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Redesign of Morphing UAV for Simultaneous Improvement of Directional Stability and Maximum Lift/Drag Ratio

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***Abstract*—This paper presents a novel method based on the artificial intelligence to redesign of morphing Unmanned Aerial Vehicle (UAV) for improvement of index consisting of directional stability and maximum lift/drag (L/D) ratio. In this study, Artificial Neural Network (ANN) based objective function is optimized with Artificial Bee Colony (ABC) algorithm. Firstly, the sweep angle is selected as input parameter and directional stability and maximum L/D ratio are selected as output parameters for ANN. ANN is trained with a small number of data obtained by the computational fluid dynamics method and the trained ANN is used for multiplying these data. Two ABC optimization algorithms with different objective functions are used to improve the index consisting of directional stability and maximum L/D ratio: While the first is used the adjustment of the ANN weights, the second is used the optimization of the ANN based objective function. Simulation results realized with limited data show that although directional stability and maximum L/D ratio have inverse relation, they are optimized equally and simultaneously. Thus, the artificial intelligence techniques provide fast and accurate determination of the optimal aerodynamic shape of UAV without time consuming and complexity caused by theoretical calculations.**

***Index Terms*—unmanned aerial vehicles, stability, artificial intelligence, neural networks, optimization.**

I. Introduction

One of the most important criteria in the Unmanned Aerial Vehicle (UAV) design is to obtain the optimum aerodynamic shape of UAV according to the desired aim, since UAV's aerodynamic shape has a significant effect on both controlled flight and autonomous flight performance. How the parameters such as the sweep angle (Λ), the dihedral angle, the taper ratio will affect the flight performance, how to set the upper and lower limits of these parameters are determined by using theoretical, numerical and experimental approaches along with the designers' experience. The validity of theoretical approaches is supported by Computational Fluid Dynamics (CFD) and experimental (wind tunnel) approaches.

In the literature, the studies on the improvement of the aerodynamic shape of UAVs, lift/drag ratio is often considered as one of the parameters that significantly affects flight performance [1-4]. In these studies, the effects of different parameters on the lift/drag ratio were investigated by CFD and wind tunnel experiments. However, since CFD method is a time consuming method, it requires several weeks of additional work for the smallest change in aerodynamic shape of UAV. In wind tunnel method, experiments and the procedures after experiments cause great costs.

In order to overcome these mentioned problems and provide UAV design simplicity, several approaches based on artificial intelligence techniques are presented in the literature [5-10]. Huang et al. trained the neural network with an acceptable error for lift, drag and moment coefficients with respect to the angle of attack to design airfoil [5]. Rajkumar and Bardina calculated the lift, drag and pitch moment as a function of Mach number and angle of attack. They obtained the training data from numerical simulations and wind tunnel experiments [6]. In the work presenting by Djavareshkian and Esmaeili, they used a combination of Particle Swarm Optimization (PSO) and Adaptive Neuro Fuzzy Inference Systems (ANFIS) to optimize the shape and the working conditions of the hydrofoil used under the sea [7]. Hacioglu designed an inverse wing profile using Genetic Algorithm (GA) enhanced with an Artificial Neural Network (ANN) and in his another study; he adapted this work with simulated annealing for better fitness [8], [9]. Secco and Mattos used ANN for calculating lift and drag coefficients as a function of the wing planform, airfoil geometry and flight condition [10]. When the studies in the literature are examined, there are no studies that examine both directional stability ($C_n\beta$) and maximum lift/drag ratio (also called maximum fines in the literature) together. Since directional stability and maximum lift/drag ratio (E_{max}) have inverse relation, simultaneous optimization of these two parameters is difficult.

