International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-3 Issue-11, April 2014

Simulation of Adaptive Neuro Fuzzy Logic Controlled Wireless Intelligent Telemetry System

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Abstract— This paper presents the simulation of a telemetry system for controlling the flow of water in water tanks used in industrial process using adaptive neuro fuzzy logic with the help of "neuro fuzzy design" module in matlab .Basically three ANFIS(Adaptive neuro Fuzzy Inference System) models are taken for simulation and then compared. First model is using single input variable "level", second model is using two input variables "level" and "flow" and third model is using three input variables "level", "flow" and "rate". All these three models are using Sugeno type fuzzy model because only Sugeno type fuzzy models can be simulated in neuro fuzzy design module of matlab. Thus all models are using single output variable "motorstatus" which is either "ON" or "OFF". Simulation is performed by taking constant and linear type output membership functions as major parameters. Training and checking of models is simulated for each type of output membership functions using two optimization methods "hybrid" and "back propagation" alternatively and number of epochs is considered 30, 60 and 120 for each method.

Index Terms—ANFIS, Neuro fuzzy design, Telemetry system, Water level control.

I. INTRODUCTION

The most important aspect in building a successful neural fuzzy model is the selection of the input variables. There is no guaranteed rule that one could follow in this process. The selection of input variables can be carried out almost entirely by trial and error.

The three types of ANFIS models are designed using:

1. Single Input Variable
2. Two Input Variables
3. Three Input Variables

In addition to the parameter selection it must be ensured that appropriate test data are used to detect over fitting of the training data set. The test data have the same format as the training data. Over fitting can be detected when the test error (difference between the measured and predicted outputs) starts increasing while the training error is still decreasing.

The following parameters are used in these ANFIS models as shown in table I:

Manuscript published on 30 April 2014.
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TABLE- I. PARAMETERS

S .no	Parameter	Description
1.	Number of epochs	It is the frequency to train the model. Number of epochs is taken here "30", "60" and "120".
2.	Method of optimization	The optimization methods train the membership function parameters to emulate the training data. The two ANFIS parameter optimization methods available for FIS training are hybrid (the default, mixed least squares and back propagation) and backpropa (back propagation).
3.	Type of output membership function	There are basically two types of output membership function: Constant and Linear

A. Training Data

The training data is a required argument to ANFIS as well as to the ANFIS Editor. Each row of training data is a desired input/output pair of the target system to be modeled. Each row starts with an input vector and is followed by an output value. Therefore, the number of rows of training data is equal to the number of training data pairs, and, because there is only one output, the number of columns of training data is equal to the number of inputs plus one. The two ANFIS parameter optimization methods available for FIS training are hybrid (the default, mixed least squares and back propagation) and backpropa (back propagation). Error Tolerance is used to create a training stopping criterion, which is related to the error size. The training will stop after the training data error remains within this tolerance. This is best left set to 0.

B. Training Error

The training error is the difference between the training data output value, and the output of the fuzzy inference system corresponding to the same training data input value, (the one associated with that training data output value). The training error records the root mean squared error (RMSE) of the training data set at each epoch. The ANFIS Editor GUI plots the training error versus epochs curve as the system is trained.

C. Checking Data

The checking data is used for testing the generalization capability of the fuzzy inference system at each epoch. The checking data has the same format as that of the training data but its elements are generally distinct from those of the training data. Due to fixed model structure of ANFIS, there is a tendency for the model to over fit the data on which is it trained, especially for a large number of training epochs.

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If over fitting does occur, the fuzzy inference system may not respond well to other independent data sets, especially if they are corrupted by noise. A validation or checking data set can be useful for these situations. This data set is used to cross-validate the fuzzy inference model. This cross-validation requires applying the checking data to the model and then seeing how well the model responds to this data.

II. ANFIS MODEL USING SINGLE INPUT VARIABLE

Firstly only single variable 'level' is selected as input variable as in [1]. This variable has three MFs (membership functions) which are named as low, medium and high. Only single output variable is required in this research work which is named as 'motorstatus' which can have only two possible MFs named On and Off, but if there is less number of output MFs than number of rules then error of parameter sharing is displayed so to avoid such type of error, number of output MFs (by name) should be equal to the number of rules. Figure 1 shows the Sugeno type system named "tank" with one input named 'level' and one output named 'motorstatus' which may be either 0 or 1 corresponding to status 'off' and 'on' respectively.
Figure 1 shows FIS editor of ANFIS model using single input variable.

