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Airfoil Optimization with Metaheuristic Artificial Bee Colony Algorithm Supported by Neural Network Trained Using Nasa-Foilsim Data

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Abstract

In this study, the wing profile, which is difficult to calculate and determine, has been optimized with the help of Foilsim data and optimization algorithms. Foilsim data provided by NASA (National Aeronautics and Space Administration) and used by many researchers, especially in developing model airplanes, has been provided to use in aircraft wing shape optimization. Although Foilsim is a very useful simulation program for designers, it cannot be used effectively in optimization processes due to its web environment. Lift coefficient is needed for Lift equation in airfoil shape optimization. Lift coefficient depends on angle, camber, and thickness of airfoil Calculation of Lift coefficient is difficult and needs heavy mathematical equations or real experiments. By using Foilsim data and optimization algorithm (Artificial Neural Networks: ANN, Artificial Bee Colony: ABC), wing angle, camber and thickness values, which are difficult to determine and calculate, were estimated and comparative experiments of the values were made. (Fixed Lift, Fixed Speed, Fixed Wing Area). Experimental results have shown that it is a useful study for airfoil shape optimization. In short, in this study, by using the Foilsim data and the optimization algorithm to provide the lifting force determined by the designer, the most suitable angle, camber, thickness values of the wing, which are difficult to determine and calculate, are determined to enable the production of efficient aircraft. The user enters the desired lift value into the ABC optimization algorithm and finds the required wing properties for the desired lift value.

1. Introduction

Many research projects in aviation include metaheuristic optimization algorithms such as Genetic Algorithms, Bee Colony Algorithm, Artificial Neural Networks, or Ant Colony Algorithm on topics such as newly optimized flight trajectories, wing shapes, control technique research (Koreanschi et al., 2017). Aerodynamic shape design is the basic step of aircraft design, wing profile optimization is the most important part of aerodynamic shape design (Ma et al., 2017). The Lift-drag ratio is perhaps one of the most important considerations in the design of wings such as airplane wings (MacEachern & Yildiz,2018).

The use of optimization methods has become common for design support tool and automated design in the aerodynamic design process (Koziel & Leifsson, 2013).

CFD (Computational Fluid Dynamics) methods are used for airfoil optimization. CFD method handles aerodynamic shape optimization in 3 different ways. These are the gradient-based method, the gradient-free method, and the surrogate model.

The Gradient-Based method also uses gradients of cost functions according to design variables. The first studies of this method for aerodynamics were made by Hick and Henne (Hicks & Henne, 1978).The disadvantages of this method are that it changes each design variable and needs to recalculate the flow area, as well as the large computational cost associated with directly evaluating gradients using the finite difference method. This method was first avoided by Jameson in 1988 by indirectly evaluating the gradient through the combined method (Jameson, 1988; Jameson, 1995). The adjacent-based optimization method is very effective, the optimum can be approached within 5-100 design cycles (Jameson & Martinelli, 2000).

Gradient-free methods are of great interest, because they have global optimization capability. Adjacent-based gradient-based optimization method has a local optimization method. For example, Genetic Algorithms and Particle Swarm Algorithm. Evolutionary algorithms (EA) are the most popular global optimization method. Evolutionary algorithms have proven to be of great importance in finding the global optimum, but the high computational cost and the need for a large number of CFD simulations make this method difficult to use (Han et al., 2013).

Design problems in engineering methods require a large number of real-time experiments and computational simulations to evaluate and provide the design objectives of the problems that are subject to various constraints (Mukesh et al., 2018). A surrogate model is an engineering method used when an outcome of interest cannot be easily measured (“Surrogate model”, 2022).

When the recent studies are examined, the surrogate model optimization attracts great attention (Han et al., 2015). The purpose of surrogate modeling is to correlate the input and output data through the trained neural network model (Sun & Wang, 2019). A surrogate model is an approximate model that is inexpensive to evaluate. This feature distinguishes it from target and constraint functions that are expensive to evaluate. Once a surrogate model is created, it can be used to replace a physical CFD model to estimate the cost function or state function during the optimization process. In this case, a surrogate model is used instead of a CFD solver, since a surrogate model is more efficient (Han et al., 2015). Today, surrogate- assisted metaheuristic optimization algorithms have been used to solve many computationally costly problems. The surrogate model was created based on many techniques. Such as Polynomial Regression, Radial basis Function, Support Vector Regression, and Artificial Neural Network (ANN).

Based on these models, metaheuristic optimization studies have been applied by various researchers for aerodynamic optimization aircraft wing design (Mar Aye et al., 2020).

In order to train the network we used in this study, we preferred the surrogate method using artificial neural networks, which does not require CFD analysis. ANN based surrogate model is trained with Foilsim Data with 3 Inputs (Angle, Camber, Thickness) and 1 Output (C_L: Lift Coefficient).

For training in ANN, a data set consisting of 8000 samples with angle, camber and thickness values was taken from Foilsim web page. In this dataset, 5-fold cross validation cross validation method was used to estimate the lift coefficient from Angle hump and thickness values. In K-fold cross validation, the input data is divided by the 'K' coefficient. For this reason, it is called K-folding. Since 5-fold cross validation is used in this study, we have 5 sets of data to train our model. Thus, the model was trained and tested 5 times. However, in each iteration, it will use the multiple of 1 for testing and all the remaining remainders for training.

In this article, with the help of the trained ANN model, the optimization problem is solved by using the ABC Algorithm. In this way, when a designer wants to design an airfoil, he can proceed to the design process with ideal airfoil parameters and benefit from our study and experiments, without wasting time and without difficult CFD methods.

