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MODELING HEAT–FLOW PROTOTYPE DRYER USING ANFIS OPTIMIZED BY PSO

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Abstract: *Chamber dryers are widely used in various industries in order to remove the moisture from solid materials efficiently. Optimizing the design and operational parameters of chamber dryers plays a crucial role in enhancing their performance and energy efficiency. In order to maintain the temperature at the desired level, it is necessary to implement a good control system. To be able to facilitate the process of finding and setting parameters of the controller, for many control algorithms it is essential to make the reliable model of the object. The aim is to develop both reliable and accurate predictive model that can assist in optimizing the design, structures, and inspection processes of chamber dryers, which will lead to enhanced energy efficiency, harvesting and improved drying performance.*

In this paper, the authors propose a novel approach for modeling heat flow transfer in chamber dryers using an Adaptive Neuro-Fuzzy Inference System (ANFIS). The Quanser chamber was selected as the object of the research because of how closely its geometry, material choice, and air flow resemble the structural properties of a dryer. To obtain the most realistic model possible, parameters of ANFIS were found using Particle Swarm Optimization algorithm. By incorporating historical operational data of experimental measurements, the ANFIS model can learn and adapt to the dynamic behavior of the dryer system.

Key words: *Design and Structures, Optimization, ANFIS, PSO, Heat-Flow Chamber Dryer, Energy Efficiency*

1. INTRODUCTION

The indoor environmental parameters such as temperature, ventilation, pollution and humidity are governed by airflow patterns. These airflow patterns form the essential link between the outdoor environment and the chamber microclimate; thus an understanding of the principles of air movement is necessary in order to provide the correct quantities of air and the proper distribution patterns to meet the needs of the application [1]. Temperature control is considered to be one of the crucial parameters [2] in numerous industries, including agriculture, where identifying heat transfer within a room or chamber is essential for designing an efficient Heating, Ventilation, and Air Conditioning (HVAC) system. Some research papers have explored this topic using fuzzy and predictive radial basis function (RBF) [3], neural networks [4], or even hybridizing those models [5] and [6].

Developing accurate heat transfer models can assist researchers and engineers in comprehending the physical mechanisms involved in energy conversion processes and enhancing the efficiency of control systems. System identification is a vital tool for creating a mathematical model that accurately represents the behavior of a physical system based on experimental data. This process is particularly important when the mathematical relationships between input and output are unknown or too complex to be easily expressed and understood. By gathering experimental data that describe the object's behavior, the created model can predict the system's output not only under the conditions in which the data was collected but also under various unknown conditions.

As already mentioned above, various techniques, including artificial intelligence, fuzzy logic, machine learning, and optimization algorithms, are widely utilized for system identification and can be found in the literature. For instance, in two studies, the authors proposed an ensemble of various neural networks and an Adaptive Neuro-Fuzzy Inference System (ANFIS) model for the prediction of heating energy consumption in NTNU campus Gløshaugen [7], [8].

Additionally, there are approaches that employ some of the metaheuristic algorithms in order to optimize the parameters of ANFIS. In [9] Authors used Particle Swarm Algorithm (PSO) and Genetic Algorithm (GA) for the time-series prediction of wind speed in Brazil. The results demonstrated that the combination of ANFIS models with these two metaheuristic algorithms can increase the prediction accuracy of the ANFIS model for all time intervals. Similarly, in another study, ANFIS-PSO model was created to improve the ability of the neuro-fuzzy approach in the prediction of agricultural drought [10].

Metaheuristics, which encompass abstract stochastic optimization methods, are frequently employed in solving both constrained and unconstrained nonlinear system problems. In this paper, system identification is performed using both linear methods, such as time-delayed transfer functions, and nonlinear methods, such as an ANFIS optimized with the PSO. This approach allows for a comprehensive analysis of system behavior.

