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ANALYSIS OF DIFFERENTS METHODS FOR UPDATING THE MODIFIED ANFIS PARAMETERS

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Abstract. *This paper aims compare differents methods for updating the modified ANFIS parameters. To make a better analysis of the influence of each method, there was a case study in which it had used a Quanser Heat Flow Experiment in order to make their identification. The results prove that the replacement of the least squares estimate method to the training of the consequent by identification from step response measurements has satisfying results as well the use of backpropagation for updating premise and consequent parameters of modified ANFIS.*

Keywords: *System identification, Modified ANFIS, ANFIS.*

1. INTRODUCTION

System identification is a field of knowlegdge in which main objective is to use the input and output data of systems to build mathematical models that represent these systems.

Modified ANFIS proposed by Fonseca (2012) is a method that identifies nonlinear systems through combination of local linear models. The technique uses backpropagation algorithm to determine the best combination of these local models in order to obtain a nonlinear model that represents the plant.

A fundamental step of modified ANFIS is obtain the local models. By default, these models are obtained using the Least Squares Estimation (LSE). However, a large number of industrial plants can be modeled by a First Order Plus Time Delay (FOPTD) Tavakoli and Fleming (2003).

Typically system identication is performed for designing controllers. Kun *et al.* (2013) developed a robust PID tuning method for unstable FOPTD process showing the importance of this technique to desing controllers. Viteckova and Vitecek (2012) show a tuning of analog and digital PI and PID controllers for FOPTD plants, it technique makes possible to obtain a non-oscillatory control process without an overshoot. Wang *et al.* (2015) takes a new active disturbance rejection control solution and presents a particular tuning method for a class of time delay system with parametric uncertainties, where complicated process dynamics is modeled as a simple first order plus large time delay (FOPTD) plant, with the difference between the actual dynamics and its model treated as disturbances to be rejected.

FOPTD systems can be identified through the step response. Thus, one obtains elements necessary to model a FOPTD system such as static gain K, time constant τ and dead time θ.

This paper presents a case study where was identified a Quanser Heat Flow Experiment with nonlinear dynamics using the modified ANFIS, changing the methods for updating the modified ANFIS parameters. Three methods were used to update modified ANFIS parameters. The first method uses the LSE to identify the local models and the second the identification from step response measurements and then update the consequent parameters. After that, use the backpropagation algorithm for updating the premise parameters. The third method is through the use of backpropagation for updating all parameters, premise and consequent parameters.

2. THEORICAL FUNDAMENTATION

The modified ANFIS proposed by Fonseca (2012), is a modification on the structure of ANFIS to obtain a systematic method for identifying, from linear identification techniques. This method gets local linear models and are combined by the modified ANFIS structure. After the modified ANFIS training is obtained a global identification of the dynamic system.

The modification made to the ANFIS consists of independently leaving the inputs of the first and fifth layers, may be the same or not, depending on the purpose and desired accuracy for the application. This method is divided into four steps.

The first step consists in dividing the plant universe of discourse in operating points,

in order to obtain linear models to represent operating regions.

It must be chosen the smaller possible number of operating points capable to satisfactorily represent the plant throughout the operating range.

As a result, the unecessary increase in complexity and computational burden are avoided.

In the second step, it is performed the identification and validation of linear models around the operating points chosen in the first step. In this step, are obtained the local models. These models are used as consequence of the modified ANFIS rules.

In the third step is performed the modified ANFIS training. At this stage, the recently identified models are combined to properly reproduce the plant nonlinear behavior throughout its universe of discourse.

The last step is the validation, in which verify the modified ANFIS ability to obtain a response approximately equal to the actual plant output for inputs that were not used during training.

Figure 1 presents an example of a modified ANFIS structure with two inputs, two membership functions and a designed linear model.

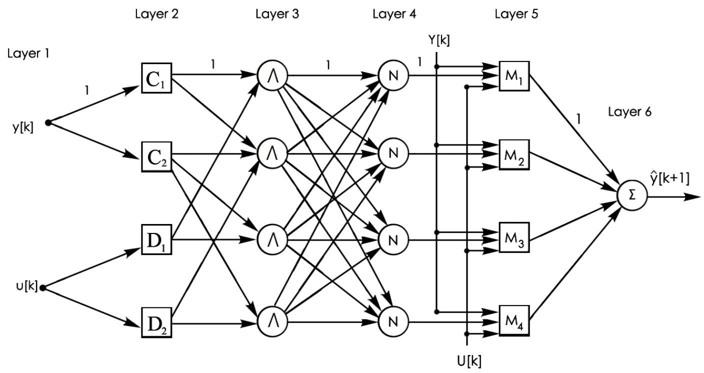


Figure 1. Modified ANFIS example of the structure.