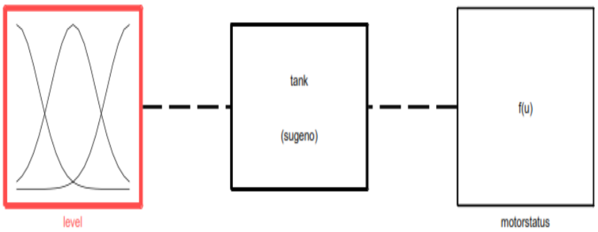

Fig 1. FIS editor displaying the sugeno type system "Tank" with one input Variable

Figure 2 shows the rule viewer of single input variable system "tank" showing the simulation according to the rules in rule editor. The following figure shows the level of tank=5.52 c.m and corresponding output is 1, showing the status of motor "On".

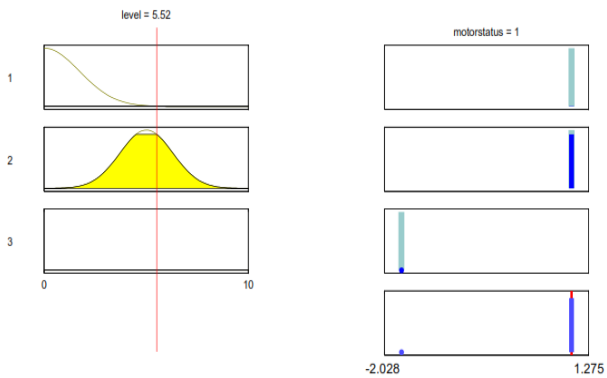

Fig 2. Rule Viewer shows the simulation with single input variable

Figure 3 shows the structure of ANFIS for "tank" system using one input variable and one output and three rules with "and" logical operation. Here one input variable "level" is shown with three MFs (Low, Medium and high) using three rules and one output with three MFs.

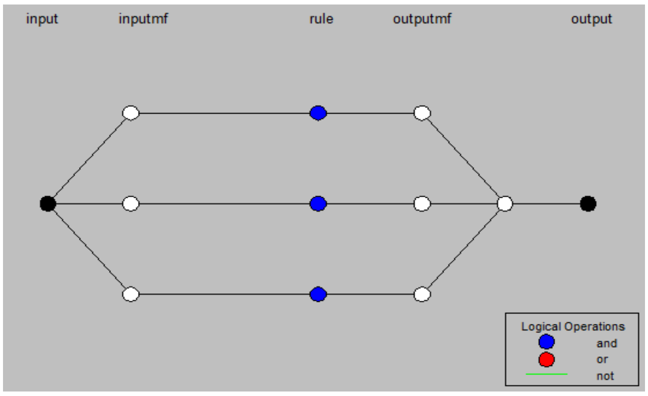

Fig 3. Structure of ANFIS for "tank system" with single input variable

III. ANFIS MODEL USING TWO INPUT VARIABLES

The Figure 4 shows the FIS editor for Sugeno type system named "Water tank 2" using two input variables 'level' and other is 'flow'.

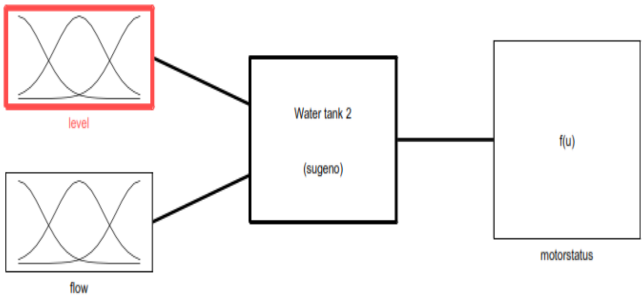

Fig 4. FIS Editor for system "Water tank 2" using two input variables

Figure 5 shows the rule viewer for "Water tank 2" system .The figure shows clearly that when the level of tank is 2.34 c.m and flow is positive the status of motor is 1 means motor is "On" to pump the water in the tank.

