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Adaptive Network Based Fuzzy Inference System (Anfis) Modeling For Super Heated Steam Temperature Control Process

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Abstract

In this paper the procedure to identify an ANFIS model from real time data is explained. The input selection of candidates was done by sequential and exhaustive searches. The performance of the models obtained based on these two input selection searches is presented. For the dataset, the sequential search performs better than the exhaustive in modeling the process. ANFIS uses a hybrid learning algorithm to identify parameters and is applied to a combination of the least squares method and the back propagation gradient descent method for training FIS membership function parameters to emulate a given training data set.

1. Introduction

System identification is the process of constructing a model to predict the behavior of a target system. Conventional system identification techniques are mostly based on linear models with fast computation and rigorous mathematical support. To model nonlinearity that inherently comes with a real world dynamic system, neuro-fuzzy modeling technique such as ANFIS is utilized.

These identification techniques require massive computation but without mathematical proofs of convergence to global minima or the like. This section presents the application of ANFIS architecture for the dynamic system identification of superheated steam temperature control process. Advanced techniques in nonlinear regression such Gauss-Newton method, Levenberg - Marquardt method, and the extended Kalman filter algorithm have been applied to ANFIS directly. The back-propagation gradient descent and a more efficient least-squares method are chosen for the parameter identification.

2. Adaptive network based fuzzy inference system (ANFIS)

ANFIS uses a hybrid learning algorithm to identify parameters of Sugeno type fuzzy [1] inference systems. It applies a combination of the least squares method and the back propagation gradient descent method for training FIS membership function parameters to emulate a given training data set.

The learning in an ANFIS is a two-stage process. During the forward pass the consequence parameters are updated using the least square estimate method or recursive least square estimate method. In the backward pass the premise parameters are updated using back propagation method. This learning process is continued until the change in output is zero. [2], [3]

3. Steps for creating ANFIS model

The various steps involved in creating a Fuzzy inference system (FIS) model from the input output data are as follows:
Load data (training, testing, and checking).
Generate an initial FIS model or load an initial FIS model. Choose the FIS model parameter optimization method: backpropagation or a mixture of backpropagation and least squares (hybrid method).
Choose the number of training epochs and the training error tolerance.
Train the FIS model by clicking.
This training adjusts the membership function parameters and plots the training (and/or checking data) error plot(s) in the plot region.
View the FIS model input versus the training, checking, or testing data output.
Verify the test data against the FIS output in the plot region. [5], [4]

4. ANFIS controller for superheated steam temperature

A detailed description of the typical control scheme for the realization of super heater outlet steam temperature control process is given in Figure 1.
A first-order Sugeno fuzzy inference system with two fuzzy rules can be expressed as [1]

Rule 1: If X is A_1 and Y is B_1, then $f_1 = p_1x + q_1y + r_1$,
Rule 2: If X is A_2 and Y is B_2, then $f_2 = p_2x + q_2y + r_2$.

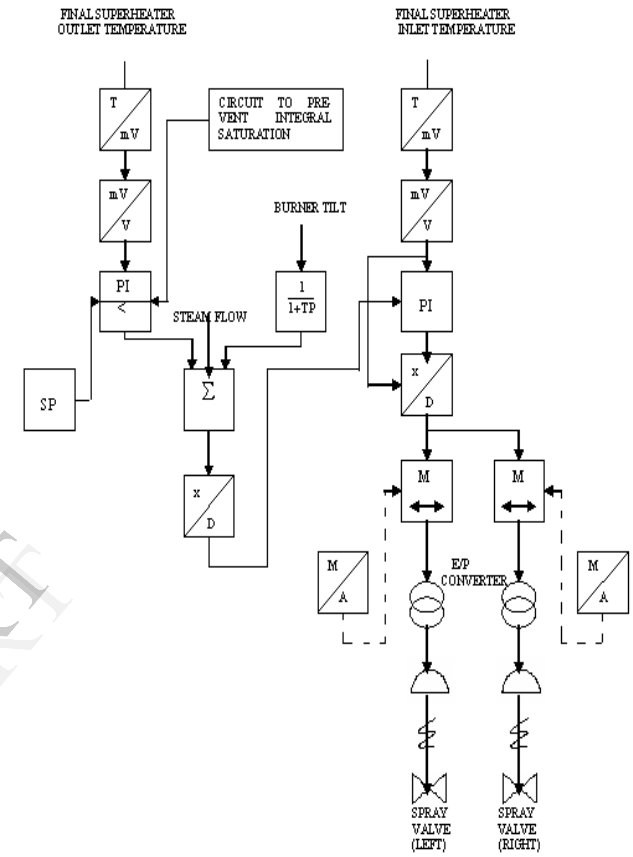

Figure 1 Control scheme for superheated steam temperature control process

Figure 2 illustrates the fuzzy reasoning mechanism that infers an output from a given input vector [x, y]. Accordingly, an equivalent adaptive network representation called ANFIS (Adaptive Network based Fuzzy Inference

System) can be derived as shown in Figure 3.

