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Predictive Analytics using Neuro Fuzzy Model and error estimation for a Dynamic Process Control

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Abstract: Empirical data collected from a real-time process controlled by a Proportional Integral Derivative controller is non-linear due to the nature of the control action and also embarked with signal noise and process disturbances that influence the control objective. A predictive model built using such data set doesn't converge due to the presence of redundancies and outliers. Hence the data collected is statistically treated to generate data sets from empirical data by eliminating the uncertainties thus adhering with the first principles. In this paper Neuro fuzzy modeling is endeavored with both the empirical data and the pretreated data and the model convergence is studied using various membership functions and training strategies. It is observed that errors are predominant with the predictive model using the empirical data while statistical treatment renders models with closer affinity. Data from different experiments are analyzed. Maximum error of 0.78 % is seen with empirical data while and the model converges with training error of 0.002 % for data reconstructed using PCA.

Keywords: *Data prediction; ANFIS; PID control; Membership functions; PCA; LSE.*

1. Introduction

The term Process control application refers to regulation of a process conditions or variable by applying a corrective action on the controlled variable to reject the effect of the disturbance on the controlled variable. PID algorithm is often used in Industrial application for closed loop control generation using the Proportional of the error (P), error integral (I) and the error derivative (D) of the error acted on by the proportional gain K, integral time Ti, and derivative time Td. However the PID algorithm has the drawback that it that cannot suit higher order and oscillatory systems.

In contrast to the conventional PID controller has a single loop with a single process variable, Advanced Control Strategies [16] like Cascade Control, Feed Forward Control, Ratio Control, and Smith Predictor Control tend to be more adaptive with multi-loops and process variables. Also the Conventional controllers nullify the disturbance on controlled variables, but adaptive controller's aims to achieve the goals and maintain the set point with an Index factor.

Fuzzy based control approach is a better alternative for control application. In contrast to the closed loop error based control strategies, Fuzzy based control is a knowledge based approach deriving rules from expert knowledge and human experience. The control strategy is based on input output relation in the form of fuzzy rules using linguistic variables [16].

Hybrid Intelligent Control Systems are frameworks with knowledge base, decision- modules, and learning strategies and are application specific. In this contest, the integration of soft-computing paradigms - Artificial Neural Networks (ANN), and Fuzzy Inference Systems (FIS) benefits from both approaches. While neural networks are systems with built in adaptive heuristics learns by virtue of its internal structure, Fuzzy inference systems are framework for reasoning.

Neuro fuzzy controller, a parallel computing connectionist architecture [1] is competent for modeling and controlling, decision making and classification for static and dynamic systems. In contrast to the traditional data processing algorithms where the input data acts on algorithms to generate output, soft computing techniques infer knowledge from data in the form of input-output relationusing machine learning algorithms. Since this class of controller wholly relies on data sets, the best performance can be guaranteed when the model gets trained with a perfect data.

This paper briefs the design of an intelligent controller for a process control. Empirical data collected from different experiments are used for modelling and error estimation. Also the empirical data is subject to various mathematical and statistical treatment for removal of outliers and the model is evaluated with the data extracts. Models were trained with Fuzzy logic membership functions viz Triangular , Generalized bell and Gaussian and it is found that the training error tends to zero with the extracted data when compared to the empirical data and also the model

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performance is comparable for both generalized bell and gaussian when compared to triangular membership function.