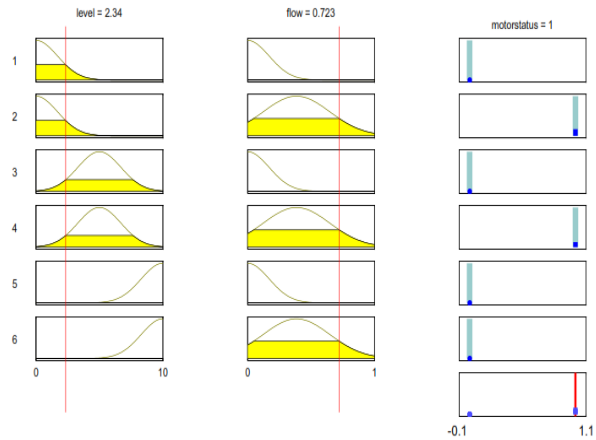

Fig 5. Rule viewer for Two Input Variables system

Figure 6 shows the structure of ANFIS of "Water tank 2" system showing two input variables ,one input variable having three membership functions and other input variable having two membership functions, six rules and one output having six membership functions.

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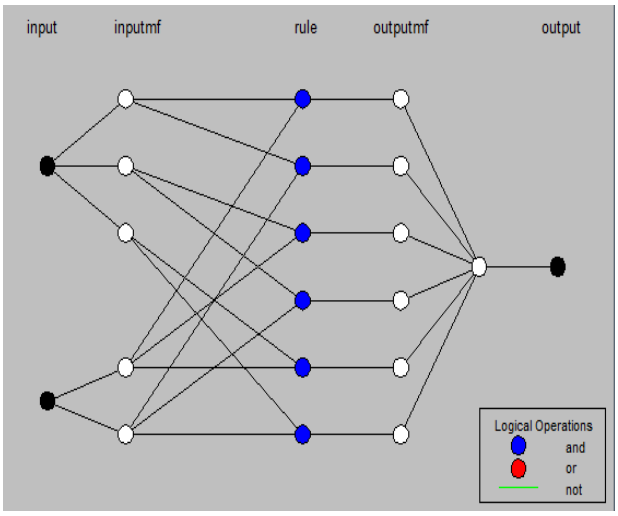

Fig 6.Structure of ANFIS for "Water tank 2" system

IV. ANFIS MODEL USING THREE INPUT VARIABLES

The Figure 7 shows the FIS editor for Sugeno type system named "Water tank 3" using three input variables 'level' , 'rate' and 'flow'.

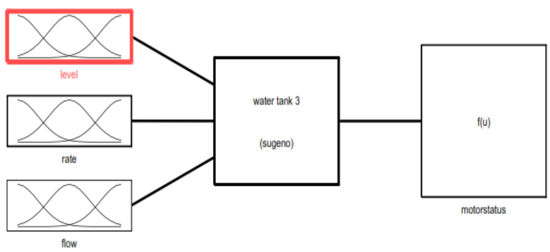

Fig 7. FIS Editor for system sugeno type system "Water tank 3" using three input variables

Figure 8 shows the rule viewer for "Water tank 3" system .The figure shows clearly that when the level of tank is 5 c. m and rate is zero means there is no change in the level height in the tank and flow is positive the status of motor is nearly 1 means motor is "On" to pump the water in the tank.

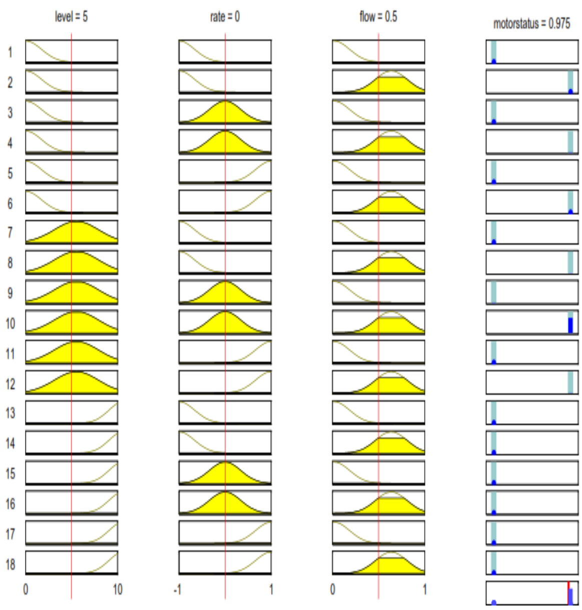

Fig 8. Rule Viewer for input variable "level" for ANFIS model of "Water tank 3" system

Figure 9 shows the structure of ANFIS of "water tank 3" system showing three input variables ,one input variable having three membership functions and second input variable having three membership functions, third input variable having two membership functions. The structure shows 18 rules and 18 membership functions and finally one output.

