an orifice plate, temperature and pressure transmitters, and a flow computer. The flow computer is used for collecting information related to temperature, pressure, and their differences under various conditions. Also the flow computer can calculate the flow rate of gas at the standard conditions. Relations used in the flow computer are quite complex and nonlinear and also measurement noise can affect this device easily. Moreover, it needs calibration at different times which is expensive. To replace the flow computer, in this paper, a type-2 fuzzy neural network (T2FNN) has been utilized to calculate the gas flow. The temperature, pressure, and pressure differences are used on either side of the orifice as the inputs of T2FNN and it considers the flow of gas as output. In this paper, the particle swarm optimization (PSO) algorithm has been utilized to train the antecedent and consequent parameters of T2FNN. Using some simulations, it has been shown that the designed T2FNN can measure the flow of gas much better than the type-1 fuzzy neural network (T1FNN) in the presence of a high level of measurement noise.

Keywords: Orifice flow meter, Process control, T2FNN, PSO.
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1. Introduction

Fluid flow measurement plays a very important role in industrial process control [1]. Also, in many trades, the flow of fluid is the main index in measuring the economic value of fluid. Orifice flow meter, working based on the differential pressure, is the most common flow meter in gas flow measurement [2, 3]. This flow meter includes a metal plate for making the differential pressure and a flow computer for measuring the gas flow. To do this, the flow computer gets its data from the transmitters and then, it calculates the flow of the gas (passing through the pipe) according to the defined formulas. It should be noted that to get the precise amount of gas flow, complex and nonlinear formulas should be considered in the flow computer. Moreover, measurement noise of the transmitters can degrade the performance of the orifice flow meter [4, 5]. Using the capability of the artificial neural networks (ANNs) and fuzzy neural networks (FNNs) in modeling the nonlinear functions, these techniques can be used instead of the flow computer to measure the flow of fluid. In this method, using some information of the fluid i.e. the pressure and temperature, as the inputs of ANN or FNN is desirable since these networks estimate the real flow of gas. ANN or FNN has the ability to map the nonlinear functions with less information about analytic models [1]. So, they can deal with the mentioned problems regarding the flow computer. It should be noted that using the estimated output of these techniques, the calibration of the flow computer is also possible. There are two different approaches to the FNNs design: Type-1 FNNs (T1FNNs) and type-2 FLSs (T2FNNs). T2FNN is an extension of T1FNN with three-dimensional membership functions. The extra dimension provides a new degree of freedom that lets the uncertainties be handled in totally new ways [6, 7]. A Type-2 fuzzy set can be visualized as a three dimensional primary and secondary membership function. The primary membership is any subset in [0, 1] and there is a secondary membership value corresponding to each primary membership value that defines the possibility of the primary membership.

In this study, due to the capability of T2FNN in modeling the nonlinear functions, this system has been utilized for calculating the gas flow. For this purpose, temperature, pressure, and pressure differences on either side of orifice are used as the inputs of T2FNN. The important issue in application of T2FNN is how to set the parameters of the consequent and antecedent parts, such as standard deviations and canters [8]. In this study, the particle swarm optimization (PSO) algorithm has been utilized to train the antecedent and consequent parameters of T2FNN. Using some simulations, it has been shown that the designed T2FNN can measure the flow of gas much better than the type-1 fuzzy neural network (T1FNN) in the presence of a high level of measurement noise.

The remaining parts of the paper are organized as follows: The flow measurement problem is presented in Section 2. The concept of T2FNN and its training procedure are considered in Sections 3. In Section 4, simulation results in validating the designed T2FNN are stated. Finally, the conclusion is addressed in Section 5.

