Nonlinear System Identification based on Modified ANFIS

José Kleiton Ewerton da Costa Martins and Fábio Meneghetti Ugulino de Araújo
Universidade Federal do Rio Grande do Norte,
Departamento de Engenharia da Computação e Automação (DCA),
Natal, Rio Grande do Norte, Brazil

Keywords: ANFIS, Modified ANFIS, Nonlinear Systems Identification, Linear Systems Identification.

Abstract: This article aims to present the nonlinear system identification by the method of modified ANFIS. The modified ANFIS is a structure proposed that is based on the traditional structure of ANFIS with some modifications as shown in the article. The importance of the choice of method parameters and its influence on the system will be discussed. For this, the identification of a coupled system of tanks with nonlinear dynamics is performed. System identification will be performed by changing the inputs and order of the consequent model and then will perform a review of the systems. The results confirm the simplicity of modified ANFIS in comparison with the traditional ANFIS while have good performance in the identification of nonlinear systems.

1 INTRODUCTION

To have a thorough knowledge of a system is necessary to examine, analyze and simulate a system of interest. Linear systems identification techniques are used since 1960 to those needs.

Linear models are widely used in different areas of knowledge. In general, this type of model is applied to a specific region known as operating point, which is necessary to make a linearization can use the model. This is necessary because most real systems are nonlinear. Industry plants are complex systems and most of them are nonlinear. Due to this nonlinearity, the identification of nonlinear systems is becoming a very important tool which is used to improve the performance of a controller, prevent the modeling of the phenomenological model and obtain a nonlinear model whitch previoles a representation more similar to the system response.

The identification of nonlinear systems is being largely performed by Artificial Intelligence techniques. The fuzzy systems and Artificial Neural Networks (ANNs) are the most used techniques.

The ANN has characteristics that make it attractive for use in applications such as the identification of nonlinear dynamical systems, such as the generalization ability and learning. According (Haykin, 2001), it is clear that a neural network draws its computing power through first, its massively parallel distributed structure, and second, their ability to learn and therefore generalize. The spread refers to the fact that the neural network produce appropriate outputs to inputs that were not present during training (learning). These two information processing capabilities make it possible for the neural networks solving complex problems (large scale) that are currently untreatable.

The ANN has disadvantages including the appropriate choice of structured network, ie, how many layers, how many neurons in each layer must have the neural network, find out what activation function of neurons in each layer, may become an arduous and exhausting work.

Among the different nonlinear identification techniques, methods based on neuro-fuzzy models are gradually becoming established, not only in the academia but also in industrial applications. Neuro-fuzzy systems combine the semantic transparency of rule-based Fuzzy systems with the learning capability of Neural Networks. Both neural networks and fuzzy systems are motivated by imitating human reasoning processes. Fuzzy systems, relationships are represented explicitly by if-then rules. In neural networks, the relations are not explicitly given, but are 'coded' in the network and its parameters. In contrast to knowledge-based techniques, no explicit knowledge is needed for the application of neural nets (Babuka, 2003).

The most used neuro-fuzzy nonlinear system identification process is the Adaptive Neuro-Fuzzy Inference Systems (ANFIS) developed by (Jang, 1993). The significance of ANFIS model is, firstly build

Ewerton da Costa Martins J. and Araújo F..
Nonlinear System Identification based on Modified ANFIS.
DOI: 10.5220/0005544905880595
In *Proceedings of the 12th International Conference on Informatics in Control, Automation and Robotics* (ICINCO-2015), pages 588-595
ISBN: 978-989-758-122-9

identification form of nonlinear system is not required, provided that ANFIS is an identification form itself. Its network weight value consists of adjustable parameters. This system can identify nonlinear systems in temperament and in result the network can approach the input and output data of the system. ANFIS gather the advantages of both fuzzy identification and neural network identification. It takes lesser computational epochs than neural network for highly real nonlinear systems. It contracts with the structure knowledge with weaken speed and strong submerge. ANFIS can also be used to control online system forecast systems output instead of real physical systems (ZhixiangHow, 2003).