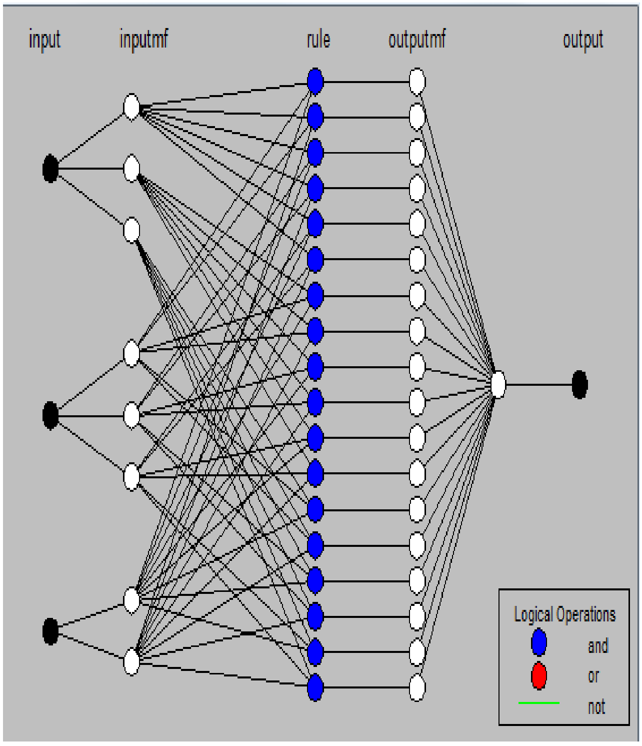

Fig 9. Structure of ANFIS for "Water tank 3" system

V. RESULTS

A. Tables

All the tables shown below represent the actual root mean square error values (RMSE) after simulation.

TABLE II
COMPARISON OF RMSE VALUES FOR TRAINING DATA USING CONSTANT OUTPUT MEMBERSHIP FUNCTION

ANFIS Model	Hybrid Method			Back Propagation Method		
	Epochs 30	Epochs 60	Epochs 120	Epochs 30	Epochs 60	Epochs 120
Single Input Variable	0.22854	0.010563	0.010407	0.21783	0.080352	0.080325
Two Input Variable	0.14618	0.00027217	0.00026823	0.067406	0.011945	0.012697
Three Input Variable	0.0001086	0.0001002	0.0001002	0.040283	0.040245	0.030642

Table II shows the different RMSE values for training data using constant output membership function for three different systems simulated using single, two and three variables. The results shows the least RMSE values for ANFIS model using three input variables in hybrid method followed by ANFIS model using two input variables ,followed by ANFIS model using single input variable. Using back propagation method least RMSE values comes with number of epochs 30 for ANFIS model using three input variables but RMSE values are greater with number of epochs 60 and 120 than that of ANFIS model using two input variables.

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The highest set of RMSE values is for ANFIS model using single input variable.

TABLE III
COMPARISON OF RMSE VALUES WITH CHECKING DATA CONSTANT OUTPUT MEMBERSHIP FUNCTION

ANFIS Model	Hybrid Method			Back Propagation Method		
	Epochs 30	Epochs 60	Epochs 120	Epochs 30	Epochs 60	Epochs 120
Single Input Variable	.010029	0.009882	0.009882	.081273	.081035	.081107
Two Input Variable	0.00029769	0.00028257	0.00030825	0.01157	0.013098	0.013066
Three Input Variable	0.00011321	0.00011321	0.00011414	0.031222	0.031172	0.027481

Table III shows the different RMSE values for checking data using constant output membership function for three different systems simulated using single, two and three variables. The results shows the least RMSE values for ANFIS model using three input variables in hybrid method followed by ANFIS model using two input variables ,followed by ANFIS model using single input variable. Using back propagation method least RMSE values for ANFIS model using two input variables followed by RMSE values of ANFIS model using three input variables. The highest set of RMSE values is again for ANFIS model using single input variable.