2. Flow Measurement

In an orifice flow meter, the orifice plate generates differential pressure in order to measure the flow rate of gas. Using temperature, differential pressure, and pressure transmitters, the flow computer can calculate the gas flow. A flow computer is an electronic computer which implements a wide selection of complex density algorithms using the analog and digital signals received from flow meters, temperature, and pressure transmitters. The Flow computer uses long, complex, and non-linear formulas to calculate the flow of gas, and therefore, the computational errors are undeniable due to noise in the data. Moreover, like other measuring devices, the orifice flow meter needs to be calibrated. For this purpose, it is necessary to calibrate a flow computer which costs much more and also requires the process to be discontinued. To deal with these problems and considering the capability of FNN in learning from the system, in this paper, T2FNN has been utilized to model the flow computer to estimate the flow of the gas. In the industrial environment, the measured data is always distorted by noise and, therefore, T2FNN is a suitable solution to tackle this uncertainty.

In this study, T2FNN has been utilized for calculating the gas flow from the static pressure, differential pressure, and temperature. In other words, these variables are used as the inputs of T2FNN, which are commonly available in industrial plants, and the flow of gas is the output of the designed T2FNN. The overall scheme of the proposed method using T2FNN is shown in Fig 1.

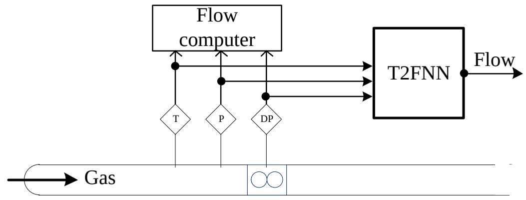

Fig. 1. The overall scheme of the proposed method in measuring the gas flow

3. Type -2 Fuzzy Neural Network

The concept of type-2 fuzzy sets was introduced by Zadeh as an extension of type-1 with the aim of being able to model the uncertainties that invariably exist in the rule base of the system [9]. T2FNNs, which benefit from type- 2 fuzzy sets, can better handle the vagueness inherent in the linguistic words which are modelled by the membership functions (MFs). Therefore, they are more suitable under circumstances where it is difficult to determine the exact MF for a fuzzy set [10]. At the type-2 fuzzy sets, the antecedents and consequents of the rules are uncertain. While a type-1 membership grade is a crisp number in [0, 1], a type-2 membership grade can be any subset in [0, 1] which is called the primary membership. Additionally, there is a secondary membership value corresponding to each primary membership one [9]. In the generalized T2FNNs [11], the secondary MFs can take values in the interval of [0, 1], while in the interval T2FNNs, they are uniform functions that only take the value of 1. The computational burden of the general T2FNNs is very high compared to the interval one. So, the use of the interval T2FNNs is more commonly seen in the literature. An interval type-2 fuzzy set, $\tilde{A}$, may be represented as [9, 12]:

$$\tilde{A} = \int_{x\in X}\int_{u\in J_x} \frac{\mu_{\tilde{A}}(x,u)}{(x,u)} \quad J_x \in [0,1] \tag{1}$$

where $\int\int$ denotes union over all admissible *x* and *u*. Also, J_x is called the primary MF of *x* and $\mu_{\tilde{A}}(x,u)$ is the secondary MF value corresponding to each primary membership value. In the interval type- 2 fuzzy sets, all $\mu_{\tilde{A}}(x,u)$ equal 1. Fig.2 shows a type-2 Gaussian MF with an adjustable uncertain mean in $[m_1, m_2]$ and a standard deviation (σ). It can be described as:

$$\mu_{\tilde{A}}(x) = \exp[-\frac{1}{2}(\frac{x-m}{\sigma})^2], \quad m \in [m_1, m_2] \tag{2}$$

It can be seen from Fig 2. that the type-2 fuzzy set has a region called footprint of uncertainty (FOU) and is bounded by an upper MF and a lower one, which are denoted as $\underline{\mu}_{\tilde{A}}(x)$ and $\bar{\mu}_{\tilde{A}}(x)$, respectively.