As shown in Figure 1, the structure inputs are **y(k)** and **u(k)**, which are the current plant output and input, respectively. For each of the inputs, we have a membership function, resulting in four rules. The linear model is used to complete each of the four rules.

It can be seen that linear models for this case are functions of the output vector **Y(k)** and input **U(k)** of the plant. Such vectors may contain current and previous values, or just the current values, making equal the inputs of identifiers and the ANFIS, allowing the ANFIS structure be maintained, since the models are functions of their inputs Fonseca (2012).

2.1 LEARNING ALGORITHM

2.1.1 BACKPROPAGATION ONLY

Similar to the classical ANFIS Jang (1993), in modified ANFIS, a hybrid algorithm that combines gradient method with least squares estimate (LSE) is used to identify parameters.

In contrast, the LSE estimation in modified ANFIS is previously performed by local model identification and only after all local models identified that backporpagation algorithm is used to update the premise parameter. Otherwise, can be used the backpropagation for updating all parameters, premise and consequents parameters.

2.1.2 IDENTIFICATION FROM STEP RESPONSE MEASUREMENTS

There are many techniques for the identification of linear systems. Some of them are based on the fact that the usual representation of a mathematical model for an industrial plant is the transfer function of transport delay, called First-order Plus Dead-Time (FOPDT) described in equation (1)

$$G_p(s) = \frac{K}{\tau s + 1} e^{-\theta s} = \frac{Y(s)}{U(s)} \quad (1)$$

This equation is characterized by three parameters: static gain K, time constant τ and dead time θ.

The following method are used in this work: Ziegler and Nichols, Sundaresan and Krishnaswamy, Nishikawa and Smith Mollenkamp (1988); Seborg (1989); Dorf and Bishop (1998); Coelho and Coelho (2004), all based on identification from step response measurements. Note that the models by classical methods of linear systems identification, get a model in continuous domain, as shown, in Equation (1) but were obtained discrete models of the system, thus Equation (2) was discretized at the sampling time of the plant. According to Coelho and Coelho (2004) the discrete transfer function is given as follows.

$$G(z) = \frac{b_0 z^{-(1+d)}}{1 + a_1 z^{-1}} \tag{2}$$

3. METHODOLOGY AND RESULTS

3.1 HEAT FLOW EXPERIMENT

The system used to perform the identification as a case study was a Quanser Heat Flow Experiment. This heat flow comprises a fiberglass chamber $50 \times 15 \times 10\ cm^3$, which is equipped with a heater, a blower and three temperature sensors which are distributed equidistantly along the fiberglass. The system has a built-in amplifier to provide power to the heater and the blower. The power supplied to the heater and the blower is controlled using analog signals. There is a tachometer assembled on the blower to measure blower speed.

Figure 2 represents heat flow. The three sensors: sensor 1, sensor 2 and sensor 3, the heater, the blower, the signal applied to the fan (Vb), the signal applied to the heater (Vh), and reading the temperature sensors corresponding S1 to the sensor 1 , S2 corresponding to the sensor 2, sensor S3 corresponding to 3.

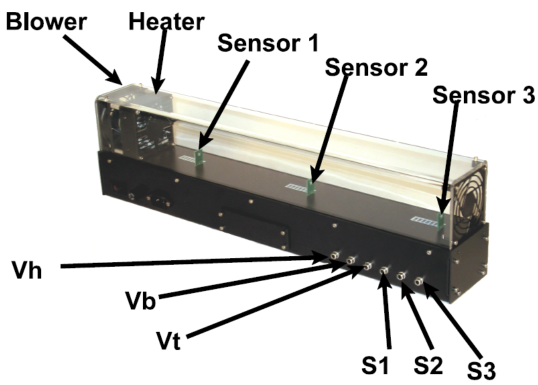


Figure 2. Quanser Heat Flow Experiment Apkarian (2014).

