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Application of an ANFIS model to Optimize the Liquid Flow Rate of a Process Control System

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Due to the nonlinear characteristics between the input & output parameters of a liquid flow rate process control, classical optimization technique is limited for this purpose. Hence computational optimization is chosen as an alternative approach. In this paper an ANFIS model was designed using trial and error based on various three different sets of experimental data sets for checking the flexibility, speed & adaptability of these soft computing technique. By the understanding of the Sugeno type ANFIS structure parameters are set to facilitate the hybrid learning rules. However, it is seen that by increasing the number of inputs response time of the model also increased. The results are in good agreement with the experimental results & can be applied to predict the performance of mass flow sensor. For the best ANFIS structure gained in this study RMSE and MAE were calculated as 2.143 & 0.504 respectively.

1. Introduction

In most of the industrial applications, there is a need to calculate the inputs to a process that will drive its outputs in a desired way and thus researcher achieve some optimum goal. In those cases, a mathematical input–output model for the process is usually derived. Most of the process control system threatened due to improper input parameter settings. To optimize the performance of a multivariable process control through the classical method is inflexible and time-consuming. The main drawback of the classical optimization is to get the response influenced by individual independent variables. When a response is measured with respect to the influence of a particular variable, then other input variables should be kept constant. In general, interactiveness between the input variables are absent in classical optimization that's why it can generate the overall effects on the independent variable with respect to a particular response. Precaution, the total number experimental trials increased which is time consuming. Hats why alternative approach is adopted where mathematical modelling (computational optimization) of the process is designed (input–output relationship) using different computational intelligence techniques.

Flow rate measurement is one of the high precision operations, performed on most of the process control industries, it suffers from the setback of various effects like the effect of energy associated with a flowing fluid through a pipe line, Doppler effect and effect of speed of the fluid suction pump etc. described by (Ahmed et al., 2006; Kole et al., 2007).To overcome all these problems an anemometer type mass flow rate measurement sensor has been described in Roy et al. (2001).Transducer output of the anemometer flow sensor is nonlinear with flowrate. Therefore, it minimizes the non-linearity characteristics of transducer output & liquid flowrate. (Dutta et al., 2018) present a comprehensive usability & effectiveness of RSM & ANOVA based on flower pollination algorithm for process parameters modelling and optimization of liquid flow processes. Here author used objective function of flow rate which is depends upon two independent variables sensor output & pipe diameter. From the appraisal it indicates that the FPA based RSM is gives the more predicted output than the FPA based ANOVA is approximately 9.0389e-6. (Dutta et al., 2018) proposed ANOVA based flower pollination algorithm to obtaine the optimum flow rate corresponding to actual flow rate, although objective function of flow rate is set up by the four-independent variable –sensor output, pipe diameter, water viscosity & water conductivity. (Dutta et al., 2018) describe a functional classifier is present in for correctly and automatically classify the actual level of the flow rate. Here author took different number of feature & classify by using unsupervised SVM & KNN algorithm to improve the prediction & accuracy of the equipment as well as process flow]. A trained neural net model is proposed by (Dutta et al., 2018) for calibrate the data of the flow sensor with better accuracy & optimizes the algorithm to determine the flow velocity passing through the pipeline after knowing the sensor output voltage, pipe diameter, liquid density, conductivity, viscosity. Average accuracy of these optimized NN model is about to 97.706%. An ANN-based FPA model is described by (Dutta et al., 2018) for a nonlinear optimization problem to find the optimal values of the coefficient of the models so that the estimated liquid flow rate best fits with the experimental results. For this purpose, author construct an objective function of flow rate in terms diameter of the experimental pipe & sensor.