2. OBJECT DESCRIPTION

The structural aspects of an agricultural dryer, including its geometry, material selection, and insulation properties, can vary depending on the specific design and intended application. Agricultural dryers typically consist of a chamber or enclosure where the drying process takes place. The chamber can be cylindrical, rectangular, or any other suitable shape, depending on the dryer's design. The geometry of the airflow path typically includes inlet and outlet openings, air distribution channels, and baffles to guide the airflow evenly through the drying material. The frame and structure of the agricultural dryer are often made of sturdy materials such as steel or aluminum. These materials provide strength, stability, and durability to support the weight of the drying material and the operational stresses [11]-[13]. Drying chamber walls, the air distribution system, and insulation properties can vary depending on factors such as the type of crop being dried, the scale of the operation, the available energy sources, and the desired drying efficiency. Design considerations should also take into account factors such as safety, maintenance, and cost-effectiveness. In this paper the Quanser chamber (Fig. 1) is selected for the heat-flow experiment (HFE), due to its resemblance to the structural characteristics of a typical dryer. The apparatus is essentially a sophisticated rheostat, consisting of an aluminum plate with three temperature sensors uniformly distributed along the conduit, a blower, and a coil-based heating unit. At various points on the plate, the thermocouples measure the temperature. Fast-setting platinum transducers are used in all three sensors. The fan speed (corresponding signal Vt) is determined using the tachometer on the blower. The provided power (Vh voltage applied to the heater and Vb voltage applied to the blower) is controlled using analog signals (S1, S2 and S3), and Quanser's software is used to gather and analyze the thermocouple data.

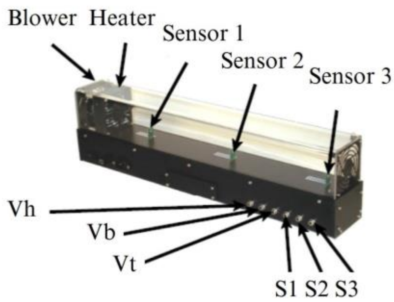

Fig. 1 HFE prototype dryer

3. System modeling

System modeling based on conventional mathematical methods is not adequately adapted for working with poorly defined systems. Important advantages that modern methods can offer comparing to the traditional ones are reflected in situations where: (a) there are many input variables, but few samples; (b) data are heterogeneous and contain multiple types; (v) a nonlinear input-output dependence must be found. Just like traditional models, modern techniques are using well-known statistical methods to evaluate the obtained performance. One of these up-to-date techniques is precisely the artificial intelligence. It includes algorithms that contain elements of the human way of thinking and solving problems, such as fuzzy logic algorithms, artificial neural networks, metaheuristic algorithms, as well as expert systems [14]. In this chapter, two mathematical models of the system will be presented: the first one is a linear model obtained through identification, and the second one is created using ANFIS.

3.1. Linear model: Transfer function with delay

To identify the mathematical representation of the heat flow system, an open-loop experiment was conducted. During the experiment, the voltages of the blower and heater were applied, and three temperature sensors were utilized to measure the temperatures inside the chamber. After five seconds, a step signal of 5V was introduced. The blower input voltage remained at 3V for the entire duration of the experiment. After 120 seconds, the experiment automatically ended. Notably, sensor 1, as being closer to the heater and the blower, showed a faster temperature rise compared to the sensors 2 and 3. Consequently, the rate of temperature increase varied across the chamber. Three models were developed, each corresponding to the temperature readings of the respective sensors. The step responses of heat flow align with the identified first-order transfer functions with delay, as represented by (1). Moreover, Fig. 2 shows the step responses of these models. In terms of the mean square error (MSE) second sensor (s2) gives the best results.

$$
\begin{aligned}
W_1(s) &= \frac{0.2523}{s+0.03563} e^{-0.198\,s}, \ \text{MSE} = 0.2096. \\
W_2(s) &= \frac{0.137}{s+0.03107} e^{-0.396\,s}, \ \text{MSE} = 0.0949. \\
W_3(s) &= \frac{0.1458}{s+0.03242} e^{-0.594\,s}, \ \text{MSE} = 0.1349.
\end{aligned}
\tag{1}
$$

3.1.1. Linear model testing

Considering the excessive noise in the output signal of sensor 3 and the larger error exhibited by sensor 1, the transfer function selected to describe the system is derived from sensor 2 (s2) using (1). This particular sensor, located in the middle of the chamber, demonstrates the smallest MSE, as indicated in Fig. 2. (left). Furthermore, a comparison is made between the model and the real object, but with a different input signal. In this case, a 4V step signal was introduced five seconds into the beginning of the experiment.