To use the heat flow, the Quanser provides an environment in Simulink / Matlab. In this environment, can been changed the heat drive voltage and blower, analyze the responses of temperature sensors and blower speed. It is worth mentioning that saturators can be used, since they do not damage the system and plant sample time

The identification was performed with system input voltage in the heater and allow the blower speed constant. The selected voltage to the blower rotating speed is the voltage where the maximum airflow was *Vb = 5 V* and chosen sensor for data capture was the S2, since it is in the middle of the chamber.

A system analysis was performed before data collect for identification, since it was necessary select which voltage signals are more appropriate to represent the system dynamics.

Hence, the system was put in an open loop and a particular voltage was applied to the heater and collected their response, for each particular voltage were conducted two tests. The voltages chosen to do the analysis were within a range from 0 to 5V, i.e, the minimum and maximum voltages that can be applied to the heater.

Start voltage from zero and increase 0.5 V each new test. For each test were sampled 30 thousand sample and the sampling time of the plant was 0.01 seconds.

Figure 3 shows the system response for the step signals applied.

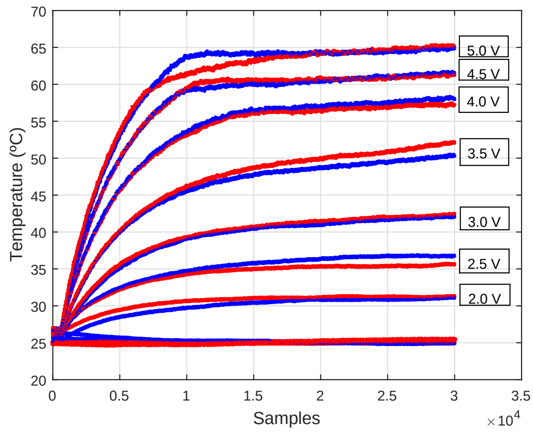


Figure 3. System responses in open loop.

In Figure 3 one can notice that there are two curves, blue and red, for each voltage signal applied.

These tests were performed to detect external environment influence, e.g., the red color of 5V curve that has a drop in temperature on the region of 1×10^4 to 1.5×10^4 samples.

We could also conclude from this experiment that with the voltage less than 2 V it was not possible to generate enough heat able to change the response read by the sensors, since the fan was at its maximum speed. They were chosen voltages of 2 V, 3 V, 4 V and 5 V to be operating points. With the operating points already defined, data collect is performed. At this step the system was put in open loop, apply a voltage and collected their response. This pair of vectors of voltage and response system was used to perform identification. This procedure was used for all operating points.

3.2 UPDATING PARAMETERS

Three methods were used to update modified ANFIS parameters.

The first uses the LSE algorithm to identify local models which are incoporated in modified ANFIS architecture and then backpropagation algorithm is used to update the premise parameters.

The second method differs from the former only in the identification, where step response measurements such as Ziegler and Nichols, Sundaresan and Krishnaswamy, Nishikawa and Smith Mollenkamp (1988); Seborg (1989); Dorf and Bishop (1998); Coelho and Coelho (2004). The third parameter update method is through the use of backpropagation for updating all parameters, premise and consequent parameters.

3.3 UPDATING WITH LSE

To perform the identification using the modified ANFIS were followed the steps described above for use in the method. Initially divided the universe of discourse plant, in four operating points, with the values 2, 3, 4 and 5 V. Around such points were obtained local models, in this case, linear models using the LSE algorithm. In order to train of each model was used a Pseudo Random Signal (PRS) type excitation signal in the system and thus collected its response. For each operating point the following strategy was used, it applied a step signal to take the system to the desired operating point, and then applied the PRS type excitation signal. Were collected 8 sets of data, each set containing 30 thousand samples, 4 sets for training and validation.

The model obtained by the LSE algorithm to a first-order system having the following structure:

$$y(k+1) = \alpha y(k) + \beta u(k) \tag{3}$$

In which the parameters α and β will be estimated.

In Table 1, the parameters found by the LSE algorithm for each local model. The model M_0 refers to the operating point around 2 V, the model M_1 to 3 V, the model M_2 to 4 V model and M_3 to 5 V.

Table 1. Parameters of the local models with LSE.

Model	$[\alpha \quad \beta]$
M_0	[0.999884 0.00166885]
M_1	[0.999924 0.00123858]
M_2	[0.999884 0.00171649]
M_3	[0.999872 0.00174174]

After the model validation, the next step was the training system, which was necessary to choose the auxiliary variables, input variables of the system's premise. In this study, it was used as auxiliary variable the current temperature of system. To collect the training set and validation of the global model, a PRS signal is generated by varying a voltage of 2 to 5 V, thus covering a wide range of operation of the plant. 180 thousand samples were collected for training and validation. Figure 4 shows the excitation signal and response system, used in the global model training.