Control of nonlinear systems based on conventional mathematical tools is a difficult job because no systematic tools are available to deal with vague and unspecified systems described by (Dutta et al., 2016) In contrast, of these different Defuzzification methods in a Fuzzy Based Liquid Flow control is explained in (Dutta et al., 2017).This paper is concerned with novel architecture called Adaptive Neuro-Fuzzy Inference System (ANFIS) to represent or approximate a liquid flow nonlinear control system. A combined neuro-fuzzy approach has seen enormous preferences recently from researchers working in different domains like in high rate waste water treatment Zhang et al.2000,modelling of TIG welded pipe joint by Achebo et al.2014, Heart Disease Prediction by (Askerzade et al., 2014),Crop Yield Forecasting by (Kumar et al., 2011),wind energy forecasting by (Song et al., 2015),modeling of Greenhouse climate by (Belelmeguenai et al., 2016), Parameter optimization for intelligent phishing detection by (Aslam et al., 2014), sales forecasting in Automotive Industry by (Alborzi et al., 2016) etc.

For this work total 134 number of experimental datasets collected from the experimental set up whose description is given in a next section. For the training purpose 117 no data is used & 17 number datasets is used for testing & as well as model validation purpose. This paper is organized as follows: after introduction, experimental set up is briefly introduced in section 2. Section 3 described the problem statement, section 4 describe the result analysis of Adaptive fuzzy inference system and finally conclusions are presented in section 5.

2. Experimental setup

The experimental work is done in a process control setup Flow & Level measurement and Control (model no. WFT -20-I) shown in figure 1. In present investigation, liquid velocity measured were in the range of0lpm - 600lpm & flow sensor voltages were calibrated against liquid flow velocities which was determined by mass flow control unit with an accuracy of 1% from the reading.

Figure 1: Block diagram of process control Diagram [8]

Here author used Transistor based Flow sensor where four transistors connected in a diametrical plane of the PVC pipe to form a Bridge type full wave rectifier. Change in water flow affects the output of the sensor signal. From the above experimental setup, we get sensor output voltage with respect to the variation of the water flow rate under the different combination of pipe diameter & water parameters.

3. Problem statement

The experimental work is carried out with the Flow & level measurement & control set up. These set up is used along with the flowing parts which are given in Table 1.

Table 1: Experimental Setup [8]

Machine/tools	Specification/Description
process control setup Flow & Level measurement and Control	Model no. WFT -20-I
Anemometer Flow sensor	Designed by the SL 100 transistor
PVC pipe	Diameter with 20mm,25mm & 30mm
Digital Multimeter	3 1/2
Rota meter	Taking the reading of the Flow rate ranging 0-600 lpm

For this work, total 134 sample data have been observed which consist of four independent variables sensor output voltage, pipe diameter, liquid (water) conductivity & viscosity. Among these 134 datasets 17 number of datasets are used for the testing purpose shown in table 2. To conduct this research, we had taken the 3 different set of pipe diameter i.e. 20mm, 25mm and 30 mm. For each of the cases we collect data of the flow rate as an experimental output data for different sensor output voltage, pipe diameter, liquid conductivity & viscosity. Liquid density is assumed to be constant as overall temperature variation of the liquid was typically less than ±0.5°C during the course of the entire experimental data are shown in table 2.

Table 2: Experimental datasets for liquid flow control process

Sensor output	Diameter	Conductivity	Viscosity	Flow rate
0.218	0.024	0.606	0.8982	0.0008
0.221	0.025	0.616	0.7797	0.0008
0.225	0.025	0.616	0.8982	0.0016
0.232	0.025	0.597	0.7797	0.0016
0.234	0.02	0.615	0.8982	0.0024
0.237	0.027	0.622	0.7797	0.0024
0.238	0.03	0.6065	0.7254	0.0024
0.239	0.025	0.616	0.8982	0.0032
0.241	0.027	0.622	0.7797	0.0032
0.245	0.024	0.6065	0.7254	0.0032
0.247	0.024	0.616	0.8982	0.004
0.247	0.025	0.622	0.7797	0.004
0.25	0.025	0.6065	0.7254	0.0048
0.256	0.025	0.616	0.8982	0.0048
0.254	0.024	0.622	0.7797	0.0056
0.259	0.03	0.606	0.7254	0.0064
0.265	0.027	0.622	0.7797	0.0072

4. Result analysis

Various experiments were conducted and the sizes of the training and checking data sets were determined by taking the classification accuracies into consideration. The data were divided into two separate sets: the training data set and the checking data set. The training data set was used to train the ANFIS, whereas the checking data set was used to verify the accuracy and the effectiveness of the trained ANFIS model for the adaptation of learning content. The optimal ANFIS model is choose by considering the least value of RMSE.

