The Aeronautical Journal (2024), 1–10
doi:10.1017/aer.2024.30

ROYAL AERONAUTICAL SOCIETY

REGULAR PAPER

Improvement of UAV thrust using the BSO algorithm-based ANFIS model

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Received: 5 February 2024; **Revised:** 7 March 2024; **Accepted:** 11 March 2024

Keywords: ANFIS; backtracking search optimisation; thrust; UAV; optimisation

Abstract
Unmanned aerial vehicles (UAVs), which are available in our lives in many areas today, bring with them new expectations and needs along with developing technology. In order to meet these expectations and needs, main subjects such as reducing energy consumption, increasing thrust and endurance, must be taken into account in UAV designs. In this study, Backtracking search optimisation (BSO) algorithm-based adaptive neuro-fuzzy inference system (ANFIS) model is proposed for the first time to improve UAV thrust. For this purpose, first, different batteries and propellers were tested on the thrust measuring device and a data set was obtained. Propeller diameter and pitch, current, voltage and the electronic speed controller (ESC) signal were selected as input, and UAV thrust was selected as output. ANFIS was used to relate input and output parameters that do not have a direct relationship between them. In order to determine the ANFIS parameters at the optimum value, ANFIS was trained with the obtained data set by using BSO algorithm. Then, the objective function based on the optimum ANFIS structure was integrated into BSO algorithm, and the input values that gave the optimum thrust were calculated using BSO algorithm. Simulation results, in which parameters such as engine, battery and propeller affecting the thrust are taken into account equally, emphasise that the proposed method can be used effectively in improving the UAV thrust. This hybrid method, consisting of ANFIS and BSO algorithm, can reduce the cost and time loss in UAV designs and allows many possibilities to be tested.

Nomenclature

UAV:	unmanned aerial vehicle
ANFIS:	adaptive neuro-fuzzy inference system
BSO:	backtracking search optimisation
MSE:	mean squared error

1.0 Introduction
Unmanned aerial vehicles (UAVs), which have shown rapid development in recent years with their different designs, are preferred in many areas such as search and rescue and mapping with their autonomous and non-autonomous types [1–3]. For this reason, it is desired that UAVs will have optimum designs and UAV performances will be maximum.

While designing UAVs, many factors such as optimum aerodynamic shape, endurance, etc. are taken into consideration. One of the main factors to consider is the thrust systems. Thrust systems, which are designed according to the purpose of use of UAVs, can be basically divided into two as electrically powered or fuel-powered engines systems. While fuel-powered engines are generally used in large-scale

UAVs produced above a certain weight, electrically powered engines are generally used in small-sized UAVs [4].

Power system in electrically powered UAVs consists of the battery, the brushless engine, the propeller and the electronic speed controller (ESC). Battery is the energy source. Since battery capacity affects the flight time of UAVs, the battery is an important part of the power system. Brushless engine converts the power of the battery into mechanical energy. Propeller connects to the brushless engine and provides the thrust. ESC acts as a switch between the battery and the engine. Since the capacity of the battery is fixed, the engine and ESC are determined in accordance with the capacity of the battery. Propellers are generally classified according to the materials used and dimensions. In addition, it is possible to classify according to the pitch angle [5]. Therefore, many parameters are taken into account in order to improve the thrust, which is an important part of the UAV power system.

While designing UAVs, contributions from many different fields such as aviation, electronics, software and hardware are taken into consideration. However, in recent years, the popularity of artificial intelligence methods based on artificial neural networks and algorithms in order to reduce experimental costs and save time encourages the use of these methods in the field of aviation. There are many studies in the literature on aviation applications of artificial intelligence methods or thrust performance [6–12]. In one of the presented studies, the efficiency obtained from the battery using variable pitch propellers was examined and the advantages of variable pitch propellers over fixed pitch propellers were revealed [13]. In another study, the discharge behaviour of the battery and its effect on performance were examined while investigating the increase of the flight range of an electric engine-powered aircraft [12]. In another study, various types and sizes of propellers were subjected to wind tunnel tests by using different types of brushless engines and ESCs, and the results were presented [14]. In another presented study, optimum design of thrust systems of UAVs is discussed. It was emphasised that battery, propeller and electric engines are more important parameters in terms of design and performance, and they focused on these three issues by eliminating other factors [7]. In another study, solar-powered batteries and different pitch propellers were used for power and thrust optimisation. It has been emphasised that the size of the electronic elements is an important factor for the UAV performance to reach its maximum value [15]. In another presented study, increasing the range of UAVs is discussed. This issue has been focused on, emphasising that flight time, that is, increasing range, is directly related to battery development [16].