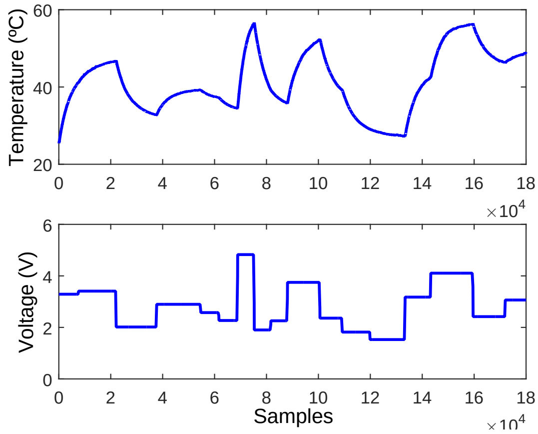


Figure 4. Collection of data.

The global model contains four membership functions, such as, bell-shaped, the initialization type of membership functions was the grid partition. The backpropagation training algorithm was used with learning rate started in 0.001, since the rate is adaptive. The chosen stopping criterion was 1000 epochs or 1×10^{-4} of Root-Mean-Square Error (RMSE). After training was made the overall model validation as shown in Figure 5.

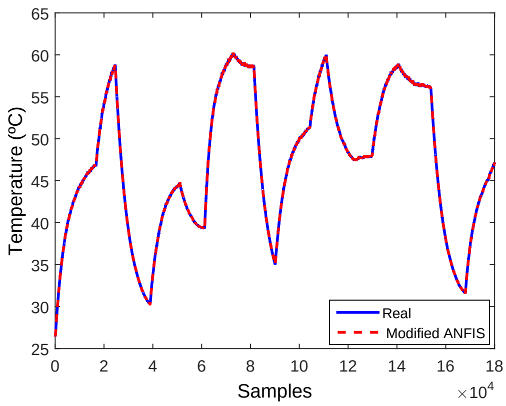


Figure 5. Validation with LSE method.

As can be seen in Figure 5, the modified ANFIS obtain a satisfactory response for a wide operating range, with a minimum difference relative to the actual curve.

For further analysis, the Figure 6 presents the error in every moment.

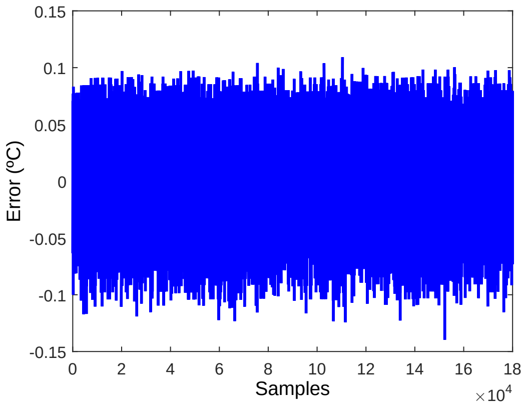


Figure 6. Error with LSE method.

By analyzing Figure 6, the highest value of instantaneous error was approximately -0.15. This error is acceptable depending on the specications. Other error values vary in the range of approximately -0.05 to 0.05 which represents a satisfactory response.

3.4 UPDATING WITH STEP RESPONSE MEASUREMENTS

This method used the same procedure as in updating with LSE, save changing the way of obtaining the local models, which is used the identification from step response measurements. The chosen techniques were: Ziegler and Nichols, Sundaresan and Krishnaswamy, Nishikawa and Smith Mollenkamp (1988); Seborg (1989); Dorf and Bishop (1998); Coelho and Coelho (2004).

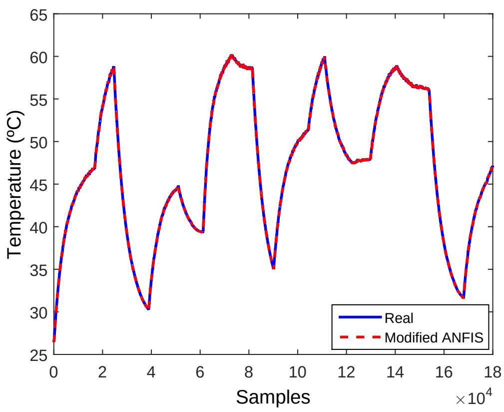
All the showed tables in this section present the parameters found by the identification from step response measurements for each local model. The model M_0 refers to the operating point around 2 V, the model M_1 to 3 V, the model M_2 to 4 V model and M_3 to 5 V.