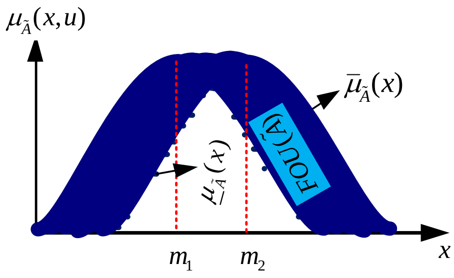

Fig. 2. Fuzzy type-2 membership function

It is worth pointing out that the T2FNNs rules and the inference engine section will remain the same as T1FNNs, but the antecedents and/or the consequents are as the type-2 fuzzy set. For reducing the type-2 fuzzy consequent to the type-1 fuzzy consequent, some methods called type-reduction approaches are explained in [13]. For this study, the center-of-set (COS) type-reduction method is used as follows:

$$Y_{\cos}(x) = \int_{y^1\in[y_l^1,y_r^1]} \cdots \int_{y^M\in[y_l^M,y_r^M]} \int_{f^1\in[\underline{f}^1,\bar{f}^1]} \cdots \int_{f^M\in[\underline{f}^M,\bar{f}^M]} 1 \Big/ \frac{\sum_{i=1}^{M} f^i y^i}{\sum_{i=1}^{M} f^i} = [y_l, y_r] \tag{3}$$

where $Y_{\cos}(x)$ is an interval set determined by its two end-points: y_l and y_r; also these parameters are calculated as follows:

$$y_l = \frac{\sum_{i=1}^{P} \bar{f}^i y_l^i + \sum_{i=P+1}^{M} \underline{f}^i y_l^i}{\sum_{i=1}^{P} \bar{f}^i + \sum_{i=P+1}^{M} \underline{f}^i}$$

$$y_r = \frac{\sum_{i=1}^{N} \underline{f}^i y_r^i + \sum_{i=N+1}^{M} \bar{f}^i y_r^i}{\sum_{i=1}^{N} \underline{f}^i + \sum_{i=N+1}^{M} \bar{f}^i} \tag{4}$$

and $\underline{f}$ and $\bar{f}$ are the firing levels; $[y_l^i, y_r^i]$ corresponds to the centroid of the type-2 interval consequent set, which can be obtained by the iterative approach which is stated in [9]; and *M* is the number of the rules. Finally, the output of the type-reduction section (real output) is passed from a defuzzifier; since fuzzy type-2 is interval, the mean of the left and right points can be used as a defuzzifier which is obtained as follows:

$$f_s = \frac{y_l + y_r}{2} \tag{5}$$

T2FNN includes inputs, a fuzzifier, an inference and a rule base, type reduction, a defuzzifier, and output. The main difference between the T1FNN and T2FNN structures is the type reduction stage.

The important issue in applying T2FNNs is how to set the parameters of the consequent and antecedent parts. During the recent years, some optimization methods have been employed to tune the parameters of the T2FNN models. These methods can basically be assigned into two categories: derivative-based and derivative-free optimization methods. Genetic algorithm (GA) [14] and PSO [15] can be considered as two main examples of the derivative-free algorithms. On the other hand, gradient descent [16], least square [17], and Extended Kalman Filter (EKF) [18] are some examples of the derivative-based optimization methods. It is worth pointing out that derivative-free methods are less likely to get entrapped in local minima.

They are also easier to be implemented because they do not need derivatives which may be hard to calculate while they generally converge faster. In this paper, due to simple relations and high convergence speed of PSO [19], this optimization algorithm has been used to train the proposed T2FNN to estimate the flow rate.