When the studies in the literature are examined, the study – which the engine, battery, propeller and ESC values that make up the UAV thrust system are considered together – is not available. In this study, these parameters, which are not directly related, are handled together and improved with artificial intelligence methods for the first time. As artificial intelligence methods, adaptive neuro-fuzzy inference system (ANFIS) and backtracking search optimisation (BSO) algorithm were preferred.

The proposed method for improvement UAV thrust is based on the BSO algorithm-based ANFIS model. Here, ANFIS provides multiplexing of data by associating different parameters from each other, but cannot select the most appropriate value. On the other hand, the BSO algorithm is not sufficient in the optimisation of parameters that are not directly related or do not contain enough data sets. In this study, since there is no direct relationship or formula between the selected input and output parameters, the ANFIS structure is chosen to relate these parameters. In addition, the BSO algorithm is used to determine the most suitable values for the improvement and optimisation of the thrust performance. In summary, ANFIS is trained with a small number of data obtained on the test platform, and during this training, the BSO algorithm was preferred instead of the classical algorithms in order to determine the ANFIS parameters optimally. Afterwards, the ANFIS model structure, whose parameters are determined optimally, is integrated into the BSO algorithm in order to realise the objective function. Thus, the optimum output value versus the optimum input value is calculated with the BSO algorithm. The proposed BSO algorithm-based ANFIS method is presented for the first time in the literature on the improvement of UAV thrust. The results presented with figures and tables emphasise that this method can be used as an alternative method in the literature as an innovative method.

2.0 Selected parameters for improvement of UAV thrust

The general name of the equipment that provides and adjusts movement and control in UAVs is called power systems [9, 14]. Power systems consist of the engine that gives the rotation movement, the batteries that provide energy to the engine, the electronic speed controller (ESC) that controls the speed of the engine and the propellers that provide the thrust. In this section, the preferred parameters in the study are briefly explained in order to improve the thrust, which is a part of the UAV power system.

2.1 Brushless engine

Direct current (DC) engines, which are preferred in many industrial, commercial and domestic applications, are simply classified as brushed and brushless. Brushed DC engines that include brush and commutator require routine maintenance of the commutators and frequent periodic replacement of the brushes. This also increases the cost. In brushless DC engines, semiconductor switches are replaced the brush and commutator. Although brushless DC engines are expensive, they are preferred in many applications such as electric automotive, electric trains, aeronautic and robotics because they are not dependent on brushes and commutators [17, 18]. In addition to this advantage, brushless DC engines have many advantages compared to other electric engines such as long lifetime, low maintenance cost, light weight, precise speed control, high torque capacity, high efficiency. In this study, brushless DC engine was preferred because of these advantages.

2.2 Battery

The battery is simply defined as an energy source that converts chemical energy into electrical energy [15]. Each unit that converts chemical energy into electrical energy in batteries is called a cell, and batteries consist of one or more cells. Batteries consisting of cell or cells are also connected in series or parallel according to the desired capacity or output voltage.

Battery selection is made by considering performance criteria such as voltage, capacity, specific energy, energy density and temperature tolerance etc. [19]. In this study, tests were carried out with two different lithium-polymer (Li-Po) batteries of 20C-2650 mAh-3S (11.1 volts) and 30C-3300 mAh-4S (14.8 volts). These batteries were preferred in the study by considering the GT2215/09 model brushless DC engine datasheet. Here, Li-Po batteries are preferred because of their high-energy density and long lifetime. The C coefficient is the coefficient that shows how fast the battery can discharge. The mAh value gives information about how many milliamperes the battery can provide in an hour and shows the capacity of the battery. The S value indicates the number of cells connected in series. The nominal voltage of a Li-Po battery cell is 3.7 volts. If the voltage of any cell of the used battery drops below 3 volts, there is a risk of completing the life of the battery, and if it exceeds 4.2 volts, there are risks in terms of safety.