2. Related work

The adaptive neuro fuzzy inference system (ANFIS) is a neuro fuzzy network with a Takagi-Sugeno type inference was introduced by Jang [2] that benefits from the learning laws of and Artificial Neural Network (ANN) and the linguistic nature of Fuzzy Logic. The effect of various membership functions in the fuzzy control of antenna azimuth position, different types of membership functions (MF) is examined in [3] where the response of triangular and trapezoidal MF are comparable, and triangular MF shows better performance in the steady-state. Models can be used to comprehend complex phenomenon [4] and interval estimation with a triangular, trapezoidal distribution functions leads to narrower MF representing uncertainties. Amalgamation of membership functions for reducing the fuzzy rules is discussed in [5] where memberships are compared and reduced to form a set of fuzzy rules. A fuzzy inference system (FIS) deploying fuzzy logic theory is a white box while ANN are black box with respect to their goals [6]. The valve in the cooler water system in a cement industry, was detected for its faults and diagnosis was done using ANFIS model and it was found that ANFIS outperformed ANN in the simulation results [7]. The authors in [8] review several Neuro fuzzy systems evolved over a decade while indicating that NFS with learning capability are good expertise and key for future intelligent application A fuzzy controller for an induction motor drive is evaluated in [9] with different MF and concluded that triangular MF is easy to implement and gives the best performance. The involvement of soft computing techniques in the real time complex system such as compressible fluid flow through pipes help us in the reduction of the long process of analytical calculations and just learn the behavior of the system with its interacting parameters [10]. Existing knowledge can be mapped with constraint sets in prediction of compressive strength for cement based mortar materials [11]. ANFIS is used prediction of corrosion behavior of the coated biomaterials [12] reveals good correlation with the experimental values with Gaussian MF and suggests that result-oriented studies can be carried out using ANFIS. A Unified Power Flow Controller is modeled in [13] using MATLAB Simulink with PI and Neuro fuzzy algorithm where Neuro fuzzy control results in low overshoots. Futuristic time series data can be predicted using past data with fuzzy functions [15] and the validation results are superior with a pi membership functions when compared to other MFs. ANN and ANFIS based prognosis tools for a four tank aircraft fuel sub system is compared in [17] where both models prove to identify and mitigate the faults, but ANFIS method is more effective. For an ANFIS model with grid partitioning, Gaussian membership achieves best RMSE when compared with trapezoidal, bell and triangular since Gaussian function represents a smooth curve with maximum data points followed by triangular membership [18]. A PID-ANFIS [19] tracks the input well with no overshoots with less settling time and for a nonlinear process that is simulated and evaluated with induced Gaussian noise. Adaptive Neuro fuzzy PID controller for predicting the performance of a fuzzy PID controller is expatiated that is trained with Levenberg–Marquardt (LM) training algorithm where it figures out that ANFP soft computing approach contributes to the indispensable improvement for predicting **performance.**

3. Experiment and Modeling

Experimental data is collected from a controlled real time process where the objective is to maintain a constant GN2 supply into a Convergent-Divergent nozzle for the process of entrainment of a closed chamber and maintain subzero condition inside the chamber. The elements of an automated process control are the compressed fluid to be controlled, sensor for the process variable, controller which controls the actuator, actuator for modulation of the control valve to regulate the fluid flow.

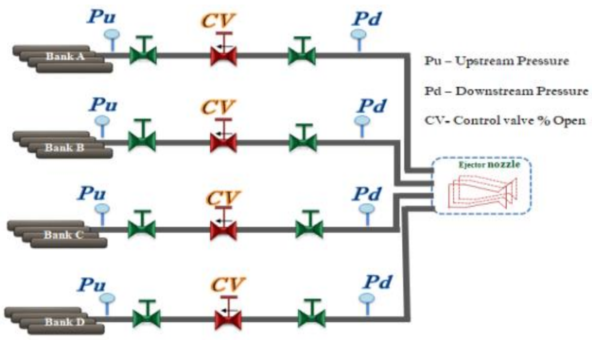

Fig. 1. Experimental Process.

3.1. Closed Loop Control

As shown in Fig 1, the system is equipped with Compressed Nitrogen gas stored in clusters of storage cylinders (Bank A B C & D), ON/OFF control actuators, Linear control actuators (CV), Sensors for upstream pressure (Pu), Downstream pressure (Pd)) and the objective function is to maintain constant pressure (Pd) at the downstream of the control valve irrespective of the source pressure depletion. The sensory signals are sampled and stored at regular intervals in a Data Acquisition System in association with the PID controller that operates the control valve in closed loop. The PID algorithm within the controller tracks the difference between the set point and the process variable (downstream pressure) and alters the controlled variable which in this case is the opening of the control valve.

PID being a mathematical approach lacks information of the process and simply tracks the error tending to minimize the error, and the control reaches saturation limits if the correction fails. PID control also induces overshoots and undershoots and settles gradually and depending on the process conditions or the actuator traits and the process takes around 15 - 20 seconds for stabilization which is quite high for a dynamic process condition apart from pneumatic loss.

3.2. Proposed Intelligent control

To overcome the drawbacks and limitation of a PID control, alternative control strategies were explored based on first principles and other state space approach and in this juncture empirical model was adhered as the best alternative owing to the adequacy of data from past PID control experiments. Conversely this process data was affected by noise and uncertainties, hence useful information from the data was extracted by statistical treatment, i.e. using Principal Component Analysis (PCA) the data set was resolved into their principal components. The principal component (PC) that encompassed the outliers was eliminated and the data set was reconstructed with the PCs that contained the useful information, thereby yielding a perfect training data set.