TABLE IV
COMPARISON OF RMSE VALUES FOR TRAINING DATA USING LINEAR OUTPUT MEMBERSHIP FUNCTION

ANFIS Model	Hybrid Method			Back Propagation Method		
	Epochs 30	Epochs 60	Epochs 120	Epochs 30	Epochs 60	Epochs 120
Single Input Variable	0.14779	0.060497	0.0052062	0.14546	.030929	.033847
Two Input Variable	0.023893	0.023582	0.023239	0.15465	0.15453	0.15321
Three Input Variable	4.3768e-07	4.3932e-07	3.72e-07	0.038894	0.03867	0.038581

Table IV shows the different RMSE values for training data using linear output membership function for three different systems simulated using single, two and three variables. The results shows the least RMSE values for ANFIS model using three input variables in hybrid method followed by ANFIS model using two input variables ,followed by ANFIS model using single input variable. Using back propagation method least RMSE values for ANFIS model using single input variables with 60 and 120 numbers of epochs followed by RMSE values of ANFIS model using three input variables with same number of epochs. When the number of epochs are 30,then the results shows the least RMSE values for ANFIS model using three input variables using back propagation method. The highest set of RMSE values is for ANFIS model using two input variables.

TABLE V
COMPARISON OF RMSE VALUES WITH CHECKING DATA USING LINEAR OUTPUT MEMBERSHIP FUNCTION

ANFIS Model	Hybrid Method			Back Propagation Method		
	Epochs 30	Epochs 60	Epochs 120	Epochs 30	Epochs 60	Epochs 120
Single Input Variable	0.14779	0.060497	0.001292	.14546	.058324	.033716
Two Input Variable	0.023095	0.0016145	0.0014544	0.095466	0.045367	0.037057
Three Input Variable	3.946E-07	3.833E-07	2.428E-07	0.038393	0.036834	0.032749

Table V shows the different RMSE values for checking data using linear output membership function for three different systems simulated using single, two and three variables. The results shows the least RMSE values for ANFIS model using three input variables in hybrid method followed by ANFIS model using two input variables ,followed by ANFIS model using single input variable. Using back propagation method least RMSE values for ANFIS model using three input variables followed by RMSE values of ANFIS model using two input variables. The highest set of RMSE values is again for ANFIS model using single input variable.

B. Graphs

In figure 10, on X-axis, Number of epochs (in number) is taken for both of the optimization methods, hybrid and back propagation method. Number of epochs is taken 30, 60 and 120 to show the effect of double number of epochs to train the systems. On Y-axis RMSE values (in number) are taken .It is observed in figure 10 that RMSE values are minimum in ANFIS model using three input variables followed by ANFIS model using two input variables followed by ANFIS model using single input variables. Thus for training data using constant output membership functions ANFIS model using three input variables performs the best in simulation of water level control in water tank.

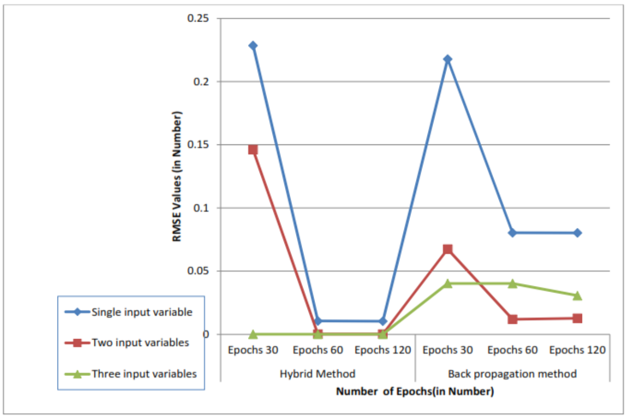

Fig 10. RMSE values for training data only using constant output membership function

Figure 11 shows that using checking data to validate the models, ANFIS model using single input variable does not perform very well as the RMSE values are quite high. ANFIS models using two variables and three variables performs approximately same in case of hybrid method but in case of back propagation method ANFIS model using two input variables performs well than ANFIS model using three input variables as RMSE values are much less than in case of ANFIS model using two input variables than that of ANFIS model using three input variables.