2.3 Electronic speed controller

The electronic circuit that controls and adjusts the speed of an electric engine is called an electronic speed controller (ESC). In addition, ESCs can provide reverse rotation of the engine and dynamic braking. Small-sized ESCs are used in electrically powered, radio-controlled small models, while large-sized electric vehicles have additional systems to control the speed of the drive engines [9, 20].

The ESC reference signal comes from the throttle, joystick or other manually given input commands. Depending on the incoming command level, speed control is provided by transistors that act as switches. The engine speed is varied, depending on the given duty cycle or switching frequency. Due to the transistors in the ESC, rapid response changes occur. Thus, a characteristic feature emerges that can be noticed especially at low speeds [21].

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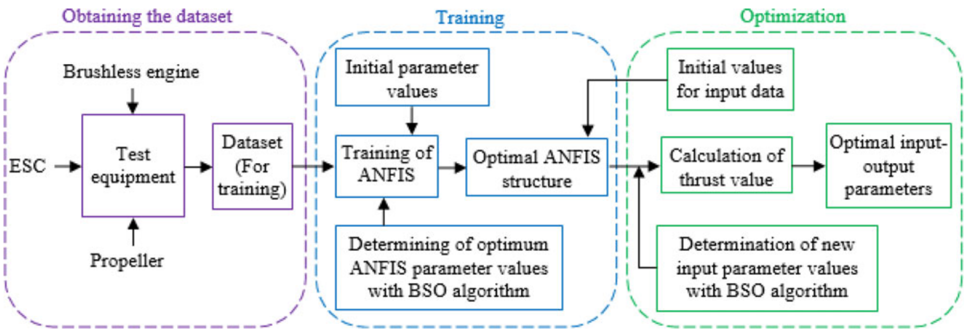

Figure 1. *Block diagram showing the stages of the proposed model.*

2.4 Propeller

The propeller can simply be thought of as a slightly twisted wing. Unlike the wing structure, the propellers have a curved leading edge and a sharp trailing edge. Propellers or aircraft wings are both aerofoils designed to generate an aerodynamic force. The direction of the propeller profile changes significantly as it progresses from root to tip. The lift surfaces on the propeller, which is similar to the wings in structure, are called blades. Propellers, which can consist of one or more blades, are generally preferred to have two to four blades in applications. Propellers can be classified in many ways such as position, pitch angle. However, the main characteristics of a propeller that determine its size are propeller diameter and propeller pitch. Propeller diameter refers to the diameter of the circle drawn by the blade tips. Propeller pitch defines the distance the propeller will move forward in a single rotation. Choosing the diameter and pitch of the propeller at appropriate values affects the thrust and speed values to be obtained. In this study, the limits in the datasheet of the selected brushless engine were taken into account when determining the values of the propeller diameter and the propeller pitch [5].

3.0 Problem definition and obtaining the dataset

In the previous section, the equipment that contributes to the UAV thrust and is preferred in the study, is briefly explained. For the optimal UAV thrust, these pieces of equipment should be selected appropriately, and multiple parameters should be considered simultaneously for this selection. This brings cost and time loss for these parameters, which are not directly related. In order to avoid the mentioned disadvantages, artificial intelligence methods (ANFIS and BSO algorithm) were used in this study.

The proposed method consists of three stages as obtaining the dataset, training and optimisation, and the block diagram of these stages is given in the Fig. 1. In order to obtain the dataset, firstly, ESC, engines of various feature, propellers of various sizes and diameters were tested in a thrust measuring device. As a result of the test, values such as thrust, current and voltage from the propeller and engine were obtained and a data set was generated. In the proposed model, propeller diameter, propeller pitch, applied current and voltage, and ESC signal values are selected as input parameters, and thrust is selected as output parameter. The input parameters determined depending on the battery and the propeller were chosen because they have a significant effect on the thrust. After obtaining the dataset, the training stage was started.