Inspired by the technological advancement and with the evolution of high speed computing machines, an empirical modelled intelligent controller is envisaged that predicts the control requirements while adapting to the process characteristics by foreseeing the dynamics. This intelligent controller is based on Adaptive Neuro Fuzzy Inference System (ANFIS), a hybrid Neuro-fuzzy system in which the fuzzy logic system and the neural network work form a single entity. It is believed that the learning capability of these systems pave solution to complex real time nonlinear problems [2]. Fuzzy logic is an intuitive approach for rule induction from observations that models any complex nonlinear functions.

3.3. Adaptive Neuro Fuzzy Inference System (ANFIS)

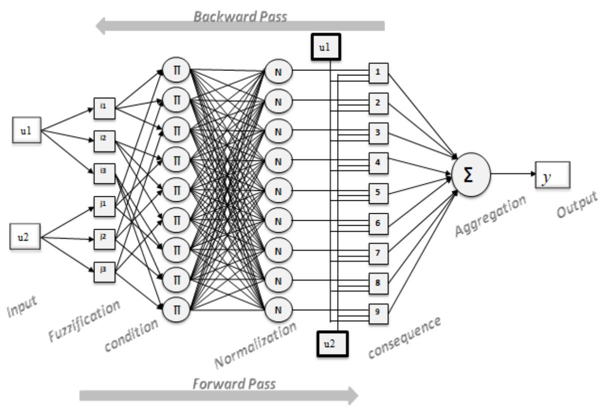

Fig. 2. ANFIS Architecture.

As shown in Fig 2 ANFIS proposed by J S R Jang [2] is a five layer supervised learning process where each layer performing a specific function.

Layer 1, fuzzifies crisp inputs to continuous variables using Triangular, Trapezoid, Gaussian or Generalized bell-shaped membership functions for fuzzification.

Layer 2, Rule layer performing a connective operation for the antecedent (if part) using as the T-norm operator for each node

Layer 3, Normalization layer determining the strength of the fuzzy rules

Layer 4, Consequent layer where the consequent (then part) combine with the normalized firing strengths

Layer 5, summing up the consequence

3.3.1. Grid Partitioning [GP]

Fuzzy inference adopts a divide-and-conquer method [16] where the input data set is partitioned into sub spaces for defining the fuzzy logic condition.

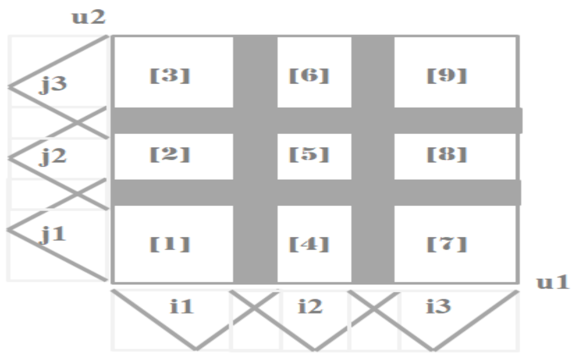

Fig. 1. Grid partitioning.

As shown in Fig 3, GP divides the input sub space as a grid without overlapping. Thus for n membership variables, 2n fuzzy sub spaces are created, the fuzzy rule acts on each region and computes the result of inference which is illustrated in Fig 3, where the two input variables u1, u2 with the membership variables ii, ji constitute the sub space.

3.3.2. Grid Partitioning [GP]

In Fuzzy logic, membership fFunction is a curve that indicates the mapping of each point in the input space with a membership value (or degree of membership) between 0 and 1 for defining uncertainties.

i.e. Membership for a fuzzy set is given by

$$\mu_{u1}: X \to [0, 1] \tag{1}$$

$\mu_{u1}(X)$ is the membership function of X in u1, X is the data set, A the fuzzy mapping referred as *Universe of Discourse*, where the membership function represents an input partition. Common MFs are the triangular, trapezoidal, Gaussian and Generalized bell.

A triangular MF is defined by [18] where the base and height of the triangle influences the fuzzification.

$$f_{(X,a,b,c)} = max(min(\frac{X-a}{b-a,}, 1, \frac{c-X}{c-b}), 0) \quad (2)$$

A Generalized bell shaped MF is defined by three parameters {a,b,c} where 'a' represents the width of the bell (curve), 'b' a positive integer, and 'c' denotes the center of the bell shape.

$$f_{(X,a,b,c)} = \frac{1}{1+\left|\frac{X-c}{a}\right|^{2b}} \quad (3)$$

A Gaussian MF with two parameters (m, σ) is also a smooth curve like the bell function where m denotes the centre of the Gaussian curve and σ the spread of the curve.

$$f_{(X,\sigma,c)} = e^{\frac{-(X-c)^2}{2\sigma^2}} \quad (4)$$

Gaussian and bell membership functions are popular common fuzzifiers known for their smoothness and nonzero values at all points.