An alternative to the identification of nonlinear systems is modified ANFIS method proposed by (Fonseca, 2012). This has obtained by modification of the ANFIS proposed by (Jang, 1993). The identification of nonlinear systems using the modified ANFIS is performed through the local linear models identified and subsequently trained by backpropagation training algorithm, and performing the combination of these local models for a nonlinear system identification which fully represents the plant. The modified ANFIS also has some advantages over the original ANFIS, as will be showing in the case study.

In this paper we present a case study where was identified 6 models using the modified ANFIS, changing the order of local models and the auxiliary variable. An order analysis of the local models was performed as well as the quantity and the importance of the auxiliary variable in the modified ANFIS. For the case study was using a didactic plant Quaser with nonlinear dynamics to perform the identification of system.

The next sections of this paper is organized as follows. Section 2 will present the main theoretical concepts necessary for the work development. Section 3 will present an application of the modified ANFIS. Section 4 will present the main results and contributions made by the development of this work.

2 THEORICAL FUNDAMENTATION

Adaptive Neuro-Fuzzy Inference Systems (ANFIS) developed by Jang (Jang, 1993), can be seen as an artificial neural network of six layers interconnected by individual weights, where each layer is responsible for an operation result in output equivalent to that found in a particular stage of a fuzzy system Takagi-Sugeno (Jang, 1993) (Jang and Sun, 1995).It is therefore an hybrid technique, Artificial Intelligence that infers knowledge using the principles of fuzzy logic to this structure and adds the possibility of the inherent learning ANN. One of the main advantages of ANFIS in relation to ANN is the way of encoding knowledge. While this one is encoded in weights, whose actions are difficult to interpret, the ANFIS knowledge is encoded in a structure that has a certain approach of logic used by humans.

2.1 Hybrid Learning Algorithm

This algorithm has been proposed with the ANFIS is a hybrid algorithm which combines the gradient method and the least squares estimate (LSE) to identify parameters. More specifically, in the forward pass of the hybrid learning algorithm, functional signals go forward till layer 4 and the consequent parametrs are identified by the least squares estimate. In the backward pass, the erro rates propagate backward and the premise parameters are updated by the gradient descent (Jang, 1993).

2.2 Backpropagation in ANFIS Model

In backpropagation algorithm is necessary to have the error estimation, the difference of the desired value and output the estimated model, so that through gradient descent is made to update the parameters. In ANFIS the estimation error is calculated through the layer 5 and so propagated to the previous layers, as can see in (Jang, 1993).

2.3 The Modified ANFIS

The modified ANFIS proposed by (Fonseca, 2012), is a modification 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 plant.

The modification made to the ANFIS consists of independently leaving the inputs of the first and fifth layers, ie, 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, around which can be obtained linear models representing operating regions. It should be chosen the least number of possible operating points, able to satisfactorily represent the plant throughout the operating range. This way, you avoid the unnecessary increase in complexity and computational cost.

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

Next, in step three, is made the training of the modified ANFIS, determining a way the models identified in the previous step should be combined to reproduce adequately the nonlinear behavior of the plant throughout its universe of discourse.

Finally, the last step is made the validation, which checks the modified ANFIS capacity to give a response that is approximately equal to the plant to a different input those presented in the training.

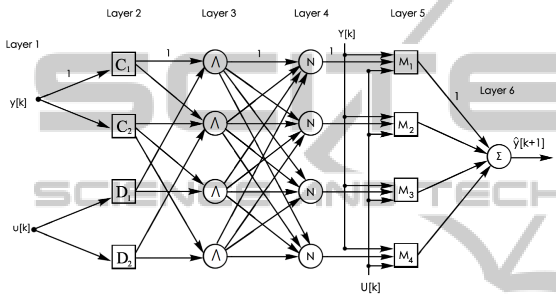

Figure 1: ANFIS modified example of the structure.