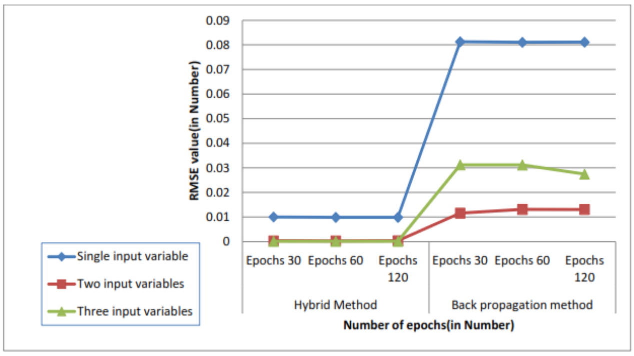

Fig 11. Comparison of RMSE values with checking data using constant output membership function

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The results in figure 13 shows the fluctuating RMSE values for ANFIS model using single input variables. ANFIS model using two input variables shows RMSE values equal to 0.02 for 30, 60 and 120 numbers of epochs using hybrid method but shows increasing RMSE values equal to approximately 0.15 in back propagation method. ANFIS model using three input variables shows best results where RMSE values in hybrid method are approximately 0 and in back propagation method RMSE values are equal to 0.04.

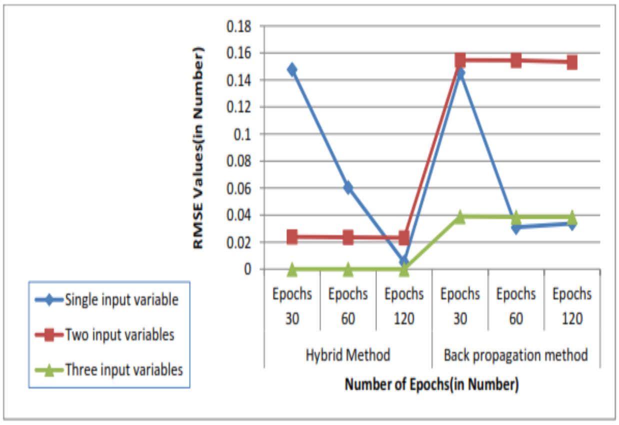

Fig 12. Comparison of RMSE values for training data only using linear output membership function

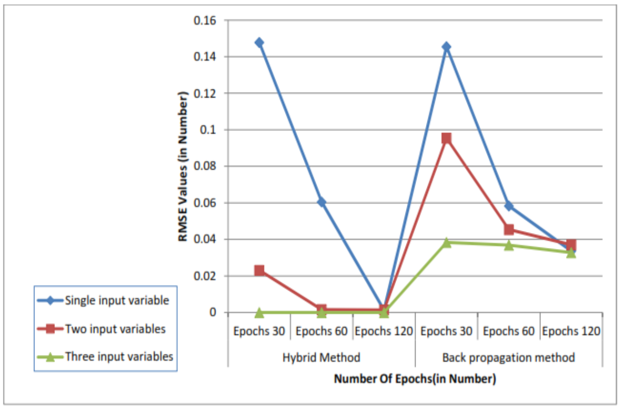

Fig 13. Comparison of RMSE values with checking data using linear output membership function

It is observed from figure 13 that again ANFIS model using three input variables performs the best using both of the methods, hybrid and back propagation method followed by ANFIS model using two input variables then followed by ANFIS model using single input variable which results fluctuating RMSE values which degrades its performance for water level control in water tanks using linear output membership functions.

VI. CONCLUSIONS

Simulation of telemetry system for water level control in tanks is performed using "Neuro Fuzzy Design" application in mat lab. Three ANFIS models are designed and simulated with varying number of input variables. All the ANFIS models are trained and validated using appropriate training data and checking data. Two types of output membership functions are used, one is constant and other is linear. The root mean square error values after training and checking three different systems using these different types of output membership functions are collected and shown in tables and analysed using graphs. The graphs shows that the ANFIS model using three input variables performs better than both of the other ANFIS models using constant and as well as linear type output membership functions. ANFIS model using single input variable does not perform well and shows high RMSE values in both the cases. ANFIS model using two input variables shows good results than ANFIS model using single input variable but shows high RMSE values than that of ANFIS model using three input variables, thus shows poor results than ANFIS model using three input variables. Thus ANFIS model using three input variables is best to simulate telemetry system to control water level in tank systems.

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