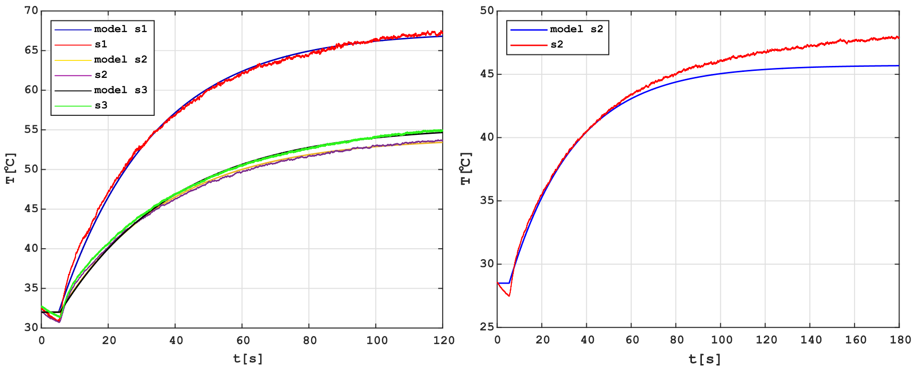

Fig. 2 Linear model: Transfer functions with delay and (left),
Linear model testing with different input (right) [15]

The obtained results, illustrated in Fig. 2 (right), reveal a significantly higher MSE of 1.1888. Moreover, there is an approximate 1.5°C difference between the model and the actual output signal in a steady state, and this discrepancy tends to amplify as we move away from the original identification point.

Consequently, it is concluded that when altering the input, this particular linear model is unsuitable for accurately representing the system.

3.2. Nonlinear model

3.2.1. General architecture of ANFIS

As an exceptional machine learning model that combines the strengths of fuzzy logic and neural networks, ANFIS is capable of creating accurate predictions, classifications, and even control algorithms, which have found applications in various domains, including complex system identification, controllers, as well as image processing.

The neural network component of ANFIS adjusts the fuzzy sets and operator settings to improve prediction accuracy. Typically, the backpropagation algorithm, a gradient descent method, is employed for this purpose to minimize the difference between predicted and actual outputs. One of the key advantages of ANFIS is its capability to handle nonlinear interactions between input and output variables. This is achieved by utilizing fuzzy sets to represent inputs and outputs, capturing complex interactions and nonlinearities. Furthermore, the neural network component of ANFIS can be trained to adapt the parameters of the fuzzy sets and operators, thereby improving the fit of the data and generating more precise predictions. The ANFIS model (with two input variables) consists of five layers, as shown in Fig. 3.

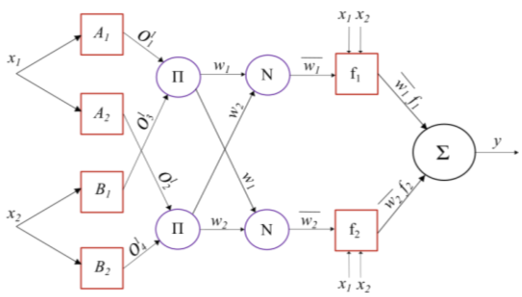

Fig. 3 ANFIS architecture

<u>First Layer</u>: The initial layer calculates the membership degree of the corresponding membership function and outputs it. Each node in this layer is flexible and can adjust its shape during training. Every input node represents an input variable and transfers the input value to the subsequent layer.

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

The membership functions μ_{Ai} and μ_{Bi} correspond to i=1,2. In the literature, Gaussian or bell-shaped membership functions are commonly used, although various other types have also been explored. One specific example is the Gaussian membership function, which is defined by two parameters.

$$G(x,c,\sigma) = e^{-\frac{(x-c)^2}{2\sigma^2}}. \tag{3}$$

<u>Second Layer</u>: In contrast to the previous layer, the nodes in the second layer remain constant. The output of each node indicates the firing strength of the corresponding rule,

w_i. A higher firing strength suggests that the rule holds greater influence in determining the final output.

$$O_i^2 = w_i = \mu_{A_i}(x_1) \cdot \mu_{B_i}(x_2), i = 1, 2. \quad (4)$$

Third Layer: This layer computes the normalized firing strength of each rule by dividing the firing strength of a rule by the sum of all firing strengths, ensuring that the values fall within the range of 0 to 1.

$$O_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2}, i = 1, 2. \quad (5)$$

Fourth Layer: This layer calculates the product of the normalized firing strength and the consequent parameter of each rule, combining them to obtain the weighted consequent values.

$$O_i^4 = \bar{w}_i f_i = \bar{w}_i (p_i x_1 + q_i x_2 + r_i), \quad (6)$$

where: p_i, q_i, and r_i are the consequent parameters.