The neuro-fuzzy structure illustrated in Figure 1 presents: two inputs, which are the plant output at the current time point **y(k)** and the input signal applied to the plant at the current time **u(k)**; two membership functions for each input variable, resulting in four rules; and a linear model designed for the conclusion of each rule, i.e, for each operating point, which in the illustrated case is four. 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 is maintained, since the models are functions of their inputs (Fonseca, 2012).

3 CASE STUDY

The chosen case study was a system of tanks coupled with nonlinear dynamics. They were a Quanser didact plant (Apkarian, 1999), consisting of two coupled tanks, also containing a pump and a reservoir. The two tanks contain a hole in its base, which allows the flow of water. The upper tank receive the pumped water from the reservoir, making it the top tank feeds the lower tank through the hole at its base and the lower tank closes a cycle with the water back to the reservoir at its orifice. The tanks have a height of 30 cm, so the liquid level can vary in a range of 0 to 30 cm. The pump receives a voltage which can vary in the range of 0 to 4 volts, makes the pump pumping the liquid to the tanks. In Figure 2, we can see a representation of the coupled tank system, as well as the schematic plan of communication. The communication software developed to plan is made via a TCP / IP server which is connected to a data acquisition board, making it possible to read the sensors and writing an electrical signal to the pump.

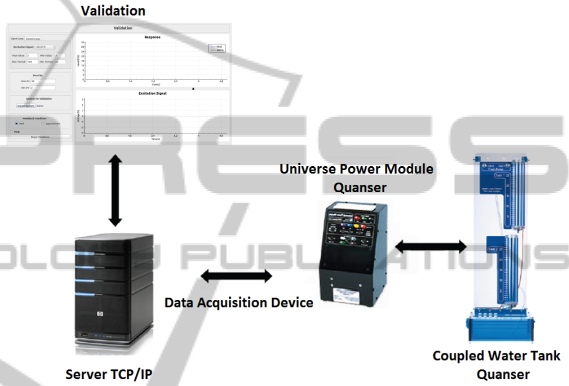

Figure 2: Comunication between software and the system.

The analysis of this case study allows an evaluation of the structure modified ANFIS, exploring its flexibility in a plant with non-linearity. Thus, the system described identification was made using the modified ANFIS. We identified six global models varying the order of local models and the auxiliary variable used in the modified ANFIS input(layer 1).The appropriate choice of local models and the auxiliary variable directly influence the modified ANFIS structure as can be seen in the figure 3.

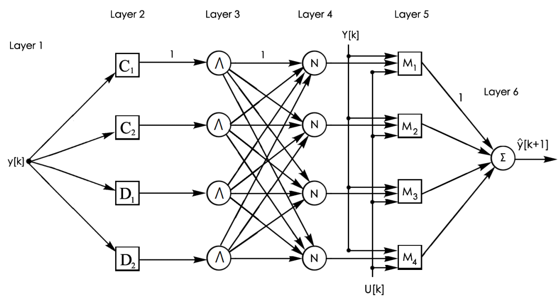

Figure 3: Structure ANFIS modified with an input.

As can be seen in Figure 3,from the structure of the modified ANFIS, a change in local order model will change the number of elements of the vector **Y(k)** and **U(k)**. For the structure with first order models: **Y(k)** =[**y(k)**] and **U(k)** =[**u(k)**], for the structure with second-order models **Y[k]** =[**y(k) y(k-1)**] and **U(k)** = [**u (k) u(k-1)**], and so on. Note that an increase in the order of the local models modified ANFIS does not cause an increase in its rule base, only increases the amount of data to be provided for calculating the model output, while keeping the simplicity of structure, bringing several advantages, such as can be seen in the comparison of ANFIS proposed by (Jang, 1993) and the modified ANFIS.

As proposed by ANFIS (Jang, 1993) an increase in the order of consequent directly implies an increased amount of input model, since the same set of model inputs is used in the consequent calculation. This increase in model input set considering the simplest case, two membership functions, each new input implies a doubling of the amount of model rules. For example, a fourth order model, ANFIS with 8 inputs would be required. If each had four membership functions, the rule base would consist of 4^8 rules, ie, 65536 rules. The training process such as it structure would be practically impossible as well as their use. Indeed, the modified ANFIS structure with one input and four membership functions still have four rule, even using the fourth-order models. Table 1 has as the ANFIS comparisons with the modified ANFIS illustrated in Figure 3, considering the number of inputs and the number of rules for the use of first to fourth order models, replacing the output functions and considering that every input are associated four membership functions.

