HEAT FLOW PROCESS IDENTIFICATION USING ANFIS – GA MODEL

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Abstract:

This paper provides a nonlinear technique that uses a fuzzy inference system and neural networks for the identification purposes of heat flow transfer in the chamber. Firstly, linear models are obtained by transfer functions with delay using Matlab identification tools for heat exchange. Three different transfer functions are provided (for three sensors in different positions along the chamber), and after it has been concluded that the second model has the smallest error, it is tested using different input. In this case, the linear model failed to represent the behaviour of the system precisely, making the error more than 1.5 C in the steady state. This was expected because linear models are trustworthy only around certain operating ranges. In order to make the new model, which will be unique and valid in the whole state space, another identification method using an adaptive neuro-fuzzy inference system (ANFIS) was presented. Furthermore, for the best performance, the ANFIS architecture was found using one of the most famous population-based optimizations: the genetic evolutionary algorithm. With two inputs and 70 parameters found by optimization (40 premises and 30 consequent) ANFIS greatly outperforms standard identification technique in terms of the mean square error. This nonlinear model was also tested on the different input, which was not used in the training process, and it was concluded that the nonlinear model identifies the real object with a neglectable error, which is 45 times smaller than the linear one.

Keywords:

ANFIS, Genetic algorithm, Identification, Optimization, Heat flow process.

INTRODUCTION

Precise temperature control is required in many processes in different industries, such as metalworking, oil refining, food processing, petro and biochemical industries, fabrication of microelectronic devices, as well as scientific applications. Effective heating, ventilation, and air conditioning (HVAC) systems in those industries mostly depend on heat transfer. Accurate heat transfer models can help researchers and engineers to understand the physical mechanisms in the energy conversion processes and to improve the efficiency of potential controllers.

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System identification is an essential tool in the process of creating a mathematical model that accurately represents the behaviour of a physical system based on experimental data. Such models are very important especially when mathematical relations between input and output are not known or when they are so complicated that they cannot be simply expressed and understood. In order to capture all of the complexity, identification implies the collection of experimental data that describe the behaviour of the system under certain conditions, and if the model that has been created is reliable, it will be able to predict the output of the system not only under the circumstances in which the data was recorded, but also under various other unknown conditions.

As the identification of heat transfer in a room or chamber is essential for designing an efficient HVAC system, some papers have already investigated this subject using computer vision: [1], a pure time delay model with fractional order pole [2], or the Takagi-Sugeno fuzzy model [3].

Various techniques and their combinations for identification purposes, that are used today, can be found in the literature. There have been an increasing number of papers in recent years in which artificial intelligence, fuzzy logic, machine learning, and optimization algorithms appear. These newer methods are often compared with some traditional, linear, or analytical models for identification. In [4] Authors proposed an approach where both - the premise and consequent parameters are updated using Genetic Algorithm (GA) and tested it on a simple pendulum, swinging through a small angle, which has been considered as a nonlinear dynamic system identification problem. It was discovered that using GA to optimize ANFIS parameters is more successful than other methods. Authors in [5] also compare ANFIS – GA along with other identification methods and prove its superior characteristics, for pendulum and two more different systems. Finally, the reliability of this method was proven in a paper [6] where the symbioses of ANFIS and a genetic algorithm for brain tumor image classification are explored and satisfactory results are proven in terms of sensitivity, specificity and accuracy.

Metaheuristics include abstract stochastic optimization method, that are often used in many constrained and unconstrained nonlinear system issues [7]. In this paper, system identification will be done using linear (time-delayed transfer functions) and nonlinear (Adaptive Neuro-Fuzzy Inference System optimized with a genetic algorithm) methods.

2. SYSTEM DESCRIPTION

Figure 1 shows the Quanser Heat-flow experiment (HFE) [8]. The system is basically an advanced rheostat, which consists of an aluminium plate, that includes a blower, a coil-based heating device, and three temperature sensors evenly spaced along the conduit. The thermocouples measure the temperature at different locations on the plate. All three sensors are fast-setting platinum transducers. The blower's tachometer is used to measure the fan speed. The delivered power is controlled by analog signals and the data obtained from the thermocouples is collected and analysed using Quanser's software.