3.3.3. Fuzzy Operation

Fuzzy aggregation combines the rule output. The T-norm (triangular norm) i.e. the fuzzy intersection operation aggregates membership functions of the fuzzy inputs

i.e $\mu_{u1\cap u2}(x) = T(\mu_{u1}(x), \mu_{u2}(x))$ (5)

$\mu_{u1}(x)$, $\mu_{u2}(x)$ are the membership function of X in u1 and u2.

3.3.4. De-fuzzification

Aggregation process results in a range of output values that is normalized for the firing strength of the rule in terms of weights. These normalized weight vectors of each neuron evolve as the coefficients of the linear first order polynomial with the input variables. The conclusion part of the fuzzy rule is arrived for the polynomial.

3.3.5. Learning

Back propagation algorithm computes the gradient of the loss function (weights at each layer) by backward propagation. ANFIS network iterates and optimizes the network parameters where each epoch has a forward and a backward pass referred as Hybrid learning [2]. In the forward pass the consequent parameters are fine-tuned using least square algorithm and in backward pass the premise parameters are computed using gradient descent algorithm. Being a supervisory algorithm the consequent and premise parameters are updated in each epoch for minimizing the error between the computed and the actual output.

3.4. ANFIS Modeling

The evolution of a precise and accurate model is the result of a well-defined data set and the membership function. Primitive data for the modeling is taken from the PID controlled process, where four sets of empirical data from different experiments are taken for model training and evaluation. The redundancies and outliers are treated mathematically using PCA decomposition techniques and the data extracts are used for training the model. Convergence of membership variables and the surface plots of the training results are depicted in the following section.

As shown in Fig 4, a two input single output controller is modelled using ANFIS toolbox. The selected data set consist of 250 data points for the Upstream pressure (Pu) and Downstream pressure (Pd) and the control valve opening (CV).

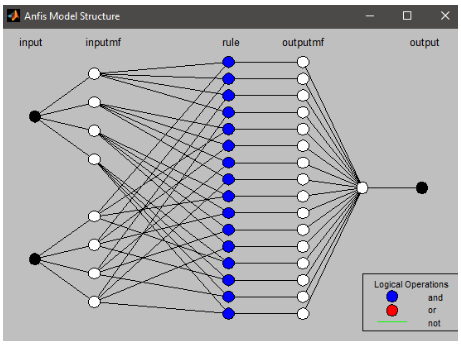

Fig. 4. Controller Model using ANFIS.

Data set is partioned into four subsets using grid partitiong and convergence of the network parameters are studied using various membership functions on the partition. The model is trained for fixed epochs using back propogation and hybrid offline learning algorithm. The overall accuracy within the range is estimated using Root Mean Square error (RMSE) metrics

. i.e. $RMSE = \sqrt{\frac{\sum_i^n e_i^2}{n}}$ (6)

Where e_i is difference between the computed output and the given output for the i^{th} data point the n is the no of data points

4. Anaysis and Discussion

A data mesh is created from the training data and the output prediction with these data points are plotted using surface graphs. The smoothness of the surface graphs indicates the model convergence. The boundaries of valid range can be estimated and the real time operations can be constaint to that limits. The membership functions are applied on the empirical data and the PCA reconstructed data as shown in Fig 5-11.

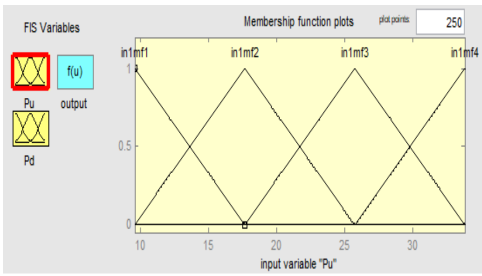

Fig. 5(a)

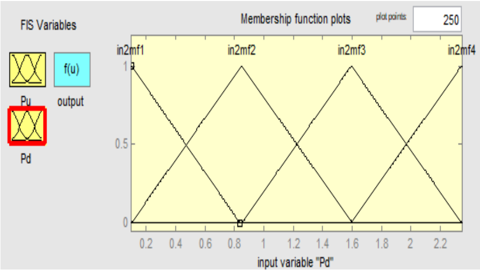

Fig. 5(b)