Table 1: Comparison between modified ANFIS with ANFIS.

	ANFIS		Modified ANFIS	
Order	Input	Rule	Input	Rule
1	2	4	1	4
2	4	16	1	4
3	6	4096	1	4
4	8	65536	1	4

As can be seen in Table 1, increasing order of the original ANFIS models causes increase of the number of inputs and exponential increase of the number of rules and thus the computational cost. Though, in modified ANFIS, the structure holds the same number of rules, even with the increasing order of the models used, allowing a higher accuracy of the model, without a significant increase in computational cost. Another advantage is that the modified ANFIS local models may have different orders of each other or even be some linear and nonlinear.

For communicate with the plant was developed a software. It allows to use the open loop plant to collect data. The implemented excitation signal was the PRS (Pseudo Random Signal), an excitation signal widely used in practice, the software also allows you to create the training set and validation set, just by the user enters the order of the model you want to train. In software itself is made the training of local models using the algorithm of least squares, as well as training of the modified ANFIS, which uses the backporpagation training algorithm to find the combination of local models through the structure of the modified ANFIS, obtaining an identification a global model.

Following the steps to use the method of modified ANFIS, first divide the plant universe of discourse in four operating points, around which were obtained linear models using the least squares algorithm. To obtain the system operating points was used the following strategic, first the second tank to be identified, that has 30 cm, was divided into four equidistant points, forming four operating ranges, $f_1 = [0\ \ 7.5\}$, $f_2 = [7.5\ \ 15\}$, $f_3 = [15\ \ 22.5\}$ and $f_4 = [22.5\ \ 30]$ cm.The operating points was defined as the average value of each operating range, thus obtaining, p_1 = 3.75cm, p_2 = 11.25cm, p_3 = 18.75cm and p_4 = 26.25 cm, as shown in figure 4.

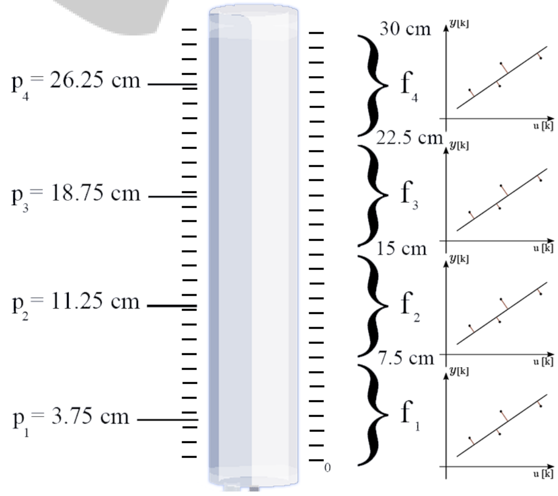

Figure 4: Operating Points.

For each operating point was used the least squares algorithm to find the local models. For the training of each model was used a PRS excitation signal in the system and thus collected your response. In generating a PRS signal is necessary to provide the maximum and minimum range so that it can generate a signal in that region. To obtain these ranges the system is put in open loop and several test were performed to find the necessary voltages that cause the system to each end of the operating ranges, f_1 , f_2, f_3, f_4 as well as each operation point, p_1, p_2, p_3 and p_4 that try to stored values. With the voltage values, it was possible to collect data for the training of each local model. For each operating point was used the following strategy, was applied a step signal that takes the system to the desired operating point and then applied the PRS excitation signal with their corresponding values of maximum and minimum range was applied, and the f_1 for p_1, f_2 for p_2 so on. Thus were collected 8 data sets, each set containing 5 thousand samples, 4 sets for training and 4 sets for validation, one set of training and validation for each model. The validation used the least squares algorithm, so for each training set were obtained two models, a first-order and second-order . In table 2 and 3 you can see the validation error for each local model identified.