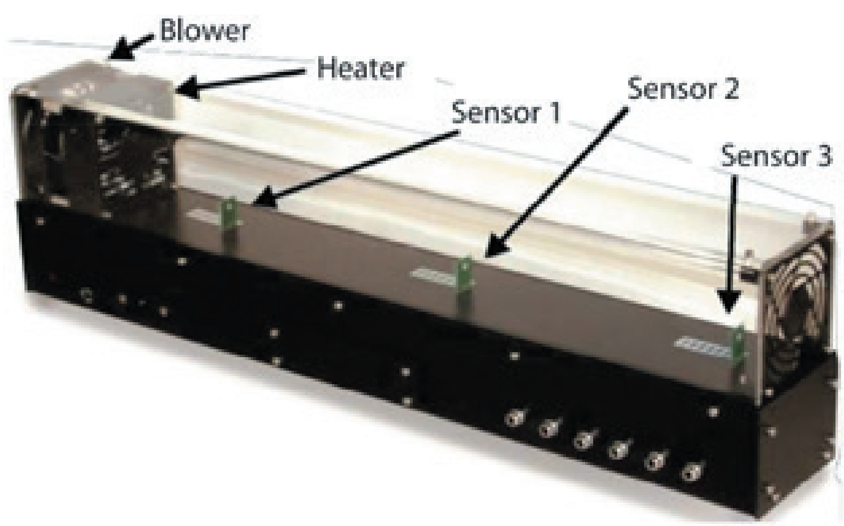

Figure 1 – The setup for Heat Flow Experiment [8].

3. LINEAR MODEL IDENTIFICATION

An open-loop experiment is carried out in order to identify the mathematical representation of the heat flow system. In this experiment, the blower and heater voltages are applied, and three temperature sensors are used to measure the corresponding chamber temperatures. Five seconds into the beginning of the experiment, a 5 V step signal is introduced. The blower input voltage stays at 3 V throughout the whole operation. After 120 seconds, the experiment automatically stops. Due to its proximity to the heater and blower, sensor 1 shows a faster rise in temperature than sensors 2 and 3. Consequently, the rate of temperature increase varies along the chamber. Three models are created, one for each sensor's temperature reading and heat flow step responses are consistent with the identified first-order transfer functions with delay, Equation 1. The linear models are obtained using Matlab identification tools (simplified refined instrument variable (IV) method SRIV, the state variable filter SVF approach and the generalized Poisson moment function GPMF) [9].

$$W_1(s)=\frac{0.2523}{s+0.03563}e^{-0.198s} \tag{1}$$

$$W_2(s)=\frac{0.137}{s+0.03107}e^{-0.396s} \tag{2}$$

$$W_3(s)=\frac{0.1458}{s+0.03242}e^{-0.594s} \tag{3}$$

Equation 1 – Linear identification models.

Figure 2 shows the step responses of these models and the following Table 1 is used to assess the quality metrics of the obtained models for sensor 1 (S1), sensor 2(S2) and sensor 3(S3): Fit to estimation data (FIT) - the fit value between the 1-step ahead predicted response of this model to measured data, also called (prediction focus); Final prediction error (FPE) - a measure of model quality by simulating the situation where the model is tested on a different data set and Mean square error (MSE) [10].

Table 1 – Quality metrics of the obtained linear models

	S1	S2	S3
FIT	95.80%	95.50%	95.77%
FPE	0.1874	0.08602	0. 08171
MSE	0.2096	0. 0949	0.1349

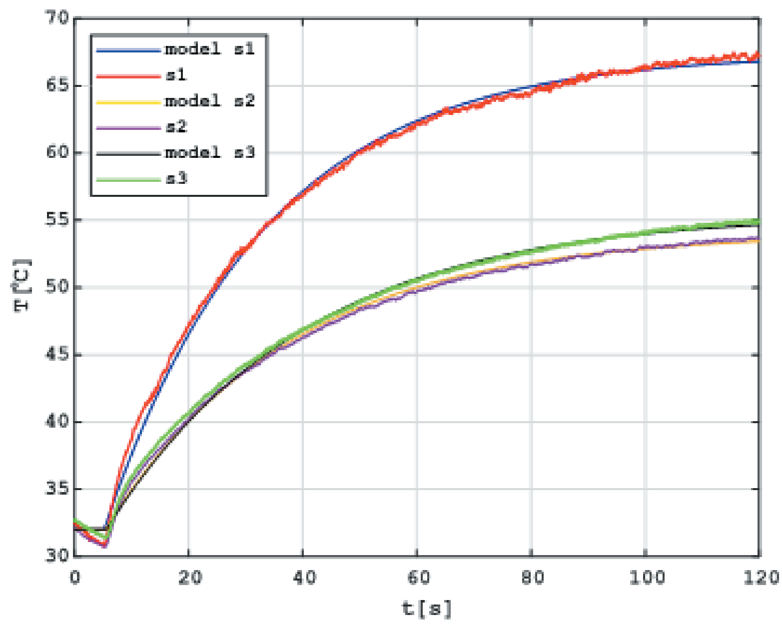

Figure 2 – Comparison: linear model and real output.