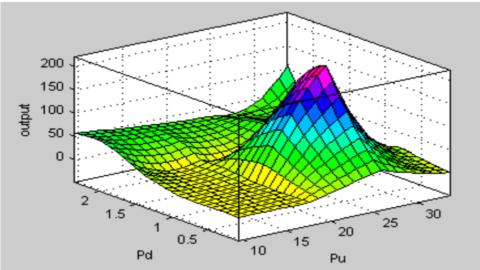

Fig. 5(c)

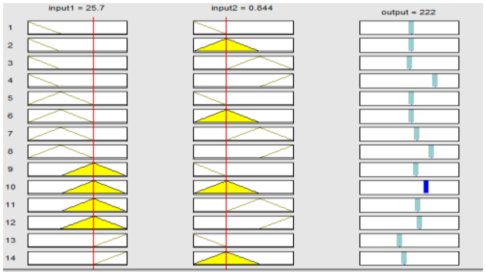

Fig. 5(d)

Fig. 5. ANFIS training with empirical data & Triangular MF.

Fig 5(a), (b) shows the input partition and the membership variables of the partitions after training for 100 epochs. Four MFs are assigned to each input. The MF partitions are unaltered for both inputs after the training. RMSE obtained is 0.354. Fig 5(c) shows the surface plot for the training range where the inputs are represented by the X, Y axis and Z axis denotes the predicted output of the controller where a nonlinear peak arises in the region [X lies between {20,25} & Y {0.5, 1.5}]. The premise-consequence in Fig 5(d) indicates that this region belongs to 3rd MF partition of input 1 (Pu) and 2nd MF partition of input 2 (Pd).

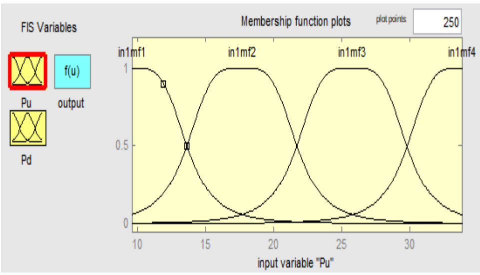

Fig. 6(a)

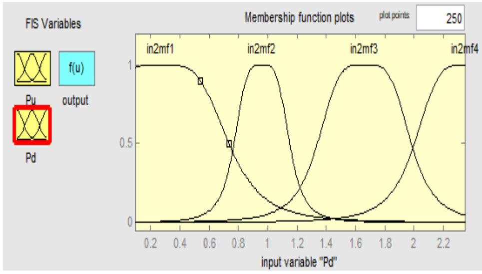

Fig. 6(b)

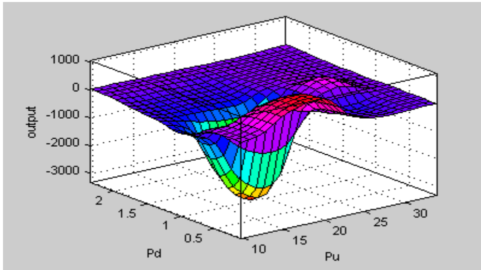

Fig. 6(c)

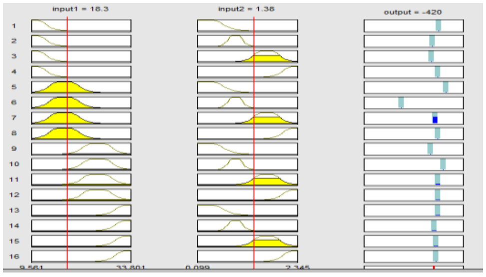

Fig. 6(d)

Fig. 6. ANFIS training with empirical data & Bell MF.

Fig 6(a), (b) shows the input partition and the membership variables of the partitions after training for 100 epochs. Four MFs are assigned to each input. The shape of the membership curve for the second input is distorted for the second MF partition after the training. RMSE obtained is 0.351. Fig 6(c) shows the surface plot for the training range and a non linear negative peak is observed. From the premise-consequence in Fig 6(d) it is inferred that 1st 2nd and 3rd MF partition of input1 (Pu) gives valid results only with the 4th MF partition of input2 (Pd). The combination of 4th MF partition of input1 (Pu) with 3rd and 4th partition of input2 (Pd) are within the range.