Table 2: Validation of local models of first order.

Model	Validation Error	Coefficient
M_1	0.04149	[0.9965 0.0167]
M_2	0.03098	[0.9975 0.0159]
M_3	0.02949	[0.9984 0.0130]
M_4	0.02432	[0.9984 0.0147]

Table 3: Validation of local models of second order.

Model	Validation Error	Coefficient
M_1	0.03896	[0.6753 0.3203 0.0030 0.017]
M_2	0.02836	[0.6604 0.3362 -0.003 0.024]
M_3	0.02800	[0.6689 0.3289 -0.0287 0.0459]
M_4	0.02284	[0.6837 0.3142 0.0208 -0.0019]

As can be seen, in table 2 and 3, the validation error value, of each local model is satisfactory, the first order and second order. However increasing the model order for all local models, does not represent a significant decrease in their validation error. Subsequently show that the validation of the global model selecting a local model of the second order will not have significant improvement.

With the validated models went to the global training system, it is required to choose the auxiliary variable, input system's variables. In this study, were used three types of auxiliary variables, the tank level 2 (L_2), the voltage applied to the pump (U) and the tank level 2 with the applied voltage to the pump ($L_2\&U$). To collect the training set and validation of the global model, a PRS signal type ranging in voltage 0 to 4V was generated, thus covering a wide operating range of the plant. 10 thousand samples were collected to validate the global model and 5 thousand sampled for training. The Figure 5, shows the excitation signal and system response, used in the global training.

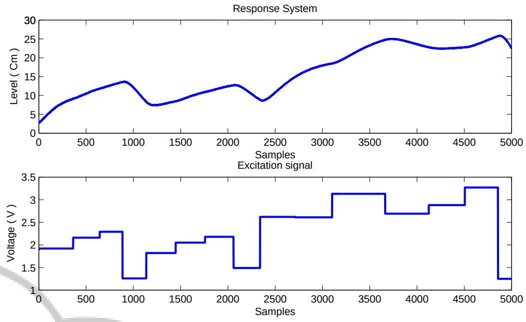

Figure 5: Collection of data.

The global model contains four bell-shaped membership functions, the initialization of membership functions was the grid partion, for the case that only has an auxiliary variable, this variable goes through all the membership functions, as in the case of two auxiliary variables, each variable involves two membership functions. The training algorithm used was backpropagation with the inicial learning rate in 0.001, since the rate is adaptive. The stopping criterion chosen was 1000 epochs or 1×10^{-4} of RMSE.In table 4 below you can see the validation error of global model identified.

Table 4: Validation of global models.

Aux. Variable	Order	RMSE	Validation Error
L_2	1	0.0317	0.0296
L_2	2	0.0302	0.0289
U	1	0.0330	0.0317
U	2	0.0326	0.0326
L_2 & U	1	0.0317	0.0297
L_2 & U	2	0.0302	0.0289

As can be seen from table 4, the identified models have proved satisfactory. The difference between the RMSEs and the validation error is small even considering the many types of second order compared to the first order, ie, the choice of a first-order model is better because it simplifies the identification as a whole and also reduces the computational cost. Simplifying identification, note that the L_2 auxiliary variable had the lowest RMSE and validation, showing the model is more efficient. Then we can see the final result of tune membership functions, that is, after training using the backpropagation algorithm. First is plotted the membership functions, for when the local model is first order, as well as the parameters of the membership functions, is plotted after the second order and the parameters of the membership functions.

Membership function of modified ANFIS with variable auxiliary L_2 and local models of first order, is show on figure 6.

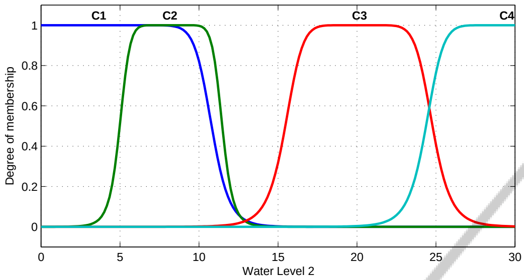

Figure 6: Tuned membership functions, first order, variable auxiliary L_2.