In this study, this problem that is not available in the literature is discussed and a novel method based on artificial intelligence techniques is presented for improvement of index consisting of two parameters mentioned above. In this context, firstly input and output parameters were identified. The sweep angle was selected as the input parameter. Sweep angle is generally used in aerial vehicles in order to decrease effects of shock waves during transonic flights [11]. However, sweep angle also improves lateral stability of aerial vehicles [12]. Therefore, in this article it is aimed to find the most suitable sweep angle value giving the optimum directional stability and maximum lift/drag ratio. For this

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reason, sweep angle was selected as input parameter and the directional stability and the maximum lift/drag ratio were selected as the output parameters for the neural model. The training data set were obtained by CFD method as a function of the sweep angle, but the numbers of data were limited due to the time consuming of the CFD method. ANN is trained with these data and the training of the ANN is possible by changing the weights. In this study, Artificial Bee Colony (ABC) algorithm was used instead of traditional learning algorithms in order to determine optimum weights. After adjusting the weights, the ABC algorithm was used for a second purpose in the next step of the study. The objective function based on the optimal weighted ANN structure obtained in the previous step was optimized to improve the index consisting of directional stability and the maximum lift/drag ratio by adapting with the ABC algorithm. The objective function was limited to the lower and upper bounds of the values available in the data set. Although few training data were produced since CFD method was a time-consuming method, the simulation results are satisfactory. Although the directional stability and the maximum lift/drag ratio have inverse relation, these parameters are optimized simultaneously and equally.

The rest of the study is as follows: In the next two sections, brief information is given about the algorithm and neural network used in the study. Then the simulation method and its results, discussion and references are presented.

II. Artificial Bee Colony Algorithm

Artificial Bee Colony (ABC) algorithm that is an optimization technique based on swarm intelligence was presented by Karaboga in 2005 [13], [14]. Researchers to solve a wide range of optimization problems used the ABC algorithm that has some fascinating features such as including few parameters, simple operation principle and easily applicable.

The ABC algorithm is an optimization algorithm that models intelligent food search behaviors of honeybees. There are three kinds of bees in the ABC: employed, onlooker, and scout bees. The basic operation principle of the ABC algorithm is as follows: Firstly, the initial food sources are generated randomly and the employed bees select a food source. The onlooker bees choose the food source with certain probability by monitoring the dances of the employed bees that store nectar and return to the hive. The onlooker bees that go to the selected food source start to store nectar like the employed bees. After a certain limit value, the employed bees who consume food sources become scout bees to search for new sources. The scout bees also continue to store nectar by finding a random food source. These steps that constitute a cycle of the algorithm continue until the reaching stopping criteria.

III. Artificial Neural Network

Artificial Neural Network (ANN), which has the basic processing element artificial neural cell called neuron, is able to learn events through examples, to create and to discover new information according to the information learned. Thus, ANN aims to give some features to the systems such as learning automatically and generalization [15-17]. While ANN has gained these abilities from humans to systems, it forms the mathematical model of a large number of neuron combinations.

In this study, feed forward ANN structure was used. In a feed forward ANN, the outputs of the cells in one layer are applied as input to the next layer via the weights. That is, the output value of the cells at any given time is only the function of the input at that moment. A basic feed forward ANN given its general structure in Fig. 1 consists of three basic parts: input, hidden and output layer. In these layers, there are five basic structures: inputs, weights, transfer function, activation function, and output [17], [18].

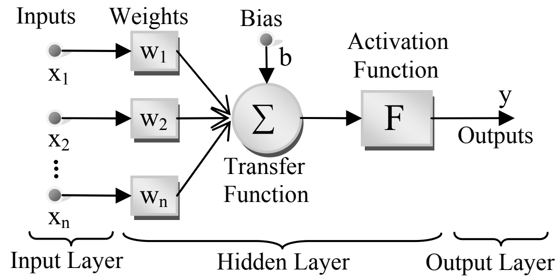

Figure 1. The general structure of a feed forward ANN

The weighted transfer function is calculated by the equation given in (1) where w is weight, x is input, n is the number of the cell input and b is bias value. The activation function determines the net output in response to this net input and transfers it to the output. In this study, to evaluate the performance of the ANN models, the Mean Squared Error (MSE) performance criterion was chosen.