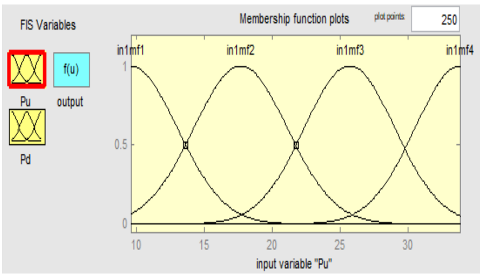

Fig. 7(a)

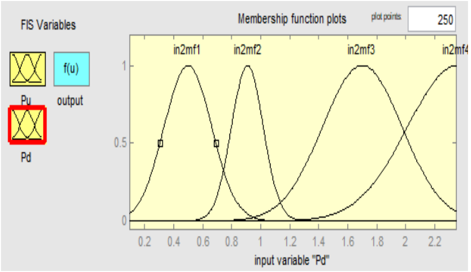

Fig. 7(b).

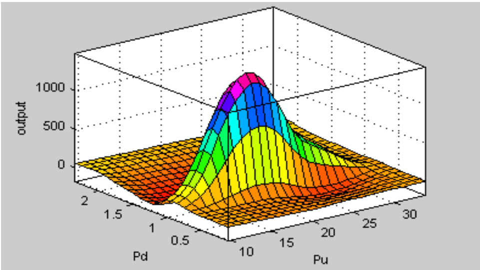

Fig. 7(c).

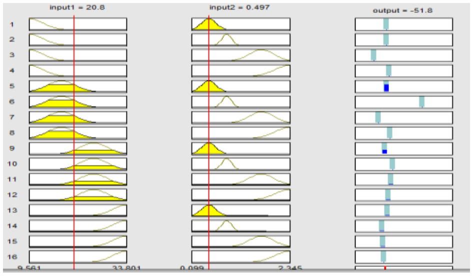

Fig. 7(d).

Fig. 7. ANFIS training with empirical data & Gaussian MF.

Fig 7(a), (b) shows the input partition and the membership variables of the partitions after training for 100 epochs. Four MFs are assigned to each input. The shape of the membership curve for the second input is completely altered after the training. RMSE obtained is 0.334. Fig 7(c) shows the surface plot for the training range and a non linear positive peak is observed. The premise-consequence inference is as seen with Gbell MF.

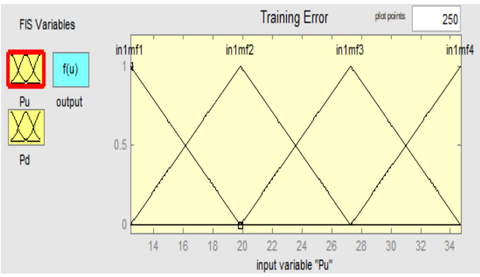

Fig. 8(a).

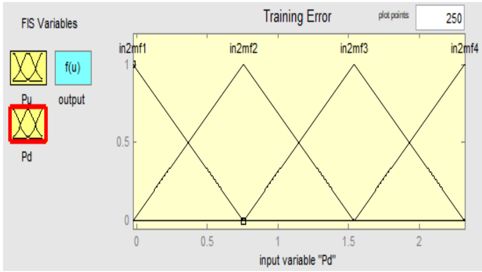

Fig. 8(b)

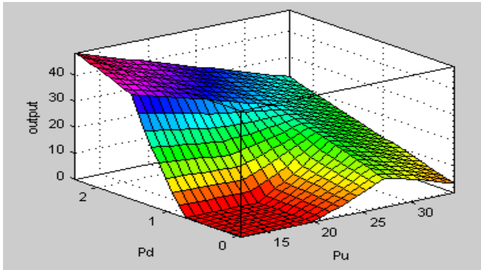

Fig. 8(c)

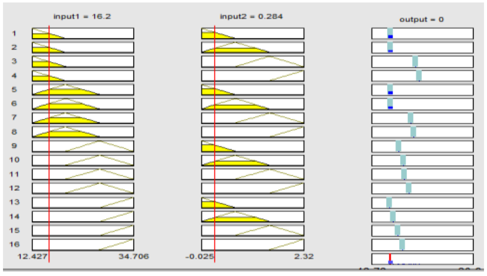

Fig. 8(d).

Fig. 8. ANFIS training with PCA constructed data & Triangular MF.

Fig 8(a), (b) shows the input partition and the membership variables of the partitions after training for 100 epochs. Four MFs are assigned to each input. The shape of the membership curve is consistent. RMSE obtained is 0.003. Fig 8(c) shows the surface plot for the training range and the surface appears to be linear except for zero values in the lower range. The premise-consequence inference in Fig 8(d) indicates that the combination of first two MFs of both the inputs results gives a zero output prediction.