The dynamics of PSO are defined as follows, which are the equations to update the position (*x*) and velocity (*v*) of the particles [20]:

$$\begin{aligned} x(t+1) &= x(t) + v(t) \\ v(t+1) &= \omega v(t) + c_1 r_1 (x_{pbest} - x(t)) + c_2 r_2 (x_{gbest} - x(t)) \end{aligned} \tag{6}$$

where ω, r1, and r2 are the random variables in [0,1] and c1 and c2 are constant parameters. Also, xpbest and xgbest are particle's best known position and the swarm's best known position, respectively. The step after creating the network is to collect data from the flow meter for T2FNN training and testing process. The input- output (target) pairs for T2FNN training can be obtained from transmitters as the flow meter is working at the standard conditions (the temperature, pressure, pressure difference on either side of orifice are used as the input and the flow of the gas is used as the output of T2FNN). Using these data, the PSO algorithm is utilized to tune the mentioned T2FNN parameters (the consequent and antecedent parameters). The stopping criterion is an important issue in application of the PSO algorithm for training FNN and ANN.

The maximum number of iteration is the most common stopping criterion for the PSO algorithm. In this study, through several simulations, we observed that the performance of PSO was improved by increasing the number of maximum iteration from 80 to 110. According to these simulations, when the maximum iteration is less than 80, T2FNN is undertrained and unable to approximate the flow computer. In contrast, the

PSO performance decreased when the number of the maximum iteration increases from 100 to 110. This may be due to the fact that the data is overtrained and sometimes overfit due to the fact that too many numbers of iterations are conducted. So, the best maximum iteration obtained is set to be 100.

4. Simulation Results

Because the input and target data have very different ranges, for training and testing the considered T2FNN, we have normalized both the desired and input data between 0 and 1. From 500 input- output pairs, about 20 percent and 80 percent have been utilized for the testing and training processes, respectively. It is worth pointing out that the root mean square error (RMSE) is defined as the cost function for PSO. The population size is set as 15 and also $c_1=c_2=2$ and $\omega=0.75$ have been used for the PSO parameters.

It should be noted that PSO tries to minimize the cost function (the mentioned RMSE) by finding the appropriate T2FNN consequent and antecedent parameters. Fig 3. shows the training process of the proposed T2FNN using PSO. Also, the MFs obtained for the three inputs of T2FNN are shown in Fig 4.From these Figs, it can be seen that PSO has minimized RMSE by finding appropriate values for the T2FNN parameters.

To evaluate the trained T2FNN better, some input-output pairs have been utilized to test the designed networks. The given data can be corrupted by the uniformly distributed nonstationary additive noise. This fact has been considered in the test process of T2FNN. Also, the testing results have been compared with T1FNN. It should be noted that the structure of the considered T1FNN is similar to T2FNN except for the fact that the MFs of T1FNN are of type-1. Therefore, to show the effectiveness of the proposed T2FNN method dealing with uncertainties, the mentioned noise with different signal to noise (SNR) levels is assumed to corrupt the input data.

The results of the testing process for the proposed T2FNN and T1FNN and the noise with SNR=50db (low power noise) are shown in Fig 5.

From this Fig, it can be seen that the performance of the testing process using T1FNN is degraded even by the low power noise. On the other hand, using the proposed T2FNN, the effect of noise on estimation of gas flow is negligible. This is due to the fact that unlike T1FNN, T2FNN benefits from the type-2 membership functions which enable it to deal with the effect of uncertainties. Therefore, it predicts the output with less error.

To better demonstrate the efficiency of the proposed method, the prediction power of this method is examined when the high level of noise (SNR=20dB) is distorting the test data. The outputs of the proposed method and the T1FNN system for this case are shown in Fig 6. From this Fig, capability of the proposed method is visible and this method has predicted the target data with less error compared to T1FNN.