$$NET = \sum_{i=1}^{n} w_i x_i + b \qquad (1)$$

IV. Simulation Results

In this section, the study is systematically presented to demonstrate the effectiveness of the proposed method. In this study, the features of our UAV ZANKA-II produced at Erciyes University, Faculty of Aeronautics and Astronautics, Model Aircraft Laboratory were utilized. Moreover, in our laboratory, a Tactical UAV (TUAV) was also produced and some results were shared in [19]. In this study, training data set were obtained from our UAV ZANKA-II using CFD analysis. An important feature of ZANKA-II is that wingspan of ZANKA-II is able to reach 1.76m after 10% percent active morphing. The parameter values obtained after the optimization process were again tested and verified using CFD on UAV ZANKA-II. The image of ZANKA-II is shown in Fig. 2 and some features of ZANKA-II are given in Table I [20-22].

Figure 2. ZANKA-II

A. Obtaining the Data Set for Selected Parameters

In this study, the sweep angle was selected as input

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parameter; the directional stability ($C_n\beta$) and the maximum lift/drag ratio (E_{max}) were selected as output parameters. The sweep angle can be defined as the angle between the 25% chord line and the lateral axis. The use of wing sweep in aircraft is to reduce the value of the number of critical mach. Wing structure without sweep angle will arrive early in the number of critical Mach, in this case it will create a shock wave and increase drag force [11]. The directional stability and the maximum lift/drag ratio are important parameters affecting flight performance. Therefore, these three parameters were selected in this study.

TABLE I. UAV ZANKA-II PHYSICAL PROPERTIES

Feature	Size
Total weight	6.5 kg
Effective weight	3 kg
Wingspan	1.6 m
Wing mean aerodynamic chord	25 cm
Aspect ratio of wing	6.4
Engine	Brushless DC motor
Theoretical maximum range	30 km
Theoretical maximum endurance	0.5 h
Velocity required for maximum endurance	50 km/h
Active morphing	Yes

Maximum lift/drag ratio was calculated based on the sweep angle ranging from 0-10 degrees using the Ansys Fluent as CFD approach. For the aircraft, mesh images are shown in Fig. 3, mesh properties are given in detail in Table II. Mesh number and quality are very important for the correctness of Ansys Fluent results. The skewness value must be at most 0.98 for the correctness of the results. The mesh skewness value of 0.93663 is obtained as shown in table. Since the value of the mesh number influences the result of the analysis significantly, it is necessary to throw the mesh at the optimum value. Increasing the number of meshes gives more accurate results and increases the analysis process. Therefore, different mesh numbers were tried and the number of meshes was increased step by step until the lift force did not change with the mesh number. Patch Conforming/Sweeping mesh method and the minimum number of elements 0.0005 were selected to obtain the optimum mesh values.

The E_{max} was calculated according to equation set in (2) by using the values of lift (c_L) and drag (c_D) coefficients obtained with Ansys Fluent. The $C_n\beta$ was determined according to equation in (3) for the values of sweep angle (Λ) ranging from 0-10 degrees [12].

$$\begin{cases} E = \dfrac{L}{D} = \dfrac{c_L}{c_D} = \dfrac{c_L}{c_{D_0} + k\, c_L{}^2} \\ \dfrac{dE}{dc_L} = 0 \quad \Rightarrow c_L = \sqrt{\dfrac{c_{D_0}}{k}}, \;\; c_D = 2c_{D_0} \\ E_{\max} = \dfrac{1}{2\sqrt{k\, c_{D_0}}} \end{cases} \tag{2}$$

$$\begin{cases} C_{n_{\beta v}} = V_v \cdot \eta_v \cdot C_{L\alpha v} \cdot \left(1 + \dfrac{d\sigma}{d\beta}\right) \\ \eta_v \left(1 + \dfrac{d\sigma}{d\beta}\right) = 0.724 + 3.06 \dfrac{S_v/S}{1+\cos\Lambda_{c/4w}} + 0.4\dfrac{z_w}{d} + 0.009 AR_w \end{cases} \tag{3}$$