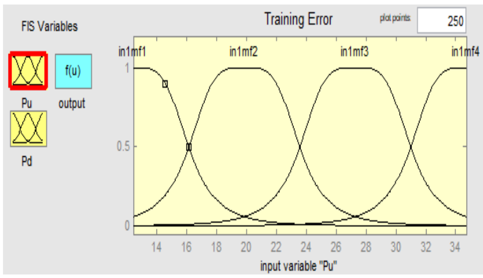

Fig. 9(a).

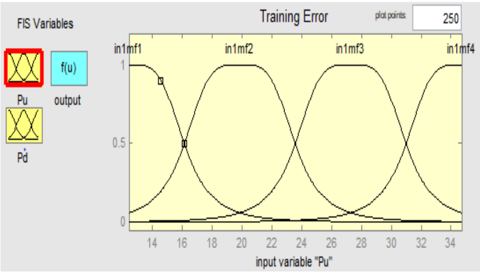

Fig. 9(b).

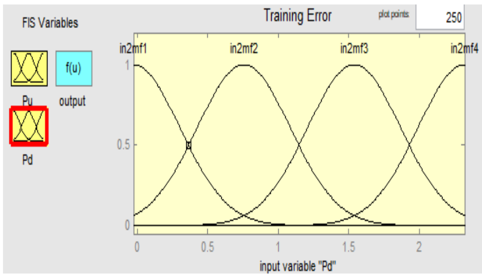

Fig. 10(b)

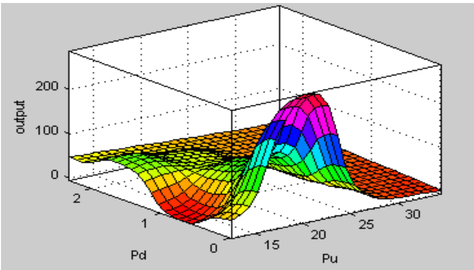

Fig. 9(c).

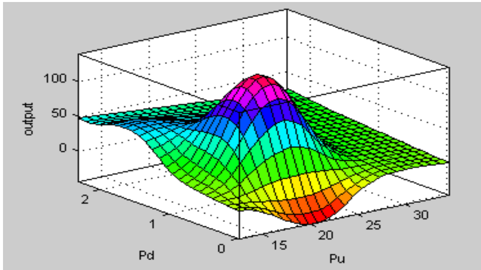

Fig. 10(c)

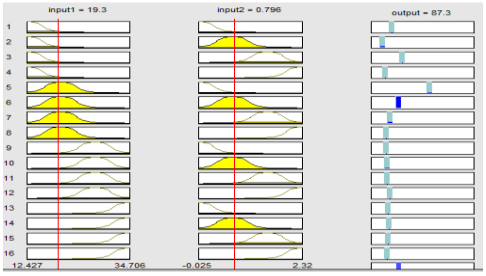

Fig. 9(d).

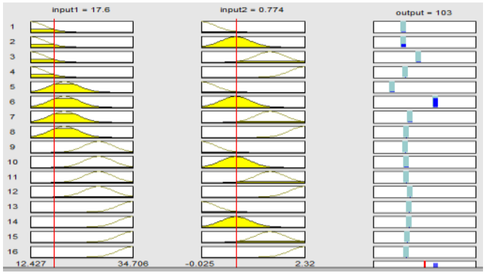

Fig. 10(d)

Fig. 9. ANFIS training with PCA constructed data & GBell MF.

Fig. 10. ANFIS training with PCA constructed data & Gaussian MF.

Fig 9(a), (b) shows the input partition and the membership variables of the partitions after training for 100 epochs. Four MFs are assigned to each input. The shape of the membership curve is consistent. RMSE obtained is 0.003. Fig 9(c) shows the surface plot for the training range and the surface appears to be linear except for one peak. The premise-consequence inference in Fig 9(d) indicates that 1st MF of input1 (Pu) and 3rd MF of input2 (Pd) shows nonconformance, similarly 2nd MF of both inputs show out of bound values.

Fig. 10(a)

Fig 10(a), (b) shows the input partition and the membership variables of the partitions after training for 100 epochs. Four MFs are assigned to each input. The shape of the membership curve is consistent. RMSE obtained is 0.003.Fig 10(c) shows the surface plot for the training range and the surface appears to be linear except for one peak. The premise-consequence inference in Fig 10(d) indicates that 1st MF of input1 (Pu) and 3rd MF of input2 (Pd) shows nonconformance, and 2nd MF of both inputs show out of bound.