3.4.1 ZIEGLER AND NICHOLS TECHNIQUE

In the Table 2 presents the parameters of the models identified using Ziegler and Nichols Technique.

Table 2. Parameters of the local models with Ziegler and Nichols technique.

Model	$[a_1 \quad b_0]$	d
M_0	[0.9998 0.0005262]	100
M_1	[0.9998 0.0009542]	100
M_2	[0.9998 0.001703]	100
M_3	[0.9997 0.002001]	100



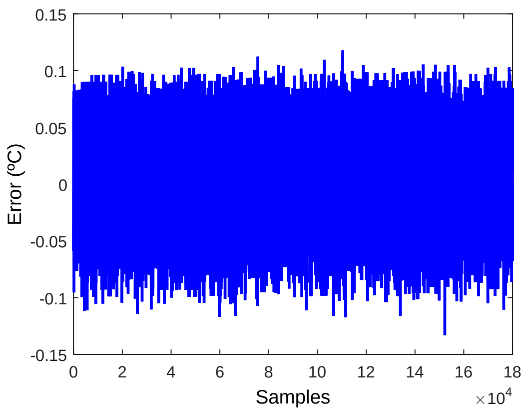


Figure 7. Validation and Error of validation with Ziegler and Nichols technique

As can be seen in Figure 7, using the presented identification method can well identify the parameters of the system because the result was satisfactory and some error peaks are observed, but this peak represents not a problem because the most error is small.

3.4.2 SUNDARESAN AND KRISHNASWAMY TECHNIQUE

In the Table 3 presents the parameters of the models identified using Sundaresan and Krishnaswamy Technique.

Table 3. Parameters of the local models with Sundaresan and Krishnaswamy technique.

Model	$[a_1 \quad b_0]$	d
M_0	[0.9998 0.00048379]	69
M_1	[0.9998 0.0008805]	26
M_2	[0.9998 0.001713]	149
M_3	[0.9997 0.001798]	9

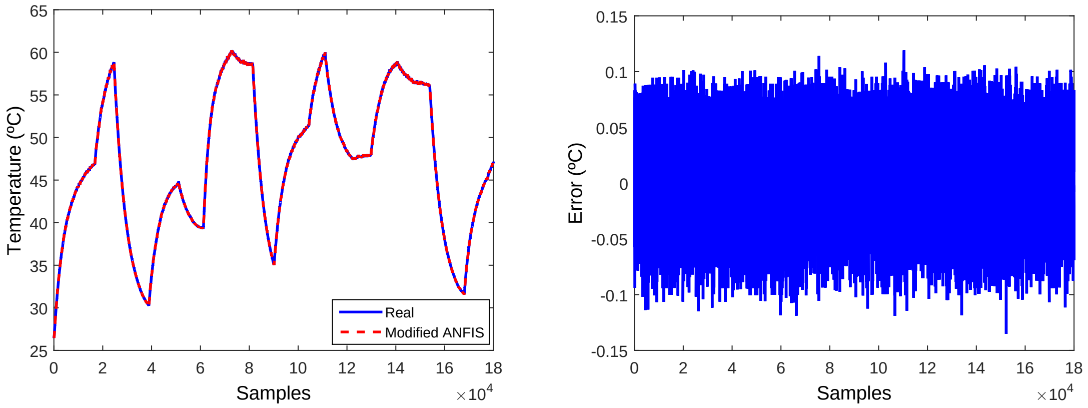


Figure 8. Validation and Error of validation with Sundaresan and Krishnaswamy technique

As can be seen in Figure 8, the model could well generalize the dynamics of the plant, leading a satisfactory result. By the curve of error it is possible to observe that error is small, as we work in mash temperatures absolute error of 0.15 is almost irrelevant.

3.4.3 NISHIKAWA TECHNIQUE

In the Table 4 presents the parameters of the models identified using Nishikawa Technique.

Table 4. Parameters of the local models with Nishikawa technique.