where k is a constant in (2). In (3), v index is vertical state, V_v is the vertical tail volume ratio, η_v is the tail efficiency factor. σ is the sidewash angle and β is the sideslip angle. S is the wing area, S_v is the vertical tail area, z_w is the distance from wing root quarter chord point to fuselage centerline, d is the maximum fuselage depth, AR_w is the aspect ratio of the wing, $\Lambda_c/4w$ is the sweep of wing quarter chord [12]. Thus, the upper and lower limit ranges for the obtained dataset are given in Table III.

TABLE II. MESH PROPERTIES

Mesh Properties	
Minimum Element Size	0.0005 m
Number of Elements	3.356919
Maximum Size	0.2 m
Maximum Face Size	0.35 m
Growth Rate	1.2
Curvature Normal Angle	18
Mesh Method	Patch Conforming / Sweeping
Skewness	0.93663

When a set of equations and the CFD method are used for each design, it is very time consuming to produce $C_n\beta$ and E_{max} data and determine the optimum value of these parameters simultaneously. In the optimization process, it is important that the objective function containing these two parameters is chosen in such a way as to facilitate calculation. For this reason, in this study, ANN based objective function was chosen. ANN was trained with a small number of generated data sets and was integrated with ABC algorithm to improve index consisting of $C_n\beta$ and E_{max}. Thus, simultaneous optimization of $C_n\beta$ and E_{max} was achieved in a simple, fast and accurate manner.

TABLE III. THE UPPER AND LOWER LIMIT VALUES OF INPUT AND OUTPUT PARAMETERS.

	Symbol	Definition	Dimension	Range Values
Input Parameters	Λ	Sweep Angle	[°]	0°-10°
Output Parameters	$C_{n\beta}$	Directional Stability	[ ]	4.5387e-03-4.6874e-03
	E_{max}	Maximum Lift/Drag Ratio	[ ]	5.088100-5.564000

B. Selecting the ANN Structure and Determining Optimally with ABC Algorithm

The number of data set is very important in determining the optimal ANN structure to be used as the objective function. However, in the previous section, it is stated that it is time consuming to generate E_{max} data set by CFD method. Therefore, ANN training was carried out with 10 data in this study. The trained ANN was used at a successful estimation of $C_n\beta$ and E_{max} values for different sweep angle values not used at training at the optimization process. The test and verification data were not used since the number of data was small. For this reason, ABC algorithm was chosen instead of traditional algorithms as learning algorithm during training in order to obtain small error value. Since the training of the network is possible by adjusting the weights, the weight values are adjusted until the error value is satisfactory. The reason for choosing the ABC algorithm is that the number of control parameters is small and the designer can easily control these parameters. In this study, control parameters

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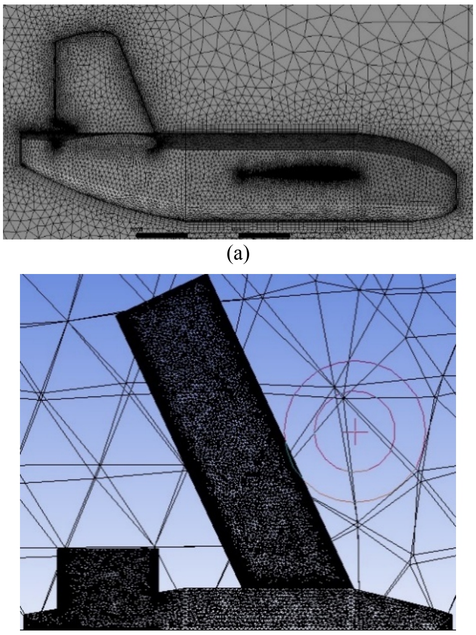
were determined as 5000 iterations and 30 runtime for 30 and 50 colony sizes, respectively. Simulations were carried out for different control parameter values, but the results of the mentioned values were presented.