4. ANFIS

The extraordinary machine learning model known as the Adaptive Neuro-Fuzzy Inference System, or ANFIS for short, combines the advantages of fuzzy logic and neural networks to produce a hybrid system that is capable of producing precise predictions and classifications. The identification and control of complex systems, as well as image processing, are just a few of the many areas in which the ANFIS model has been used.

The manner in that ANFIS corrects for model inaccuracies using fuzzy if-then rules learned from input-output data is what makes it so effective. The neural network element of ANFIS modifies the fuzzy sets and operator settings to increase prediction accuracy. Back-propagation, a gradient descent algorithm used to reduce the difference between forecast and actual outputs, is typically used for this purpose.

The power of ANFIS to manage nonlinear interactions between input and output variables is one of its key advantages. This is so that complicated interactions and nonlinearities can be captured by the fuzzy sets used to represent the inputs and outputs. Additionally, the neural network element of ANFIS can be trained to change the parameters of the fuzzy sets and operators, enhancing the data's fit and producing predictions that are more precise.

The ANFIS model (with two input variables) consists of five layers, which are:

- Input Layer: This layer on the output gives the degree of membership for the corresponding membership function. All of the nodes have adaptive character, so the shape of the membership function can be changed during training. Each input node represents one input variable and passes the input value to the next layer:

$$O_i^1 = \mu_{A_i}\left(x_1\right), O_{i+2}^1 = \mu_{B_i}\left(x_2\right), i = 1,2.$$

Equation 2 – The first layer output.

μ_{A_i} and μ_{B_i} represent membership functions for i=1,2. Gaussian or bell-shaped membership functions are most often encountered in the literature, and many others have been tried as well. For example, the Gaussian membership function is given by two parameters as:

$$G\left(x,a,\beta\right) = e\frac{\left(x - c\right)^2}{2\sigma^2}.$$

Equation 3 – Gaussian membership function.

- Fuzzification Layer: Unlike the previous layer, the nodes of the second layer are fixed. The output from the node represents the firing strength of the rule w_i. A large firing strength indicates that the rule is more dominant in deciding the final output.

$$O_i^2 = w_i = \mu_{A_i}\left(x_1\right) \cdot \mu_{B_i}\left(x_2\right), i = 1,2.$$

Equation 4 – The second layer output.

- Rule Layer: As well as the previous layer, this layer consists of fixed nodes. Each node in this layer corresponds to one rule and combines the membership values from the fuzzification layer to produce the firing strength of the rule. The firing strength of a rule represents the degree to which the input values satisfy the conditions of the rule.

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2}, i = 1,2.$$

Equation 5 – The third layer output.

- Defuzzification Layer: This layer consists of nodes that combine the firing strengths of the rules to produce a crisp output value. There are different defuzzification methods that can be used, such as the centre of gravity method or the weighted average method.

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i\left(p_i x_1 + q_i x_2 + r_i\right)$$

Equation 6 – The fourth layer output.

$\{p_i, q_i, r_i\}$ is a set of the consequent parameters.

- Output Layer: This layer consists of a single node that represents the output variable of the system. The output node receives the crisp output value from the defuzzification layer and produces the final output value.

$$O_i^5 = y = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} = \left(\overline{w}_1 x_1\right)p_1 + \left(\overline{w}_1 x_2\right)q_1 + \overline{w}_1 r_1 + \left(\overline{w}_2 x_1\right)p_2 + \left(\overline{w}_2 x_2\right)q_2 + \overline{w}_2 r_2$$

Equation 7 – The fifth layer output.

The ANFIS structure contains two groups of parameters: premise parameters and rule consequence parameters. Training the ANFIS network involves determining these parameters using an optimization algorithm, and since the first development of ANFIS, different training approaches have been proposed: derivative-based (gradient), heuristic and hybrid.