ANFIS 1 has three inputs having the membership function number (3*3*3) which is shows in table 3. These three input parameters are controlled by sensor output voltage, pipe diameter & experimental liquid viscosity. All these three input parameters have three membership function like high, medium & low. Test result shown in table 3.

ANFIS 2 has four input membership function 3*3*3*3 shows in table 4. Here author include another input parameter, experimental liquid conductivity. Every input parameter i.e. sensor output voltage, pipe diameter, liquid viscosity & liquid conductivity has three membership function small, medium & large test result shown in table4.

*Table3: ANFIS 1 structure information (membership function 3*3*3)*

ANFIS parameter type	ANFIS1			ANFIS2			ANFIS3		
No of inputs	3			3			3		
Membership function type	Gaussian			Triangular			Generalized Bell		
Number of membership function	3*3*3			3*3*3			3*3*3		
Training datasets	40	80	117	40	80	117	40	80	117
Checking datasets	06	12	17	06	12	17	06	12	17
Epoch number	20	30	40	20	30	40	20	30	40
Number of nodes	78			78			78		
Number of linear parameters	27			27			27		
Number of Nonlinear parameters	27			27			27		
Total number of parameters	54			54			54		
Number of fuzzy rules	27								
Input combination	Low, Medium, High								
RMSE	5.910	5.665	5.072	4.523	4.43	4.721	7.261	6.437	5.35
MAE	1.392	1.3352	1.195	1.066	1.046	1.11	1.933	1.517	1.2617

Table 4: ANFIS 2 structure information (membership function 3 3*3*3)*

ANFIS parameter type	ANFIS1			ANFIS2			ANFIS3		
No of inputs	4			4			4		
Membership function type	Gaussian			Triangular			Generalized Bell		
Number of membership function	3*3*3*3			3*3*3*3			4*3*3*3		
Training datasets	40	80	117	40	80	117	40	80	117
Checking datasets	06	12	17	06	12	17	06	12	17
Epoch number	20	30	40	20	30	40	20	30	40
Number of nodes	249			78			78		
Number of linear parameters	108			27			27		
Number of Nonlinear parameters	26			27			27		
Total number of parameters	134			54			54		
Number of fuzzy rules	108								
Input combination	Low, Medium, High								
RMSE	3.676	4.366	5.260	3.58	4.170	4.320	5.044	5.501	6.129
MAE	0.8650	1.028	1.238	0.8436	0.9825	1.018	1.1854	1.2932	1.4352

Table 5: ANFIS 3 structure information (membership function 5 3*3*3)*

ANFIS parameter type	ANFIS1			ANFIS2			ANFIS3		
No of inputs	4			4			4		
Membership function type	Gaussian			Triangular			Generalized Bell		
Number of membership function	5*3*3*3			5*3*3*3			5*3*3*3		
Training datasets	40	80	117	40	80	117	40	80	117
Checking datasets	06	12	17	06	12	17	06	12	17
Epoch number	20	30	40	20	30	40	20	30	40
Number of nodes	305			305			305		
Number of linear parameters	135			135			135		
Number of Nonlinear parameters	28			42			42		
Total number of parameters	163			177			177		
Number of fuzzy rules	135								
Input combination	Very low, Low, Medium, High, Very High								
RMSE	3.53	3.494	4.532	2.7654	3.486	3.795	4.712	4.856	5.819
MAE	0.7818	0.8224	1.066	0.6515	0.8205	0.8889	1.107	1.140	1.3662