(a)

(b)

Figure 3. Mesh images of Aerial. Side view (a); Top view (b)

After these selections, different simulations were carried out to determine the number of hidden layers and the number of neurons in hidden layers. The choice of the number of neurons is important. If the number of neurons is small, the neural network may not be able to approach the desired output. If the number of neurons is chosen too much, over-learning can occur, meaning that the ANN structure gives the correct result for several test data, but does not give the correct result for other situations. In order to demonstrate the effectiveness of the proposed method, it is aimed to obtain effective results with a simple network structure. For this reason, a network structure with a single hidden layer, which block diagram was given in Fig.4, is selected and simulations were made for different neuron numbers in this hidden layer.

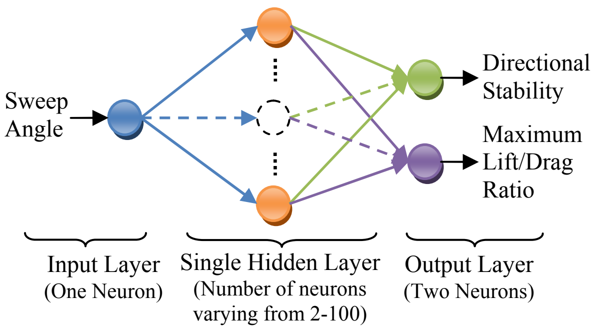


Figure 4. The block diagram of selected ANN structure

In addition, in this study, a feed forward ANN was preferred. As activation functions, logarithmic sigmoid and tangent sigmoid functions were preferred since they were frequently used in the literature. The MSE performance function was used to evaluate ANN performance.

The results of the simulations made for the specified properties are given in Table IV. Fig.5 shows the iteration-MSE change graph of ANN models. From Table IV, the best MSE value was obtained as 2.9356e-04 with 50 colony sizes in logsig activation function in 1x5x2 ANN structure. In addition to the data given in Table IV, simulations were realized for different numbers of neurons, but results are not given in table because the MSE values were not better. The MSE values of simulations realized with 25, 50, 75, 100 neurons and logsig activation function were 3.9315e-04, 4.8810e-04, 4.2200e-04, 5.8545e-04 for 30 colony sizes, respectively; 3.5776e-04, 3.7333e-04, 5.4214e-04, 3.9500e-04 for the 50 colony sizes, respectively. Similarly, the MSE values of simulations made with 25, 50, 75, 100 neurons and tansig activation function were 1.7706e-03, 2.7294e-02, 8.9849e-02, 9.7303e-02 for 30 colony sizes, respectively; 9.1536e-04, 6.4231e-02, 1.0636e-01, 1.5042e-01 for the 50 colony sizes, respectively. The best, worst, average MSE values and standard deviation values obtained in the optimum ANN model were given in Table V.

TABLE IV. THE BEST MSE VALUES OBTAINED FROM THE END OF TRAINING OF ANN WITH THE ABC ALGORITHM FOR DIFFERENT ACTIVATION FUNCTIONS WITH DIFFERENT NUMBERS OF NEURONS IN THE HIDDEN LAYER

Hidden Layer	Activation Function	Colony Size=30	Colony Size=50
		Training Error (MSE)	Training Error (MSE)
2	Logsig	7.7606e-04	7.4387e-04
	Tansig	2.7435e-03	2.2615e-03
3	Logsig	5.9273e-04	5.6144e-04
	Tansig	2.9009e-03	1.5468e-03
4	Logsig	5.0888e-04	4.0992e-04
	Tansig	1.3981e-03	1.1068e-03
5	Logsig	3.6162e-04	**2.9356e-04**
	Tansig	7.9233e-04	8.8391e-04
10	Logsig	3.5461e-04	3.7843e-04
	Tansig	6.8856e-04	**5.1859e-04**
15	Logsig	**3.3260e-04**	3.1463e-04
	Tansig	**3.5944e-04**	6.2941e-04