One optimization algorithm can be used to set all parameters, or the parameters in the premise of ANFIS are set by one algorithm, and the parameters of the consequence by another algorithm. When using one of the gradient algorithms, there is a risk of getting stuck in a local minimum, and this is exactly what paved the way for metaheuristic algorithms [11]. An extensive review of the recent literature shows that metaheuristic algorithms are far more common than gradient algorithms and that their number is still growing Figure 3 [11].

The most well-known and most frequently used are Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), as well as optimization based on the movement of grey wolves (GWO) and whales (WOA), differential evolution (DE), harmony search (HS), firefly algorithm (FA), mine blast algorithm (MBA), cuckoo search (CS) and artificial bee colony (ABC).

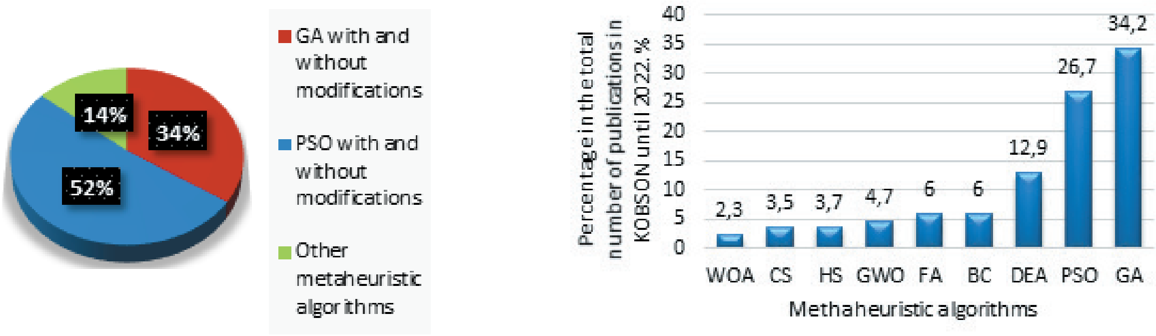

Figure 3 -The ratio of representation of metaheuristic algorithms in hybrid ANFIS structures (right). Percentage of papers on KOBSON when ANFIS and metaheuristic algorithms are keywords (left) [11].

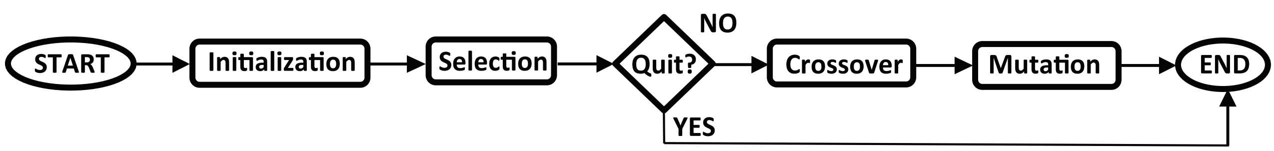

Figure 4 - Flow chart of Genetic algorithm.

5. GENETIC ALGORITHM

Genetic algorithms are an optimization technique used to solve nonlinear or nondifferentiable optimization problems. They use concepts from evolutionary biology to search for a global minimum - an optimization problem. The name genetic algorithm comes from the fact that this method mimics evolutionary biology techniques, by starting with an initial generation of candidate solutions that are tested against the objective function. Secondly, the subsequent generations of points from the first generation are generated through things such as selection crossover and mutation.

The selection retains the best-performing parent from one generation to the next, i.e. if there are parent 1 and parent 2, and these are the values of the variables in the optimization problem from the previous generation, they will make it through to the next generation just because they performed well in the previous generation through selection. Because they performed well, they might also be used for crossover, where common similarities between the different parent variables will be selected. Keeping those similarities will enable the algorithm to create children variables that will be in the next generation.

The genetic algorithm, as one of the first population-based stochastic algorithm, has been successfully applied in various fields and its flowchart can be seen in Figure 4. All additional information can be found in [12].