In the training stage, ANFIS was trained for the input and output parameters selected from the dataset obtained on the test platform. During this training, the BSO algorithm was preferred instead of traditional algorithms in order for the obtained output value to approach the desired output value; that is, to adjust the ANFIS parameter values in the most appropriate way. As a result of the training, the optimum ANFIS structure with the smallest error value was selected, and the training stage was completed and the optimisation stage was started.

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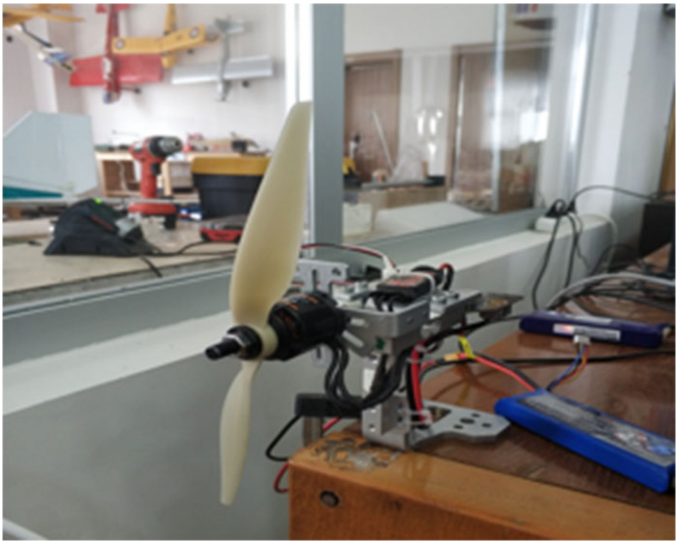

Figure 2. *Test stand prepared to obtain dataset.*

In the optimisation stage, the improvement of the UAV thrust was discussed. For this purpose, the BSO algorithm was used again. The ANFIS structure, which has the most appropriate parameter values, is integrated into the BSO algorithm as the objective function. By using ANFIS as an objective function, it is aimed to relate the propeller, battery and thrust parameter values, which are not directly related, and to optimise them equal importance and simultaneously with the BSO algorithm. With the ANFIS-based objective function, which is limited to the lower and upper limits for the input and output parameter values, the output parameter was optimised against different input parameters. Therefore, it was calculated which input parameter values are more suitable for the output obtained in a way that maximises the UAV thrust. Thus, simple, fast and satisfactory results can be obtained by considering the battery and propeller data of equal importance with the BSO algorithm-based ANFIS method in the improvement of UAV thrust.

3.1 Obtaining the dataset

In this study, GT2215/09 model brushless DC engine belonging to the grand turbo series produced by EMAX Company was chosen. The thrust test of the brushless engine was carried out using version 1.1.4 of the graphical user interface program of the 1580 model test device. The Skywalker 40A ESC of the Hobbywing brand was used to adjust the engine speed. For the required electrical energy, Li-Po battery with voltage values of 11.1 volts and 14.7 volts was preferred. In order to observe the effect of engine performance, propellers of various lengths and pitches – 10×5, 10×7, 11×5.5, 11×7, 11×8 and 12×6 – were used. By using combinations of battery and propeller values, tests, pictured in Fig. 2, were carried out on the thrust, torque, propeller and system efficiency of the brushless engine.

In this study, it was find enough to take around 25–30 samples between 1,050 and 2,000 ESC values. The engine was run for 2 s at each point within these specified intervals. Therefore, the sitting time was determined as 3 s. Considering that the engine did not need a cooling time between two points, this value was chosen as 0 s. Thus, the engine, after reaching the maximum value, reduced its speed to the minimum value to cool itself. In order to limit the torque value of the engine between two sample points, the total operating time between the two sample points was set to 10 s. In this time interval, a transition was made from one point to another in 4 s, the current speed was worked for 3 s at the point reached, and the average of 10 sample values at equal intervals for the remaining 3 s was recorded in the data file.