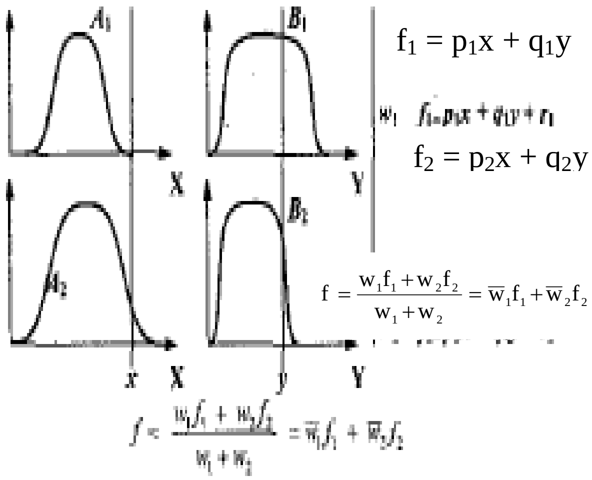

Figure 2 Fuzzy reasoning

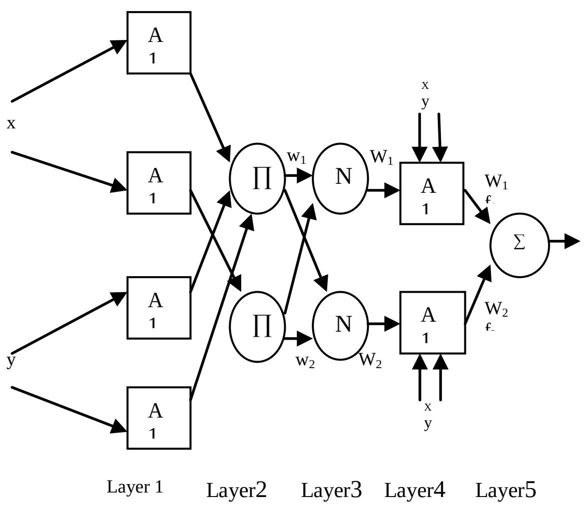

Figure 3 ANFIS structure

In Figure 3, layer 1 computes the membership grades; layer 2 combines the membership grades to form the firing strengths; layer 3 normalizes the firing strengths; layer 4 generates the contribution from each rule, and layer 5 produces the final output. The modifiable parameters in layer 1 determine the shapes and positions of membership functions, and those in layer 4 specify the output linear equation of each rule. As layer-1 parameters are nonlinear, the back-propagation gradient descent is used to update them. For those linear parameters in layer 4, a more efficient least-squares method is chosen to identify them. This is the hybrid learning method used for simulation. [2]

For identification of the superheated steam temperature control process, input-output data pairs are collected. Two hundred and eighty such data pairs, collected from real time measurements of the process variables have been utilized. [6]

5. Input selection

The first step in using ANFIS for system identification is input selection, i.e., to determine which variables should be the input arguments to the ANFIS model. Once the inputs are fixed, the ANFIS model structure, such as the style for input space partitioning, the numbers and types of membership functions on each input, and so on, can be specified.

For the modeling of the superheated steam temperature process, the input candidates are partitioned into two disjoint sets as follows

Y = {y(k – 1), y(k - 2), y(k – 3), y(k – 4)},
U = {u(k - l), u(k - 2), u(k - 3), u(k - 4), u(k - 5), u(k - 6)}.

The heuristic approach to input selection is to treat all the input candidates equally and select the best inputs sequentially .[17] That is, 10 ANFIS models are constructed first, with single input, and the one with the smallest training error is selected. Then based on the selected model, another different input is added, and the best one from 9 ANFIS models with two inputs is chosen, and so on. For simplicity, the ANFIS models are assumed to have grid partitioning and that each input has two generalized bell membership functions defined by

$$\mu A_i(x) = \left[1 + \left| \frac{x - c_i}{a_i} \right|^{2b_i} \right]^{-1} \tag{3.23}$$

where {ai, bi, ci) is the parameter set. Thus the number of fuzzy rules is 2^n, where n is the number of input arguments. The error curves for the input selection process are shown in Figure 4 which makes use of the sequential search described, where the selected inputs and training errors are plotted.