TABLE V. MSE AND STANDARD DEVIATION VALUES OBTAINED FOR DIFFERENT ASSUMPTION

Performance Criteria		Logsig	Tansig
MSE	The best	2.9356e-04	3.5944e-04
	The worst	9.3014e-04	9.1950e-02
	Average	5.8489e-04	1.3477e-02
Standard deviation		1.4616e-04	2.3176e-02

C. Estimating the Maximum of ANN Based Objective Function by ABC Algorithm

In estimation problems, it is very important to define the objective function for the optimization algorithm. To improve the index consisting of $C_n\beta$ and E_{max} in this study, the ANN based objective function was chosen in the estimation of the sweep angle. The reason for selecting ANN based objective function is to replicate a small number of data sets and to make a more accurate estimate of the sweep angle to improve the index consisting of $C_n\beta$ and E_{max} by using the learning and generalization feature of the ANN.

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However, $C_n\beta$ was improved which is our priority aim in this study.

In order to determine the ANN-based objective function optimally, simulations were made with different assumptions in the previous step. From Table IV, the ANN structures with the smallest error values for different activation functions were determined as the optimum structure and the objective function was integrated into the ABC algorithm. Since the objective function is based on ANN, a fast solution is made without too many iterations in the optimization process. For this reason, the control parameters of the ABC algorithm were selected to 50 iterations and 1 runtime for 30 and 50 colony sizes, respectively.

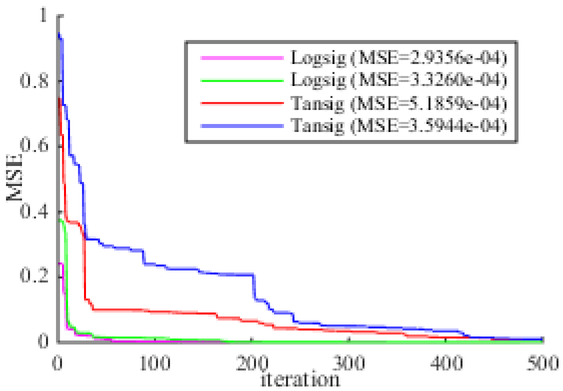

Figure 5. The iteration-MSE graph of the ANN models

In Table VI and VII, the MSE values and input/output values are given for the simulation results realized with the objective functions based on optimum ANN structure (1x5x2 for logsig activation function with 50 colony sizes and 1x15x2 for tansig activation function with 30 colony sizes). For logsig activation function, while $C_n\beta$ and E_{max} were estimated as 4.6084e-03 and 5.2305 at 7.1640° in the first iteration, $C_n\beta$ and E_{max} were estimated as 4.6119e-03 and 5.2225 at 7.3179° in the 50th iteration. For tansig activation function, while $C_n\beta$ and E_{max} were estimated as 4.5394e-03 and 5.3053 at 5.7791° in the first iteration, $C_n\beta$ and E_{max} were estimated as 4.5394e-03 and 5.3198 at 5.6731° in the 50th iteration.

TABLE VI. THE MSE, AND INPUT-OUTPUT VALUES OBTAINED IN THE OPTIMIZATION PROCESS FOR LOGSIG ACTIVATION FUNCTION

Logsig Activation Function				
Iteration	**Optimization Error (MSE)**	**Obtained Input Values**	**Obtained Output Values**	
		Λ	$C_{n\beta}$	E_{max}
1	7.7321e-01	7.1640°	4.6084e-03	5.2305
2	7.7266e-01	7.3880°	4.6136e-03	5.2188
3	7.7251e-01	7.3283°	4.6122e-03	5.2220
4	7.7251e-01	7.3283°	4.6122e-03	5.2220
5	7.7251e-01	7.3252°	4.6121e-03	5.2221
10	7.7251e-01	7.3171°	4.6119e-03	5.2226
50	7.7251e-01	7.3179°	4.6119e-03	5.2225