6. NONLINEAR MODEL IDENTIFICATION

As sensor 3 output a signal that is too noisy, and sensor 1 has a larger error than sensor 2, the transfer function describing the system is chosen to be the one obtained from sensor 2 (s2). This sensor is in the middle of the chamber and according to the Table 1 mean square error of the transfer function obtained with this sensor is the smallest in relation to the actual behaviour of the object. A second transfer function from Equation 1 has been chosen, and a comparison has been made between the model and the real object, but with a different output signal (this time, five seconds into the beginning of the experiment, a 3V step signal is introduced). As can be seen from Figure 5, the mean square error, in this case, is much higher and amounts to 0.4495. The difference between the model and the real output signal is about 1.5^0C in a steady state, and it has the tendency to grow as we go further from the original identification point. For precise industries, this can cause enormous problems. It is concluded that when changing the input, this model (blue line) is not suitable for the representation of the system (red line).

This is expected because the linear model is only valid around a certain point. In order for there not to be an infinite number of points (and therefore an infinite number of models), ANFIS is extremely suitable. Such a model would potentially be valid for the entire state space, and the end result would actually be only one model.

In the previous section, two groups of parameters that can be updated (premise and consequence) were shown, and in this section, that update will be clarified. The objective is to determine the best values for these parameters that reduce the difference between the output of the ANFIS model and the desired output for a certain set of input data.

Since, in this paper, ANFIS uses Gaussian membership functions from Equation 3, the premise parameters are denoted as σi (the standard deviation) and ci (centre). The sum of the parameters in all member functions makes up the total number of underlying parameters. In this paper, the total number of premise parameters is 40 (2 inputs, 10 Gaussian membership functions with 2 parameters). Furthermore, it is clear from the defuzzification layer, Equation 7, the consequent parameters are denoted with pi, qi, and ri. The ANFIS structure in this paper has a total of 30 consequent parameters (because there are 3 parameters for each rule, and there are 10 rules in total). So, in summary, there are a total of 70 parameters that need to be optimized, using the GA metaheuristic approach, in the provided ANFIS architecture. The effectiveness of an ANFIS model on a certain data set should be assessed by the fitness function, and in this paper, the mean squared error is used, as one of the most common functions and in order to make the comparison with the linear identification.

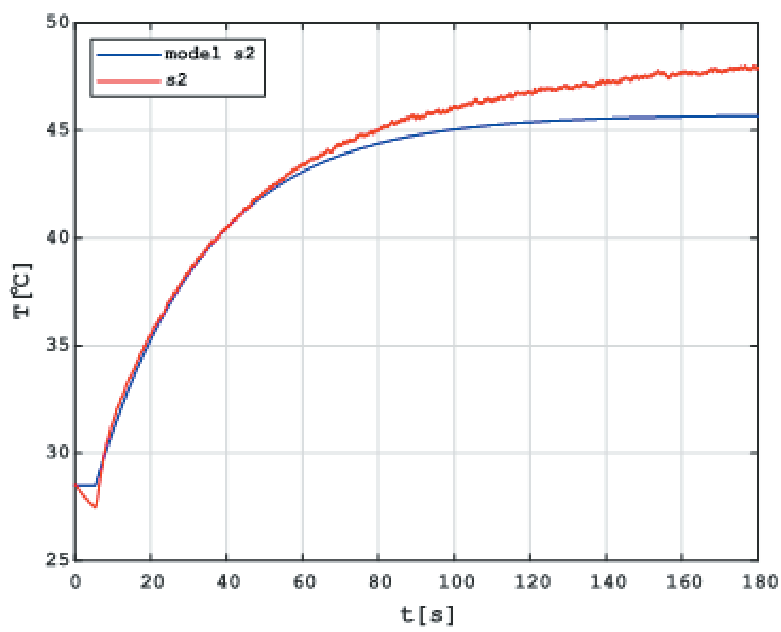

Figure 5 - Comparison linear model and real object for s2 and input signal 3V.

Just for comparison purposes, first, the ANFIS model was trained with the same voltage values as in Figure 2 (after five seconds, a 5V step signal is introduced and the blower input voltage stays at 3V the whole experiment) for s2. Results can be seen in the next Figure 6, where behaviour of the real system is noted in green, linear model in blue and ANFIS in red line. Mean square error of the ANFIS model is equal to 0.0011945, and MSE of the linear model is significantly higher (it can be found in the second column, third row, in Table 1 for sensor 2) and is 0.0949.

Furthermore, another experiment is done. The ANFS model was created using different input voltages: 1.5V, 2V, 3V, 3.5V, 4.5V, and 5V (while the blower input voltage stays at 3V), and it was tested for an input it was not trained on: 4V. The same input was provided for the linear model with the second transfer function in Equation 1. Figure 7 shows the model performances in this case, and the mean square error for the ANFIS model is 0.009864.