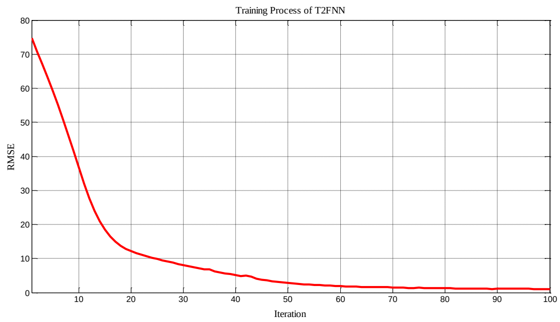

Fig. 3. Training process of the proposed T2FNN using PSO

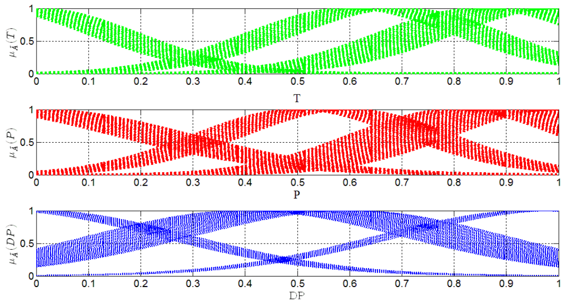

Fig. 4. The obtained MFs for T2FNN after the training process

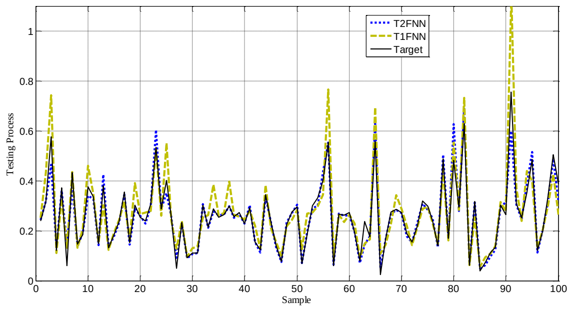

Fig. 5. Testing processes for T2FNN and T1FNN (SNR= 50 dB)

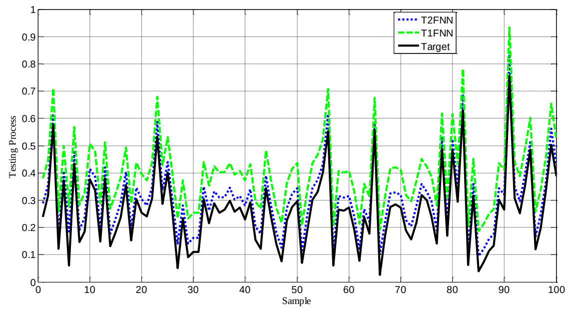

Fig. 6. Testing processes for T2FNN and T1FNN (SNR= 20 dB)

To illustrate a qualitative comparison between the proposed T2FNN method and the T1FNN one, the calculated RMSE for different SNRs has been illustrated in Table 1. From this table, it is clear that in different levels of noise (with SNR from 20 to 50 dB), the testing performances obtained by the proposed T2FNN method are much better than those of the type-1 method at the noisy data environment. These results are expected due to the main characteristic of the type-2 fuzzy systems in their handling of uncertainty through their FOU.

Table.1.
RMSE related to the test process using the proposed T2FNN and T1FNN

SNR(dB)	*Proposed T2FNN*	*T1FNN*
50 dB	*0.0045*	*0.0065*
40 dB	*0.005*	*0.010*
30 dB	*0.008*	*0.035*
20 dB	*0.11*	*0.220*

5. Conclusion

In this paper, using the modeling properties of the soft computing approaches, a T2FNN has been utilized to estimate the flow of gas. In this method, the temperature, pressure, and pressure differences on the either side of orifice are considered as the inputs of T2FNN and it considers the flow of gas as the output. Using a given set of the input–output training data, PSO has been exploited to tune the parameters of the designed T2FNN model. It has been discussed that by appropriate setting of the number of iteration in PSO, we can avoid the problem of over/ under-training in designing T2FNN. It is worth pointing out that the designed T2FNN can be used to replace as well as to calibrate the flow computer, which benefits from the complex and nonlinear formula to calculate the flow of gas. Using some simulations, it has been shown that the designed T2FNN model can measure the flow of gas much better than T1FNN in the presence of a high level of measurement noise.

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