Fifth Layer: The final layer sums up the weighted consequent values from all rules to generate the overall output of the ANFIS system.

$$O_i^5 = y = \sum_i \bar{w}_i f_i \frac{\sum_i w_i f_i}{\sum_i w_i} = (\bar{w}_1 x_1) p_1 + (\bar{w}_1 x_2) q_1 + \bar{w}_1 r_1 + (\bar{w}_2 x_1) p_2 + (\bar{w}_2 x_2) q_2 + \bar{w}_2 r_2. \quad (7)$$

3.2.2. PSO algorithm

The Particle Swarm Optimization (PSO) algorithm is a metaheuristic technique inspired by swarm behavior, aiming to find optimal solutions by simulating particle movement and interaction in a search space. Each particle represents a potential solution and adjusts its position based on local and global best-known positions. Particle movement follows the principles of exploration and exploitation. Exploration occurs through random velocity adjustments, allowing particles to explore different areas. Exploitation involves particles being attracted to the best-known positions, converging towards promising areas. In each iteration, particles update their velocities and positions using mathematical formulas based on their current state and best-known positions. The process continues until a stopping criterion, like a maximum iteration limit or satisfactory solution, is reached, as shown in Fig. 4. PSO has been successfully applied to a wide range of optimization problems, including engineering design, scheduling, data clustering, and neural network training. This algorithm was introduced by Dr. James Kennedy and Dr. Russell Eberhart in 1995. and since then, the PSO has gained popularity as an effective optimization technique and has been further developed and extended by various researchers [16]. There have even been instances where some new metaheuristic algorithms have been accused of bearing similarities to PSO in terms of population-based search and the concept of updating solutions based on local and global information [17] and in terms of the concept of attraction and movement of individuals within the population [18].

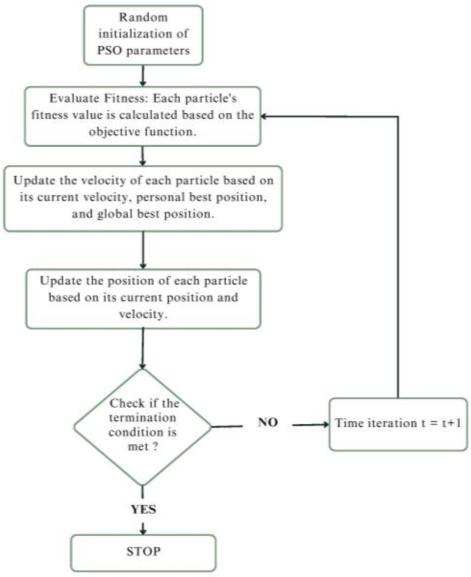

Fig. 4 Flowchart of PSO algorithm [16]

The ANFIS structure comprises two sets of parameters: premise parameters and rule consequence parameters. The process of training the ANFIS network involves determining these parameters through an optimization algorithm. Over time, various training approaches have been proposed for ANFIS, including derivative-based (gradient), heuristic, and hybrid methods. There are two possible strategies for parameter setting: using a single optimization algorithm to set all parameters or employing different algorithms for setting the premise and consequence parameters separately. In this research, the first approach is used, where PSO is combined with ANFIS in order to obtain the best possible results.

Gradient algorithms, while effective, can be susceptible to getting trapped in local minima. This limitation has paved the way for the emergence of metaheuristic algorithms. A comprehensive analysis of recent literature reveals that metaheuristic algorithms are more prevalent than gradient algorithms, and their popularity continues to grow (as depicted in Fig. 5 [14]). Some of the widely known and frequently used metaheuristic algorithms include Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Grey Wolf Optimization (GWO), Whale Optimization Algorithm (WOA), Differential Evolution (DE), Harmony Search (HS), Firefly Algorithm (FA), Mine Blast Algorithm (MBA), Cuckoo Search (CS), and Artificial Bee Colony (ABC).