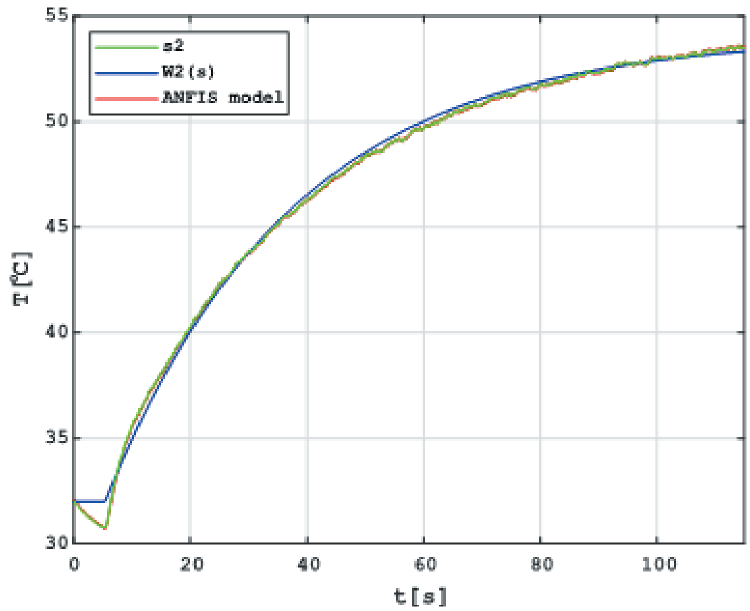

Figure 6 - Comparison: Linear VS ANFIS model.

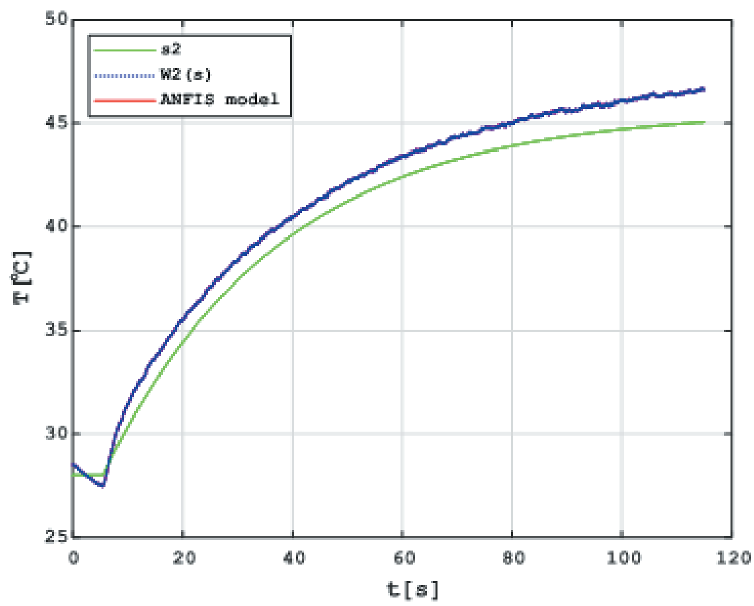

Figure 7 - Linear VS ANFIS model for input signal 4V.

7. CONCLUSION

After experiments presented in this paper, it is easy to notice that the ANFIS nonlinear identification method has shown superiority over standard identification. This is because the standard method uses the linear model with transfer function and delay, which will operate only around a certain point. On the other hand, ANFIS is capable of handling highly nonlinear systems with multiple inputs and outputs, which allows it to model more complex systems. This flexibility is not possible with the standard linear model, and it is crucial for decision-making in complex systems. Hence, it can be concluded that ANFIS can adapt to changes in the system and, moreover, it can handle noisy data and fully follow the dynamics of the system. ¬The model made by ANFIS will be more accurate and efficient compared to the basic ones, even in cases when the input is set to be a voltage that has not been used for training.

In order to guarantee the best performance, parameters for such an ANFIS model (premise and consequent) are found using one of the well-known metaheuristic method: genetic optimization algorithm, which is the first population-oriented stochastic algorithm. The fitness function is set to be the mean square error. Further research will be based on comparing different metaheuristic algorithms and maybe different kinds of optimization - not only parameters, but also the number of rules. Also, it is possible to change membership functions in ANFIS and make a comparison between a few different ones.

8. ACKNOWLEDGEMENTS

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