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4.0 Methods

4.1 ANFIS

ANFIS has a hybrid learning procedure involving fuzzy inference system and artificial neural networks. A fuzzy inference system has an understandable and clear procedure as it depends on people's decision making, but may not be with sufficient precision. On the other hand, neural networks offer exact solutions, but lack clarity in decision making. At this point, ANFIS is an effective method that is revealed by combining the successful sides of both methods [22].

In the literature, it is available many fuzzy inference systems that have the same working principle but use different membership functions. In this study, the Sugeno-type fuzzy inference system was preferred. The main advantage of the Sugeno-type fuzzy inference system, which is frequently preferred in the literature, over other systems is that it optimises parameters easily [23, 24].

ANFIS basically consists of five layers. In the first layer, the initial parameters and number of rules are determined by selecting the membership function. In the second layer, the firing strength is calculated for each rule by multiplying the membership values of the inputs. In the third layer, normalised firing strengths are calculated by dividing the firing strength of any rule by the sum of the firing strength of all rules. In the fourth layer, the weighted values of the rules are calculated for each node. In the fifth layer, the actual output of ANFIS is obtained by summing the outputs obtained for each rule [22].

4.2 BSO algorithm

BSO algorithm, which was first introduced to the literature in 2013, is a new generation optimisation algorithm that has been successfully used in engineering problems [25]. Compared to many search algorithms, the problem-solving performance of BSO algorithm, which has only two control parameters, becomes advantageous, as it is not overly sensitive to the initial values of control parameters. Although BSO algorithm has a simple structure, it can take advantage of the experiences of previous generations by storing a population from the previous generation in its memory. With these features, BSO algorithm can offer effective and fast solutions to different optimisation problems [25–30].

BSO algorithm consists of five phases as initialisation, first selection, mutation, crossover and second selection. In the initialisation phase, initial values such as control parameters are determined for the BSO algorithm. In the first selection phase, a new historical population is used to calculate the search direction at each selection and the population members are randomly reordered. In the mutation phase, a new population is generated through previous experiences and mutation. In the crossover phase, the final state of the population is obtained by proportional mixing of the components in the population. Here, among the population members, those with good values according to the optimisation problem are used to determine the target population individuals. In the second selection phase, the better one is selected by making comparison and the update process is performed. The best value found is checked by re-comparison with individuals from the entire population at each iteration. The algorithm continues its cycle until the maximum number of iterations is achieved or the fitness value provides the preconfigured conditions [25].

5.0 Simulation results

The proposed method for improvement of UAV thrust is based on the BSO algorithm-based ANFIS model. In the BSO algorithm-based ANFIS model, the propeller diameter, propeller pitch, applied current and voltage, and ESC signal values are selected as input parameters and thrust is selected as output parameters.

In the study, while obtaining training dataset, tests were carried out using combinations of propellers (sizes of 10×5, 10×7, 11×5.5, 11×7, 11×8, 12×6) and batteries (3S and 4S), and around 25–30 samples were taken for each combination. During the test, the ESC signal value was selected between 1,050 and 2,000 ms.

Table 1. *The best MSE values obtained in BSO algorithm-based ANFIS training*

Number of rule	Colony size	Iteration	Number of membership function (for each input)	Number of parameter	MSE
32	30	1,000	[2 2 2 2 2]	222	8.7060e-04
		2,500	[2 2 2 2 2]	222	4.6264e-04
		5,000	[2 2 2 2 2]	222	3.5173e-04
		10,000	[2 2 2 2 2]	222	3.3672e-04
	50	1,000	[2 2 2 2 2]	222	1.0337e-03
		2,500	[2 2 2 2 2]	222	5.3226e-04
		5,000	[2 2 2 2 2]	222	4.0080e-04
		10,000	**[2 2 2 2 2]**	**222**	**2.5861e-04**
48	**30**	10,000	[2 2 2 2 3]	321	3.2693e-04
		10,000	[2 2 2 3 2]	321	2.7346e-04
		10,000	[2 2 3 2 2]	321	3.1378e-04
		10,000	**[2 3 2 2 2]**	**321**	**2.7151e-04**
		10,000	[3 2 2 2 2]	321	2.7329e-04
	50	10,000	[2 2 2 2 3]	321	2.7454e-04
		10,000	[2 2 2 3 2]	321	3.1121e-04
		10,000	[2 2 3 2 2]	321	2.8375e-04
		10,000	[2 3 2 2 2]	321	2.7755e-04
		10,000	[3 2 2 2 2]	321	2.8525e-04