TABLE VII. THE MSE, AND INPUT-OUTPUT VALUES OBTAINED IN THE OPTIMIZATION PROCESS FOR TANSIG ACTIVATION FUNCTION

Tansig Activation Function				
Iteration	**Optimization Error (MSE)**	**Obtained Input Values**	**Obtained Output Values**	
		Λ	$C_{n\beta}$	E_{max}
1	4.2218e-01	5.7791°	4.5394e-03	5.3053
2	4.1246e-01	5.6939°	4.5394e-03	5.3168
3	4.1238e-01	5.6916°	4.5394e-03	5.3172
4	4.1228e-01	5.6887°	4.5394e-03	5.3176
5	4.1211e-01	5.6805°	4.5394e-03	5.3187
10	4.1205e-01	5.6729°	4.5394e-03	5.3198
50	4.1205e-01	5.6731°	4.5394e-03	5.3198

V. CONCLUSION

In this study, the effectiveness of artificial intelligence methods is emphasized and the use of these methods in aviation field is evaluated with a new example and a novel method.

For this purpose, the features of our Unmanned Aerial Vehicle (UAV) ZANKA-II produced at Erciyes University, Faculty of Aeronautics and Astronautics, Model Aircraft Laboratory were utilized. First, morphing parameters were determined and data were obtained using ZANKA-II by Computational Fluid Dynamics (CFD) method. The sweep angle was selected as the input parameter; the directional stability ($C_n\beta$) and the maximum lift/drag ratio (E_{max}) were selected as the output parameters. Since $C_n\beta$ and E_{max} have inverse relation, a good objective function should be defined in the optimization algorithm to be able to simulate these two parameters simultaneously. In this study, the objective function was based on Artificial Neural Network (ANN). Thus, it was aimed to make the parameter estimation more accurately by using the generalization and learning feature of ANN. As the optimization algorithm, the Artificial Bee Colony (ABC) algorithm was chosen since ABC algorithm is convenient for the designer due to three control parameters and used effectively in the literature. The ABC algorithm was used for two purposes in this study. The first use was the adjustment of ANN weights, and the second use is to maximize the objective function based on the optimal weighted ANN structure to determine the appropriate sweep angle to improve the index consisting of $C_n\beta$ and E_{max}.

In the simulation results, the value of $C_n\beta$ increases while the value of E_{max} decreases. However, this decrease in the E_{max} value is kept to a minimum as much as possible against the increase in $C_n\beta$ value. So that $C_n\beta$ is improved which is our primary aim. When looking at simulations made with different assumptions, it was seen that the best ANN structure was obtained in 50 colony sizes with 5 neurons and logsig activation function. When looking at the optimization process, the simulation realized with tansig activation function is 87.47% better than realized with logsig activation function. In the simulations realized with logsig activation function, while $C_n\beta$ value improved by 0.076%, E_{max} value decreased by 0.152%. In the simulations realized with tansig activation function, while $C_n\beta$ value improved little, E_{max} value improved by 0.271%. On the other hand, if we take the initial conditions of UAV design, in the simulation results, $C_n\beta$ value improved by 1.587%, E_{max} value decreased by 6.137% for logsig activation function,

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and $C_n\beta$ value improved by 0.015%, E_{max} value decreased by 4.389% for tansig activation function. The obtained results obtained were tested and verified on ZANKA-II by CFD method.

Simulation results realized with few data show that the artificial intelligence techniques could prevent time loss with fast, simple and accurate determinations in UAV designs and in the improvements in designs. In addition, enhancing the number of data set may increase the accuracy of the proposed artificial intelligence techniques based approach. The proposed method can be successfully used in determining the optimal aerodynamic shape of UAV by using different data set.

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