Analyzing the distribution of the membership functions of the figure 6 , we can observe that the C_2 membership function is practically in C_1, implying that two rules are being used simultaneously in this range, ie, both are important in this region.

Membership function of modified ANFIS with variable auxiliary U and local models of first order, figure 7.

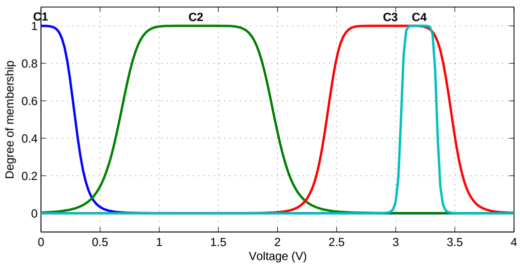

Figure 7: Tuned membership functions, first order, variable auxiliary U.

Observing figure 7, can be noted that the membership function C_4 operates in a small strip and is still contained in membership function C_3, implying that this region is necessary to use two models to achieve a satisfactory response.
Membership function of the modified ANFIS with variable auxiliary $L_2\&U$ and local models of first order,can be seen at figure 8 and 9.

In figure 8 and 9 because the distribution of the membership functions, that when we are using two auxiliary variables, the auxiliary variable most significant has a better distribution. In this case with the distribution of the membership functions of

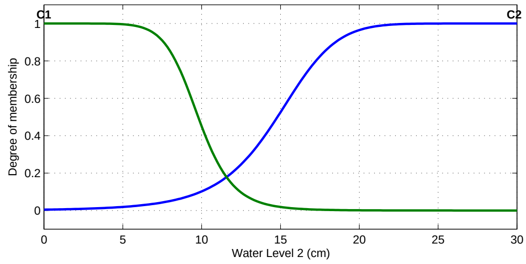

Figure 8: Tuned membership functions L_2, first order, variable auxiliary $L_2\&U$.

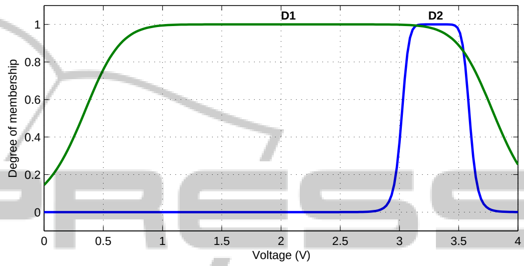

Figure 9: Tuned membership functions U, first order, variable auxiliary $L_2\&U$.

L_2, noted in range of 5 to 20 cm begin to have the intersections of the membership functions, implying that in this range of values are required to use two models to get a satisfactory response, unlike the auxiliary variable U, where a small range of values are necessary to use two models.

In table 5,are show the parameters of the membership functions for first-order models.

Table 5: Membership Functions first order.

Aux. Variable	M.Fs.	Coefficient
L_2	C_1	[7.1428 6.4285 3.6568]
	C_2	[3.2446 4.8170 8.2258]
	C_3	[4.6598 4.0548 20.1214]
	C_4	[5.1140 4.4732 29.4848]
U	C_1	[0.4034 4.0289 -0.1135]
	C_2	[0.6563 3.9998 1.3212]
	C_3	[0.5309 4.5379 2.9468]
	C_4	[-0.1526 5.3381 3.1970]
L_2 & U	C_1	[12.1111 5.5156 -2.3279]
	C_2	[15.1054 3.9358 29.9124]
	D_1	[1.7458 5.2769 2.06597]
	D_2	[0.2878 4.5000 3.3052]

Membership function of the modified ANFIS with variable auxiliary L_2 and local models of second order, can be seen at figure 10.