Model	$[a_1 \quad b_0]$	d
M_0	[0.9997 0.0007365]	1321
M_1	[0.9997 0.001308]	1440
M_2	[0.9997 0.002448]	1313
M_3	[0.9997 0.002521]	973

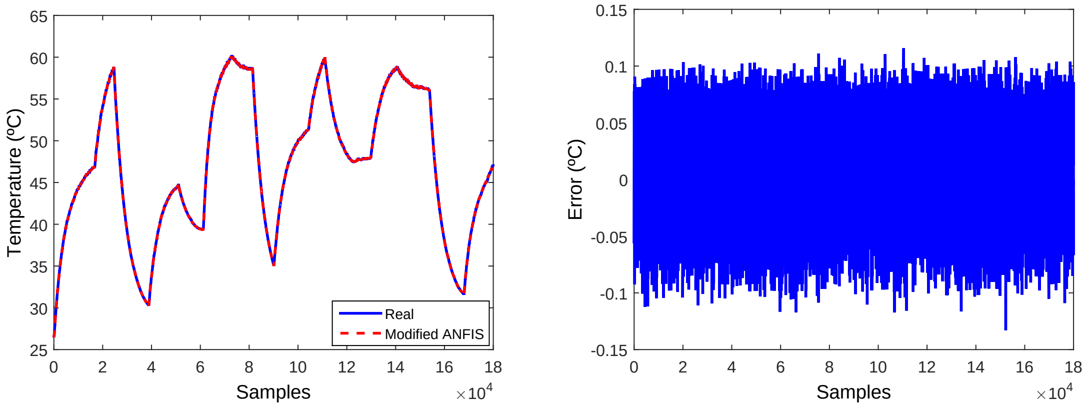


Figure 9. Validation and Error of validation with Nishikawa technique

As can be seen in Figure 9 modified ANFIS obtain a satisfactory response. A small error value with its average attempting to zero is observed by analysing the error curve.

3.4.4 SMITH TECHNIQUE

In the Table 5 presents the parameters of the models identified using Smith Technique.

Table 5. Parameters of the local models with Smith technique.

Model	$[a_1 \quad b_0]$	d
M_0	[0.9998 0.0005334]	200
M_1	[0.9998 0.0009102]	50
M_2	[0.9998 0.001713]	200
M_3	[0.9997 0.002024]	150

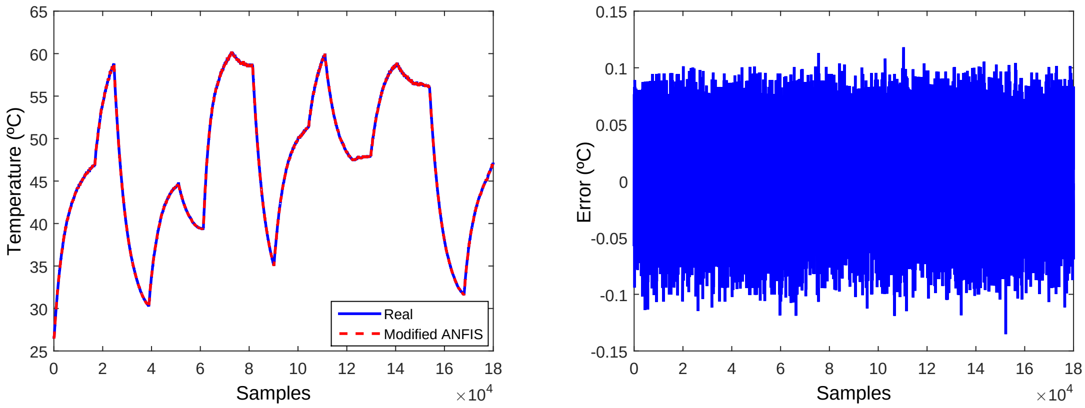


Figure 10. Validation and Error of validation with Smith technique

Figure 10 shows the comparison between the model and actual response of the system. From the figure, it shown that the model able to perform approximately as the actual system. Analyzing the error curve knowing the error is the difference of real systems and models identified, it is possible to see that the error values vary in a small range, plus the error of the sensor, proving that have a satisfactory response.

3.5 UPDATING WITH BACKPROPAGATION ONLY

This method is different from the other two presented because it lacks the step of identifying the local models. To use this method, the values of the consequent modified ANFIS were generated randomly and they were updated along with the backward pass using the backpropagation training algorithm. An important feature is the use of a different learning rate for the backward pass and the attendant was necessary because the use of adaptive learning rate was diverging training to solve this problem was to create a new learning rate only for the consequent. In Table 6 shown parameters found by the backpropagation for the consequent parameters.