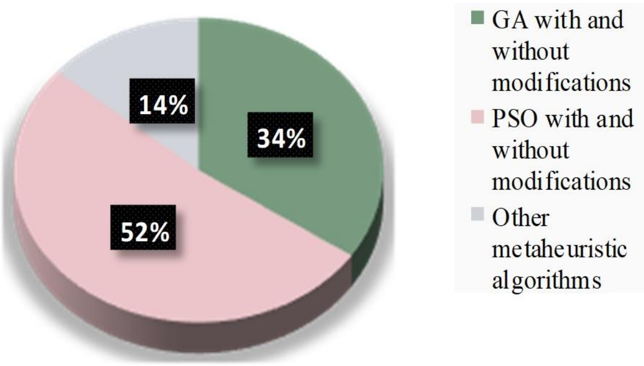

Fig. 5 Percentage of papers on KOBSON when ANFIS and metaheuristic algorithms are set as keywords [14]

3.2.3. ANFIS optimization and experimental results

To avoid an infinite number of identification points and models, an alternative model for heat flow exchange in the chamber is created. This model is nonlinear and it is intended to be valid for the entire state space. For this purpose, ANFIS is particularly suitable.

In this paper, ANFIS utilizes Gaussian membership functions, as shown in (3), where the premise parameters are represented by σ_i (standard deviation) and c_i (center). The total number of underlying parameters is determined by the sum of parameters across all membership functions. In this case, there are 40 premise parameters (2 inputs, 10 Gaussian membership functions with 2 parameters). Additionally, the consequent parameters, denoted as p_i, q_i, and r_i, are identified from the fourth layer, as indicated in (6). The ANFIS structure in this paper encompasses a total of 30 consequent parameters (3 parameters per rule, with a total of 10 rules). To summarize, the ANFIS architecture presented in this paper involves a total of 70 parameters that need to be optimized using the PSO metaheuristic approach. Evaluating the effectiveness of the ANFIS model on a specific dataset is done through a fitness function, with the MSE being commonly used for comparison with linear identification approaches. The ANFIS model was constructed by employing various input voltages, including 1.5V, 2V, 3V, 3.5V, 4.5V, and 5V while maintaining a constant blower input voltage of 3V. To assess its performance on an untrained input of 4V, the same input was also applied to the linear model utilizing the second transfer function from (1). Fig. 6 presents the performance of both models under these conditions, with the ANFIS model yielding a MSE of 0.0003 (blue line). The results demonstrated that the ANFIS model optimized by PSO outperformed both the standard linear model (which MSE, in this case, is 1.1888, green line) and even ANFIS – GA model that has been made in previous research [15] for the same purposes (which MSE was 0.009864). This case study showed that combining ANFIS with PSO algorithm can provide excellent results in the real world problem of identification dryer model.

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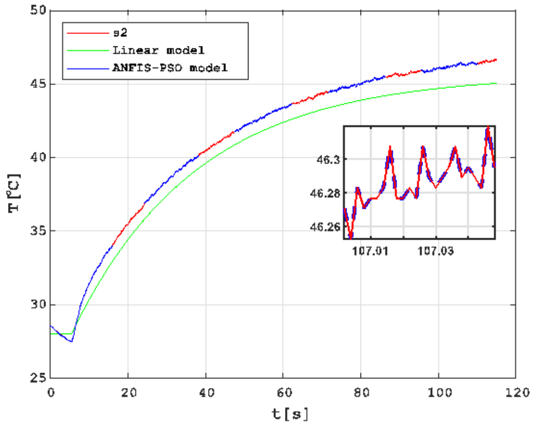

Fig. 6 Comparison of the linear model and ANFIS optimized with the PSO algorithm

4. CONCLUSION

After conducting experiments outlined in this paper, it becomes evident that the ANFIS nonlinear identification method exhibits superiority over standard identification approaches. The standard method relies on a linear model with a transfer function and delay, which only operates effectively around a specific point. In contrast, ANFIS possesses the capability to handle highly nonlinear systems and this flexibility is crucial for decision-making in intricate systems. To ensure optimal performance, the parameters of the ANFIS model, both premise and consequent, are determined using a well-known metaheuristic method called Particle Swarm Optimization. The improvement that this paper provides to the problem of finding the dryer model is reflected in the MSE, which drops from 1.1888 with the classical method to 0.0003 with ANFIS. Therefore, it can be concluded that the ANFIS model outperforms basic models, even when faced with input voltages that were not included during training.

This research could contribute not only to the identification of dryer models, but also to temperature control in them. Enhancing the performance and energy efficiency of chamber dryers heavily relies on optimizing their design and operational parameters. An effective control system is crucial for maintaining the desired temperature levels. To facilitate the parameter configuration process for the controller, it is imperative to establish a reliable model of the object. This model will aid in optimizing the processes of chamber dryers, ultimately resulting in improved energy efficiency, increased yield, and enhanced drying performance.