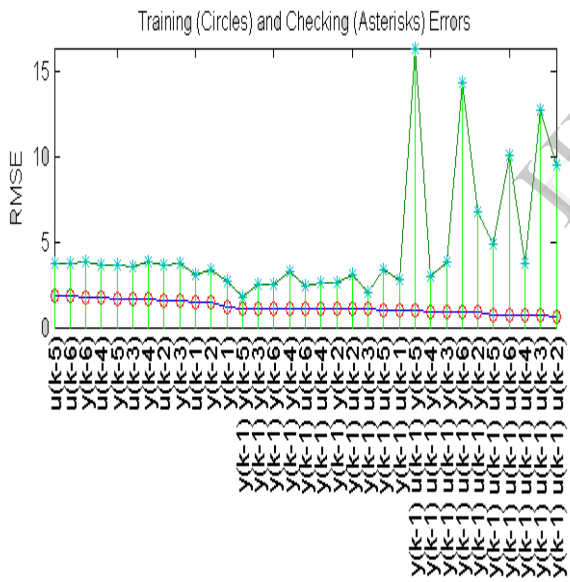

Figure 4 Sequential search based selection

Another more computation intensive approach is to do an exhaustive search on all possible (and reasonable) combinations of the input candidates . From the heuristic search described earlier, it seems that two input arguments are too few for ANFIS to get all necessary information. Moreover, since we are modeling a dynamical system, [9] ,[8] it is reasonable to take two inputs from Y and one from U to make a total of three inputs to the ANFIS model. This results in 36 ANFIS models, each with 8 fuzzy rules. Figure 4 shows the performance of these 36 ANFIS models. The error curves for the input selection process are shown in Figure 5 using the exhaustive search.

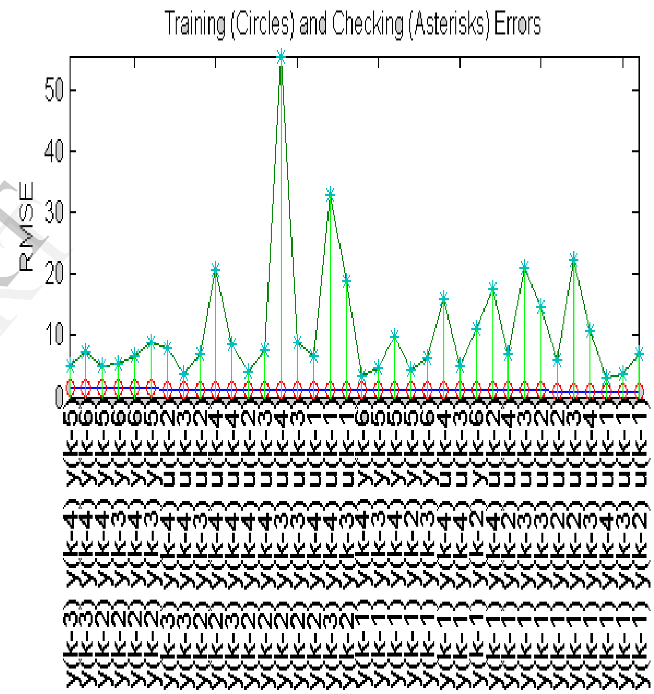

Figure 5 Exhaustive search based selection

Each ANFIS is trained for a single epoch, which corresponds to a single application of least-squares methods to identify consequent parameters that specify each rule's output equation.

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6. Performance of the ANFIS models

The testing dataset numbering 140 is applied to the ANFIS models obtained and their performance is compared.[11] The performance of the models based on sequential search is shown in Figure 6 and those based on exhaustive search in Figure 7. The performance is taken after 100 epochs of training.

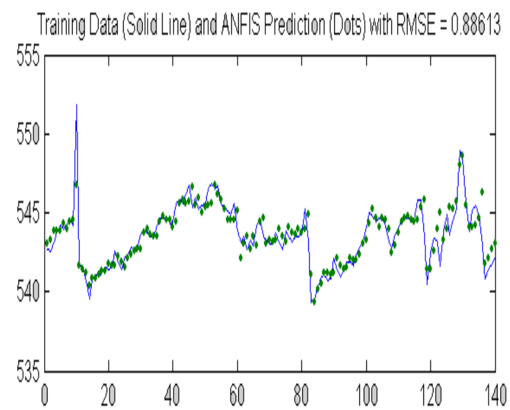

Figure 6 Performance of models based on sequential search

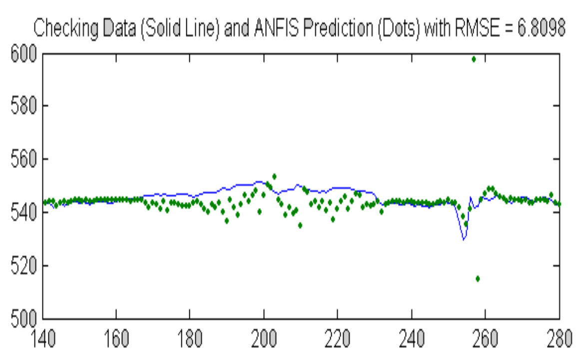

Figure 7 Performance of models based on exhaustive search

It is evident from the performance curves that the test Root Mean Square Error for the ANFIS models based on sequential search is 0.88613 and for those models based on exhaustive search is 6.8098. Thus a procedure to identify a nonlinear model based on ANFIS is demonstrated. [10]

7. Conclusion

In this section Adaptive Network based Fuzzy Inference Systems (ANFIS) is effectively used for generation of membership functions to model the process variables of a superheated steam temperature control process. The inputs to the system are obtained by making real time measurements of process variables. The performance of the various membership functions in tracking the input output data set is compared. The design of an ANFIS based controller is carried out. The rule base for various membership functions is automatically generated and the surface plot is shown for a combination of inputs and output.

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