Table 6. Consequent parameters found by the backpropagation.

Model	$[a_1 \quad b_0]$
M_0	[0.985736 0.225443]
M_1	[0.970636 0.415911]
M_2	[0.968773 0.491395]
M_3	[0.994112 0.0861666]

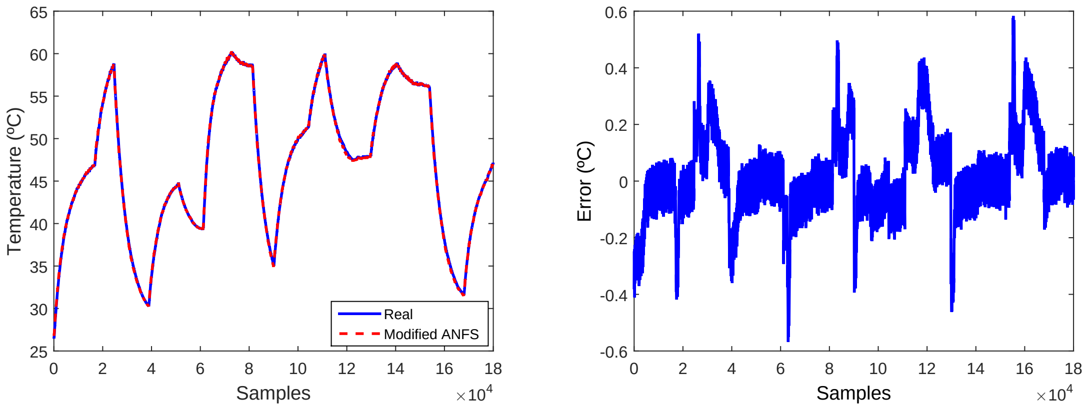


Figure 11. Validation and Error of validation with backpropagation method

As can be seen in Figure 11, modified ANFIS obtain a satisfactory response for a wide operating range, with a minimum difference relative to the actual curve and the error peak occurs when there is a sudden change of system response, but quickly back to a small error as the response grows or descending gradually.

3.6 COMPARISON BETWEEN METHOS

To perform the comparison between the different methods, the Table 7 shows the validation error using each method. This strategy was used because the observation through the graphics is almost imperceptible, as both validation curve as the validation error curve are very similar.

Table 7. Validation of global models.

Method	Validation Error
LSE	0.0339304
Ziegler and Nichols	0.0344925
Sundaresan and Krishnaswamy	0.0343579
Nishikawa	0.0345694
Smith	0.0343264
Backpropagation only	0.145014

As can be seen in the Table 7, all errors are considered small. In order to compare the modified ANFIS with local models using the LSE algorithm and local models obtained from identification from step response measurements the difference is small because the identification from step response measurements presenting very similar parameter values as obtained through the algorithm LSE and even Nishikawa technique that resulted in the highest difference values relative to the others, the premise parameters of the modified ANFIS are updated to give a satisfactory response.

The methods that has previously identified local models has a lower error than just using the backpropagation only, because the previously identified local models are validated and the backpropagation algorithm was update only the premise parameters, in case of the backpropagation use for updating all the parameters, premise and consequent parameters, more complex is to find a global minimum more the fact that the initializations of the parameters is random which can lead the algorithm to converge or not.

4. CONCLUSIONS

This work presented the use of different methods for updating the parameters of the modified ANFIS. The substitution of the LSE algorithm identification by identification from step response measurements for the identification of local models the modified ANFIS proved satisfactory response, as can be seen in the results.

Updating the consequent using the step response measurements has a significant importance for the diffusion and use of the modified ANFIS since that identification by step response measurements is widely used in industry. This way can be used the models already identified and used by the industry for incorporate the local models of modified ANFIS.

Using backpropagation for updating all parameters, premise and consequent parameters, also obtained a satisfactory response, but showed limitations depending on the learning rate and the values generated at initialization of the consequent parameters that can make the identification differ. The results show that the way of updating the modified ANFIS parameters using the identification provided from local models, either LSE algorithm or identification from step response measurements has a better response compared to the use of backpropagation to update all parameters.

5. ACKNOWLEDGEMENTS

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7. RESPONSIBILITY NOTICE