*Table 6: ANFIS 4 structure information (membership function 3*3*3*3*3)*

ANFIS parameter type	ANFIS1			ANFIS2			ANFIS3		
No of inputs	5			5			5		
Membership function type	Gaussian			Triangular			Generalized Bell		
Number of membership function	3*3*3*3*3			3*3*3*3*3			3*3*3*3*3		
Training datasets	40	80	117	40	80	117	40	80	117
Checking datasets	06	12	17	06	12	17	06	12	17
Epoch number	20	30	40	20	30	40	20	30	40
Number of nodes	524			524			524		
Number of linear parameters	243			243			243		
Number of Nonlinear parameters	30			45			45		
Total number of parameters	273			288			288		
Number of fuzzy rules	243								
Input combination	Low, Medium, High								
RMSE	2.94	2.948	3.347	2.143	2.166	2.277	3.306	3.502	3.766
MAE	0.6932	0.6940	0.7887	0.504	0.510	0.5315	0.774	0.820	0.867

ANFIS 3, four input membership function 5*3*3*3 shows in table 5. In this model author include the five-membership function into the flow rate parameter. Among the four inputs parameters sensor output voltage has five membership function like very large, large, medium, small, very small & rest of the three inputs pipe diameter, fluid viscosity & liquid conductivity has three membership function small, medium & large. Testing result shown in table.5.

ANFIS 4, five input membership function 3*3*3*3*3 shows in table 6. ANFIS 4 is similar to the ANFIS 3 the basic difference is author include another input parameter, experimental liquid density. All the five inputs parameters have three membership function slarge, medium and small. Testing result shown in table.5.

5. Conclusion

Modelling & optimization of liquid flow control in a process industry is an interesting task for the researchers. Generally, most of the process control industry liquid flow rate is depends upon the voltage output of sensor, diameter of the pipe, viscosity, liquid temperature &conductivity of the experimental liquid. In present work Initially,134 number of measurements (i.e. liquid flow rate) have been observed from laboratory at different experimental conditions (i.e. for different values of pipe diameter and sensor voltage, flow rate, liquid conductivity, viscosity). Among this data sets 117 number of datasets used for train purpose by using ANFIS & rest 17 number of datasets is used for testing purpose. In this study, main aim of the author is to model the liquid flow control process to find a relationship between liquid flow rate, pipe diameter ,sensor output voltage, water viscosity, conductivity& density .For this modelling purpose initially author used Fuzzy for implement the three different types of membership function & number of membership function for the input & output process variable while ANN is design anon-linear models to establish the relation between the variables of liquid flow control process. Now, finding out the suitable ANFIS based model is essentially a non-linear optimization problem. To find out the optimal values of the coefficient of the models using some suitable selection of ANFIS hybrid optimization so that estimated liquid flow rate fit best with the experimental results. For this purpose, author proposed four different ANFIS model in respect to the number of inputs parameter, nature of membership function, number of membership & number of train datasets to observe their efficiency for the modelling of liquid flow control process.

This paper introduced the application of Adaptive Neuro-Fuzzy Inference System in process control industry. The numbers of fuzzy rules taking from the human experts were insufficient hence to increase the efficiency the Neural Network model is used to determine a complete fuzzy rule system & solved the problem of incompleteness in fuzzy rule. From the table 3,4,5 &6 it seen that lowest value of RMSE is 2.143 and the highest value of the RMSE is 4.43. Among four ANFIS model ANFIS 4 was selected as the best fit model to deliver the learning parameter of liquid flow process control due to its lowest RMSE, highest efficiency & correlation. From the table & graph the following conclusion are made:

To build an ANFIS architecture type & number of membership functions are very important

The number of membership function & training data sample have positive effects on the production ofAcceptable system output.

Increase the number of membership function doesn’t increase the model performance but leads toModel over

fitting.
Number of training sample produce more acceptable results.
Increase of epoch number helps to overcome the problem of over fitting.
Results of these test indicate the most important factors to get good performance.
More detailed and accurate modelling of the liquid flow control process by increasing the number of membership functions of an input& output variable is the future aspect of this work. Moreover, except the hybrid ANFIS evolutionary algorithm how the efficiency, accuracy, convergence speed, stability and success rate of the present process control is improved by the met heuristics optimization technique is also future aspect.

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