After the training dataset were obtained, ANFIS was trained in the first step of the simulation; that is, the parameters of the ANFIS structure were optimised by using BSO algorithm. Mean squared error (MSE) was chosen as the performance criterion to show the performance of the optimisation. Thus, it is aimed to minimise the MSE value with BSO algorithm and to calculate the parameter values that will give the optimum ANFIS structure. Total number of parameters to be calculated for optimisation of ANFIS structure parameters varies depending on the number of inputs, the number of rules, the type and number of membership functions, selected.

For this purpose, different models by using 32 and 48 rule numbers were created for the five-input-single-output structure, and a triangular membership function was preferred in each model. In ANFIS, a minimum of two membership functions must be used for each input. The number of 32 rules was obtained by using two membership functions for each input. The number of 48 rules was obtained by using two membership functions for four inputs and three for a single input. Considering the studies in the literature and the dataset used, increasing the number of rules is not appropriate in terms of time and practicality [31]. In the models formed with 32 rules, the control parameters of BSO algorithm were preferred as 20 runtimes and 1,000, 2,500, 5,000 and 10,000 iteration numbers for each of the 30 colony and 50 colony sizes, respectively. In the models formed with 48 rules, the control parameters of BSO algorithm were preferred as 20 runtimes and only 10,000 iteration numbers using the combinations of membership function numbers (two or three) for each of the 30 colony and 50 colony sizes. In Table 1, the best MSE values obtained as a result of BSO algorithm-based ANFIS training simulations for different rules and colony numbers are given.

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Table 2. *Input and output values obtained as a result of the optimisation phase*

			Obtained input values						Obtained output value
Number of rule	MSE (Training)	MSE (Optimisation)	Propeller diameter	Propeller pitch	Current	Voltage	ESC		Thrust
32	2.5861e-04	5.3449e-01	11.36	5.34	29	16.80	2000		1.77
48	2.7151e-04	5.3506e-01	12.39	7.61	29	15.81	2000		1.70

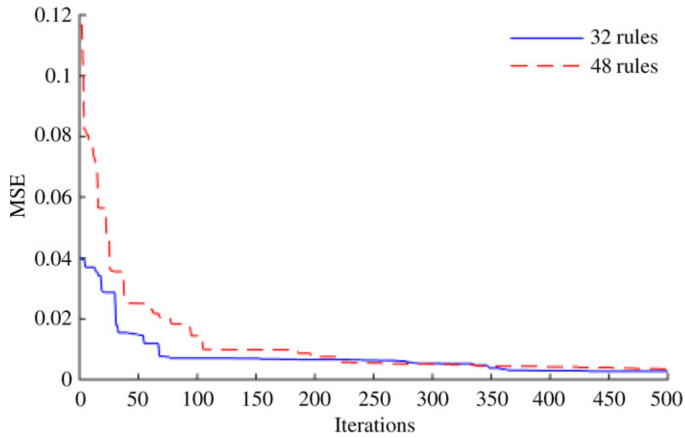

Figure 3. *Iteration-MSE change graph for better models obtained for 32 and 48 rules during the training phase.*

It is seen from Table 1, for 32 rules that the ANFIS structure with an MSE value of 2.5861e-04 in the simulation with 50 colony sizes and 10,000 iterations, is better than other structures. For 48 rules, it is seen that the ANFIS structure with an MSE value of 2.7151e-04 in the simulation with 30 colony sizes and 10,000 iterations and the combination of [2 3 2 2 2] membership function is better than the other structures. As a result of the simulations made with 32 and 48 rule numbers, the iteration-MSE change graph for the models determined to be better is given in Fig. 3. In Fig. 3, the first 500 iterations are presented for clarity.