As mentioned in section 2.5, four set of empirical data (Ref –T10B, T10C, T11C, T11D) were used for the analysis. Modeling with different membership functions and learning algorithms were attempted. The data sets were reconstructed after PCA decomposition using the first two principal components by which the outliers in the training data got eliminated.

The RMSE errors observed in the training of the ANFIS with different data sets are illustrated in Fig. 11 (a) & (b). The RMSE for different MFs are shown in red, green and blue. It can be seen that for empirical data, the errors are dominant while with the pretreated data set the errors tend to zero.

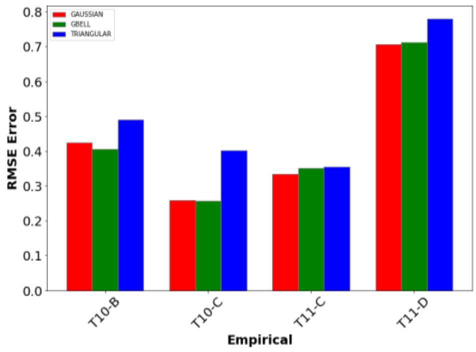

Fig. 11(a). RMSE -Empirical.

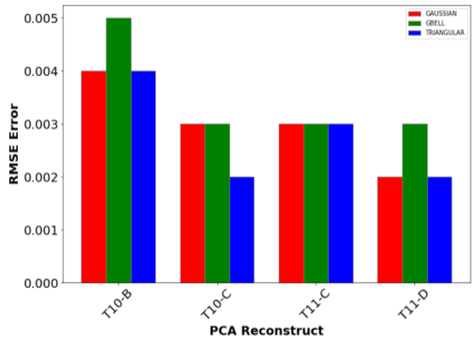

Fig. 11(b). RMSE -PCA Reconstruct.

Data set	MF		T10-B	T10-C	T11-C	T11-D
Empirical	Triangular	Hybrid Epoch=100	0.491	0.402	0.354	**0.779**
		BP, Epoch=1000	0.662	0.657	0.694	1.056
	G Bell	Hybrid Epoch=100	**0.405**	0.256	0.351	0.712
		BP Epoch=1000	0.744	0.851	0.872	1.125
	Gaussian	Hybrid Epoch=100	0.425	0.259	**0.334**	**0.707**
		BP Epoch=1000	0.937	1.029	1.197	1.219
PCA Reconstruct	Triangular	Hybrid Epoch=100	0.004	0.002	0.003	**0.002**
		BP Epoch=1000	0.140	0.132	0.132	0.143
	G Bell	Hybrid Epoch=100	0.005	0.003	0.003	0.003
		BP Epoch=1000	0.249	0.247	0.294	0.271
	Gaussian	Hybrid Epoch=100	0.004	0.003	0.003	0.002
		BP Epoch=1000	0.620	0.489	0.499	0.483

Table 1 summarizes the error estimates for combination of data, learning algorithm and membership functions. It can be seen that the reconstructed data renders a precise model with hybrid learning while back propagation algorithm shows poor convergence.

The above study revealed that the empirical data gives better results with Gaussian MF and Generalized Bell MF when compared to triangular MF and the training converges faster with hybrid learning than with back propagation. This indicates that the given data is nonlinear and triangular MF works well for linear data set. Whereas for the data set show similar results for all the three MFs since the pretreatment results in removal of outliers and nonlinear components from the data set.

5. Conclusion & Future works

Empirical data obtained from a real time process PID control experiment that controls a compressible fluid flow could be used for modeling an intelligent controller that is believed to overwhelm the conventional PID controller. The concepts of fuzzy system, Soft computing dealing with a neural networks and Fuzzy logic blend was examined and the models were defined and executed using MATLAB toolbox. The errors are well within the tolerance limits and also the model performance is in line with the hypothesis. But for adhering to the real time requirements, coding of ANFIS algorithm has to be done in low level languages for implementation in high speed and parallel computing device or embedded platforms.

Though significant improvement is seen with the pretreated data when compared with the empirical data further improvement can be achieved with a real data from the process from an open loop control. PID controller can then be replaced by the intelligent ANFIS controller that will bring down the feedback lag while maintaining the downstream pressure.

DECLARATIONS

Data availability : There is no data availability in this research.

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Ethical Approval : This article does not contain any studies with human participants or animals performed by any of the authors.

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Chrystella Jacob: Conceptualization, Methodology, Software, Field study. Data curation, Writing-Original draft preparation, Software, Validation, Field study **Sasipraba T:** Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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