Note figure 10 is very close figure 6 , the C_2 membership function of figure 10 is a little more open about the membership function of figure 6's C_2. Probably this small opening helped the second-order

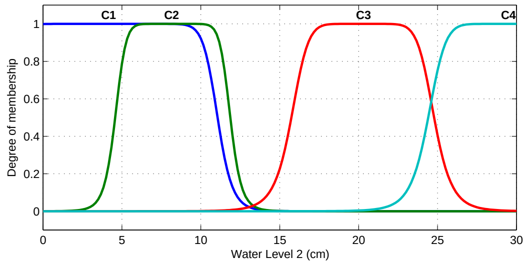

Figure 10: Tuned membership functions, second order, variable auxiliary L_2.

model has a small improvement over the first order.

Membership function of the modified ANFIS with variable auxiliary U and local models of second order, figure 11.

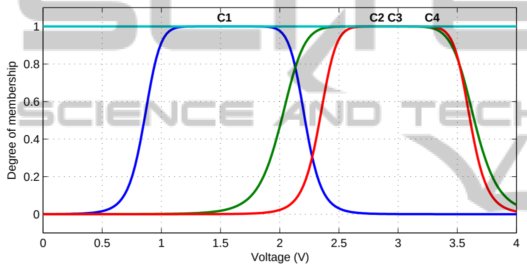

Figure 11: Tuned membership functions, second order, variable auxiliary U.

Analyzing the distribution of membership functions of the figure 11, we can observe that the C_4 membership function have degree one for the entire universe of discourse, ie, this model is always contributed to get a satisfactory response.

Membership function of the modified ANFIS with variable auxiliary L_2 & U and local models of second order, can be seen at figure 12 and 13.

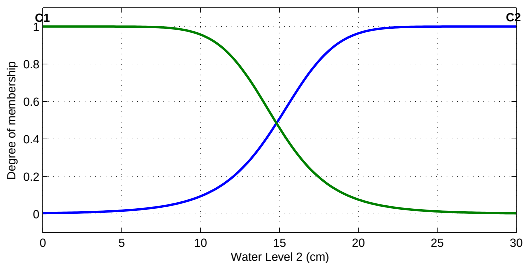

Figure 12: Tuned membership functions L_2, first order, variable auxiliary $L_2 \& U$.

As can be seen in figure 12 and 13, because the distribution of the membership functions, the L_2 auxiliary variable is practically alone in influencing

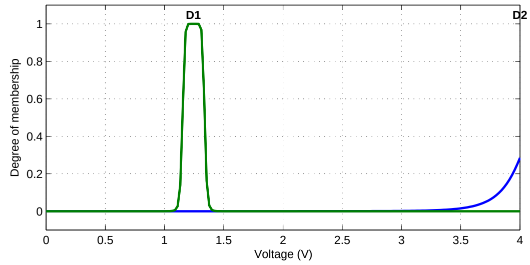

Figure 13: Tuned membership functions U, first order, variable auxiliary $L_2 \& U$.

systems, as the auxiliary variable U stay with degree of membership nearly zero for almost all signals, giving understand that this variable auxiliary can be eliminated.

In table 6, We can see the parameters of the membership functions for second-order models.

Table 6: Membership Functions second order.

Aux. Variable	M.Fs.	Coefficient
L_2	C_1	[6.8437 7.3526 4.216]
	C_2	[3.6495 5.2303 8.2199]
	C_3	[4.5231 4.0712 20.2577]
	C_4	[5.1006 4.4761 29.5083]
U	C_1	[0.6797 4.9155 1.5348]
	C_2	[0.8154 4.0786 2.8290]
	C_3	[0.6360 4.4164 2.9728]
	C_4	[-36.3879 4.1613 3.3451]
L_2 & U	C_1	[14.8221 4.0758 -0.1267]
	C_2	[15.0364 3.9921 29.9672]
	D_1	[-0.0931 4.8961 1.2454]
	D_2	[0.9008 4.0225 5.0098]

The results obtained with the ANFIS modified's auxiliary variable L_2 and first-order models in consequent proved better in a general context, we will analyze its validation curve and the validation error.

The validate of the modified ANFIS, it was made a test with the open-loop system where a PRS excitation signal with amplitude varying from 0 to 4 volts was generated, the modified ANFIS was feedback to the output of the plant. In the figure 14 shows a graphical comparison of real solution (blue line), modified ANFIS's output (red line).