After the selection of the most suitable ANFIS structure in the training phase, the thrust optimisation phase was started. Here, the selected ANFIS structure was integrated into the BSO algorithm as the objective function. Thus, how the thrust is affected by the choice of battery and propeller is examined and it is aimed to obtain the optimal thrust value. In this process, the control parameters of the BSO algorithm were selected as 30 and 50 colony sizes, 50 iterations and 10 runtimes. As a result of the simulations, the best MSE value obtained for 32 rules during the optimisation phase was calculated as 5.3449e-01. The best MSE value obtained for 48 rules during the optimisation phase was calculated as 5.3506e-01.

In Table 2, the input and output values obtained for the optimal structures with the smallest MSE values for 32 and 48 rules are given. When Table 2 is examined, it is seen that the input values obtained are between the lower and upper limit values determined for the optimisation process. It is seen that the thrust value obtained with the model with 32 rules is better than the thrust value obtained with the model with 48 rules. Table 2 emphasises the suitability of the simulations performed with the proposed models. In Fig. 4, the comparison of the obtained output values with the actual output values is presented. When Fig. 4 is examined, it can be seen that the values obtained in the simulation results made with the proposed models are satisfactory when compared with the actual results.

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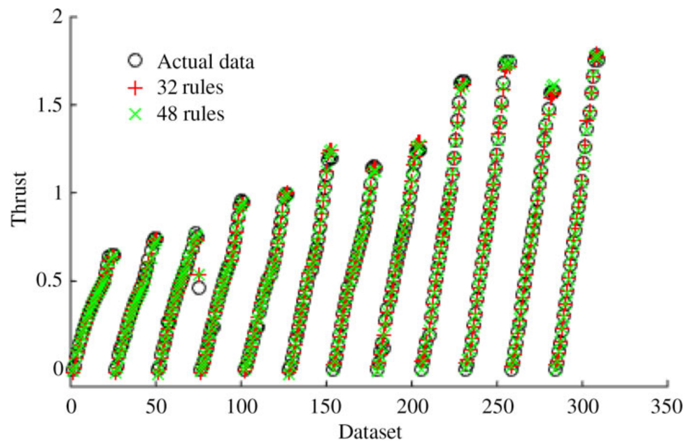

Figure 4. *Comparison of the obtained output values with the actual output values.*

6.0 Conclusions

In this study, BSO algorithm-based ANFIS model is presented for the first time to improve thrust performance. By associating the engine, battery and propeller, which are not directly related, ANFIS provides increasing of a small number of data, but it is insufficient in the optimisation phase where the most appropriate value can be selected. While BSO algorithm is sufficient in the optimisation phase where the most appropriate value can be selected, it is not sufficient in relating the parameters. In this study, in the proposed method for improvement of the UAV thrust, the ANFIS structure is chosen to relate all the selected input and output parameters, and BSO algorithm is preferred to determine the most appropriate values for the improvement and optimisation of the thrust performance.

In the simulations made for all models formed using different rules, membership functions, colony sizes and iteration numbers, it has been paid attention that the input parameters affect the thrust output equal importance and simultaneously. Obtained results are presented with tables and figures. When the results are evaluated in general, it is seen that the number of 32 rules is better than the number of 48 rules. The satisfactory MSE values obtained as a result of the simulations emphasise that the proposed method can enable the evaluation of different possibilities and can be an alternative to the studies in the literature. In addition, it is seen that in UAV thrust designs, this novel model can provide effective results for different parameter values by reducing the time loss and contribute to the studies of other researchers.

Data availability statement. All data used during the study are available from the corresponding author by request.

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Cite this article: Konar M., Arık Hatipoğlu S. and Akpınar M. Improvement of UAV thrust using the BSO algorithm-based ANFIS model. *The Aeronautical Journal*, https://doi.org/10.1017/aer.2024.30