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REFERENCES

1. Norton, T., Sun, D. W., Grant, J., Fallon, R. and Dodd, V. (2007) *Applications of computational fluid dynamics (CFD) in the modelling and design of ventilation systems in the agricultural industry: A review*. Bioresource technology, *98*(12), pp. 2386-2414.
2. McCartney, L. and Lefsrud, M., (2018) *Protected agriculture in extreme environments: a review of controlled environment agriculture in tropical, arid, polar, and urban locations*. Applied engineering in agriculture, 34(2), pp. 455-473.
3. Ardabili, S.F., Mahmoudi, A. and Gundoshmian, T.M., (2016) *Modeling and simulation controlling system of HVAC using fuzzy and predictive (radial basis function, RBF) controllers*. Journal of Building Engineering, 6, pp. 301-308.
4. Mahmoodi, N.M., Taghizadeh, M. and Taghizadeh, A., (2018) *Mesoporous activated carbons of low-cost agricultural bio-wastes with high adsorption capacity: preparation and artificial neural network modeling of dye removal from single and multicomponent (binary and ternary) systems*. Journal of Molecular Liquids, 269, pp.217-228.
5. Soyguder, S. and Alli, H., (2009) *Predicting of fan speed for energy saving in HVAC system based on adaptive network based fuzzy inference system*. Expert Systems with Applications, 36(4), pp.8631-8638.
6. Ardabili, S.F., Najafi, B., Ghaebi, H., Shamshirband, S. and Mostafaeipour, A., (2017) *A novel enhanced exergy method in analyzing HVAC system using soft computing approaches: A case study on mushroom growing hall*. Journal of Building Engineering, 13, pp.309-318.
7. Jovanović, R.Ž., Sretenović, A.A. and Živković, B.D., (2015) *Ensemble of various neural networks for prediction of heating energy consumption*. Energy and Buildings, 94, pp.189-199.
8. Jovanović, R.Ž. and Sretenović, A.A., (2017) *Ensemble of radial basis neural networks with k-means clustering for heating energy consumption prediction*. FME Transactions, 45(1), pp.51-57.
9. Khosravi, A., Machado, L. and Nunes, R.O., (2018) *Time-series prediction of wind speed using machine learning algorithms: A case study Osorio wind farm, Brazil.* Applied Energy, 224, pp.550-566.
10. Aghelpour, P., Bahrami-Pichaghchi, H. and Kisi, O., (2020) *Comparison of three different bio-inspired algorithms to improve ability of neuro fuzzy approach in prediction of agricultural drought, based on three different indexes.* Computers and electronics in agriculture, 170, p.105279.
11. Salve, S. and Fulambarkar, A.M., (2021) *A solar dryer for drying green chili in a forced convection for increasing the moisture removing rate.* Materials Today: Proceedings, 45, pp.3170-3176.
12. Akpan, G.E., Onwe, D.N., Fakayode, O.A. and Offiong, U.D., (2016) *Design and Development of an Agricultural and Bio-materials Cabinet Tray dryer.* Science Research, 4(6), pp.174-182.
13. Kishk, S.S., ElGamal, R.A. and ElMasry, G.M., (2019) *Effectiveness of recyclable aluminum cans in fabricating an efficient solar collector for drying agricultural products.* Renewable Energy, 133, pp.307-316.
14. Vesović, M.V. and Jovanović, R.Ž., (2022) *Adaptive neuro fuzzy Inference systems in identification, modeling and control: The state-of-the-art.* Tehnika, 77(4), pp.439-446.
15. Vesović, M. and Jovanović, R., (2023) *Heat Flow Process Identification Using ANFIS – GA Model.* In Proc. To be Published: *Sinteza 2023-International Scientific Conference on Information Technology and Data Related Research*. Belgrade: Singidunum University.
16. Shi, Y., (2004) *Particle swarm optimization*. IEEE connections, 2(1), pp.8-13.
17. Yang, X.S. ed., (2013) *Cuckoo search and firefly algorithm: theory and applications* (Vol. 516). Springer.
18. Weyland, D., (2015) A critical analysis of the harmony search algorithm—How not to solve sudoku. *Operations Research Perspectives*, *2*, pp.97-105.

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