As can be seen in figure 14, the modified ANFIS able to identify the dynamics of the plant with an error considered small for the dimensions of the tanks coupled system. For a more detailed analysis, we can observe in the figure 15, which helps us to realize the error in every moment.

By analyzing figure 15, we see that the highest value of instantaneous error was approximately -0.15

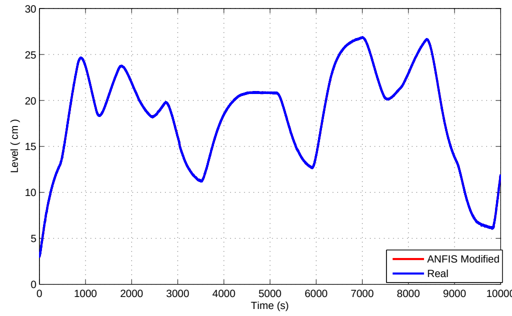

Figure 14: Validation of the modified ANFIS.

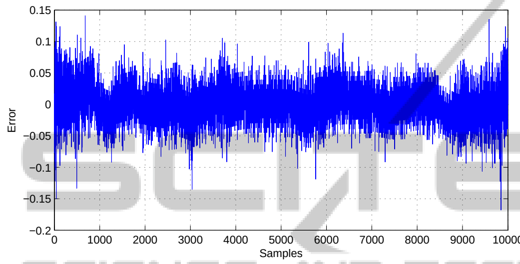

Figure 15: The modified ANFIS validation error.

cm. Regarding the dimensions of the tank a -0.15 cm error is a percentage error of 0.5% which is acceptable depending on the specications. Other error values vary in the range of approximately -0.2 to 0.2 cm which represents a percentage of 1%.

4 CONCLUSIONS

The identification of the models, shown in the result session, using the modified ANFIS shows the importance of choosing the auxiliary variable. The appropriate choice of the variable auxiliary consistent with the problem can simplify the identification, removing other variables that have little or no influence on the system. It was also shown the importance of order of the model consequent. As seen in the results are not always increased in the order of local models imply significant improvements systems.

Due the flexibility and simplicity of modified ANFIS method was observed several advantages over ANFIS, since the dissociation of the inputs to the first and fifth layer, the method makes it possible to conduct training of models which would be unfeasible with ANFIS due the large computational effort. With the dissociation of first and fifth layer is also possible to increase the accuracy of model without increasing the number of rules, that is, a more accurate system without significantly increasing the computational effort.

As seen from the results of the modified ANFIS identification method achieved satisfactory results, since it has small error values for training and validation, showing its potential for use in identification of non-linear systems.

ACKNOWLEDGEMENTS

ANP, MCT, FINEP and by Petrobras financial support through project PFRH-220.

REFERENCES

Apkarian, J. (1999). *Coupled Water Tank Experiments Manual*. Canada.

Babuka, R. (2003). Neuro-fuzzy methods for modeling and identification. In *Recent Advances in Intelligent Paradigms and Applications*.

Fonseca, C. A. G. (2012). *Estrutura ANFIS Modificada para Identificao e Controle de Plantas com Ampla Faixa de Operao e no Linearidade Acentuada*. Doutorado, UNIVERSIDADE FEDERAL DO RIO GRANDE DO NORTE - UFRN.

Haykin, S. S. (2001). *Redes Neurais*. Bookman Companhia Ed, 2nd edition.

Jang, C.-T. S. E. M. (1997). *Neuro-fuzzy and soft computing A Computation Approach to Learn and Machine Intelligence*. Prentice- Hall.

Jang, J.-S. R. (1993). Anfis: Adaptive-network-based fuzzy inference system. In *IEEE Transactions on Systems, Man and Cybernetics*.

Jang, J. S. R. and Sun, G. T. (1995). Neuro-fuzzy modeling and control. In *IEEE*.

ZhixiangHow, QuntaiShen, H. (2003). Nonlinear system identificationbased on anfis. In *International Conference on Neural Networks & Signal Processing*.