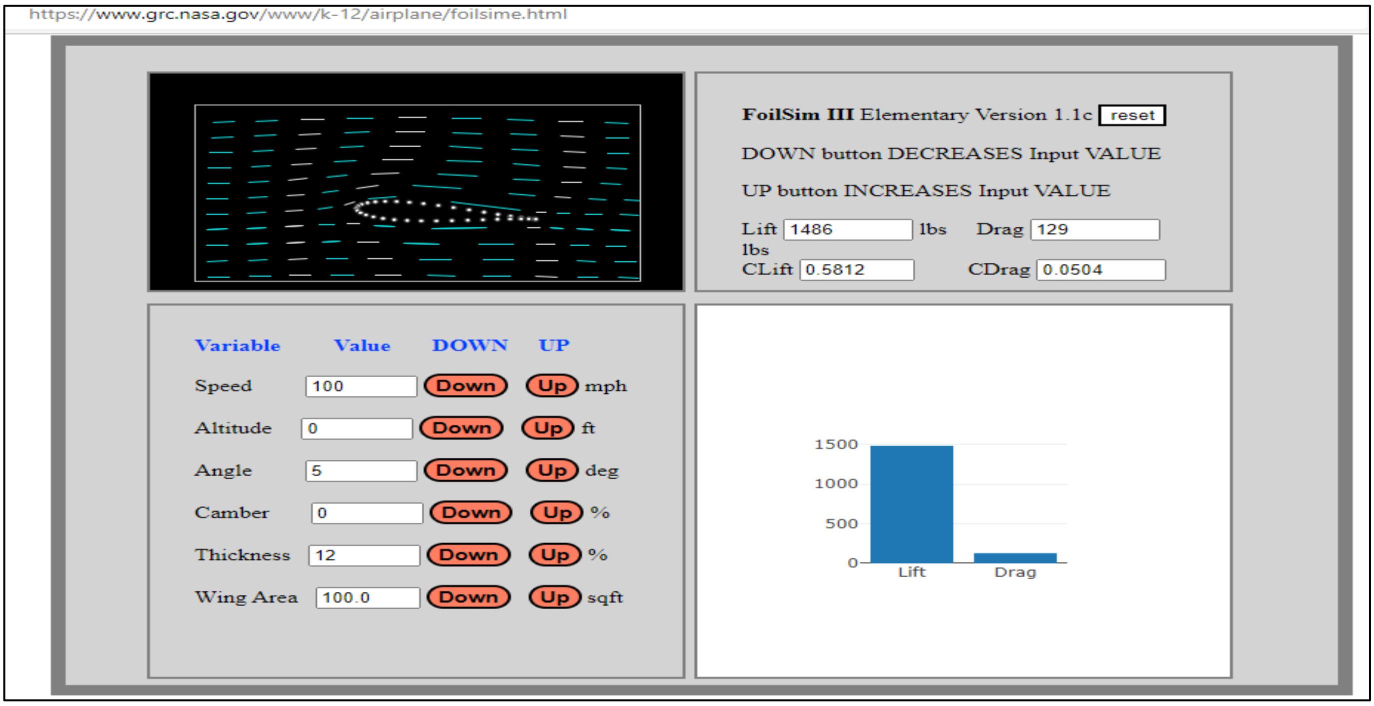

Figure 1. Foilsim Webpage and User Interface

2. Materials and Methods

2.1 Problem Definition

In this study, an optimization approach with a surrogate model is presented to predict airfoil parameters. The most commonly used method for aircraft aerodynamics is the lift-drag ratio, as it determines the aircraft's range and endurance. Foilsim is web software that works in the web environment and provides information to the designers about the amount of lift and drag according to the parameters of the aircraft wing (angle, camber, thickness, velocity, and wing area).

Although Foilsim is a very useful simulation program for designers, it cannot be used effectively in optimization cannot be solved without using algorithms, this problem has been handled in this study.

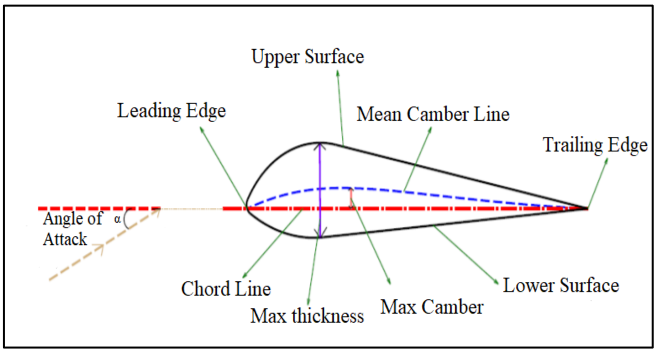

Figure 2. Airfoil Shape

The image in Figure 2 is obtained when a wing is cut parallel to the direction of flight (in the direction of the fuselage).

Angle of attack is the angle that the oncoming airflow makes with the airplane flight line and the chord line. The change in angle of attack affects the lift. Camber is the line connecting the points between the upper and lower surfaces of the wing profile along the chord line. In symmetrical profiles, this is already the chord line. The distance from any point of the camber line to the chord line is called the camber. The largest of these is called the maximum camber.

Thickness is the distance obtained by drawing perpendicular to the chord line between the upper surface and the lower surface of the profile. Chord Line is called the line connecting the leading and trailing edges. Leading Edge is the edge where the oncoming air contacts the wing. Trailing Edge is the edge where the oncoming air leaves from the wing.

The lift value of the wing is calculated by the lift equation. The lift equation is as given Equation 1.

$$L = C_L x \frac{\rho x V^2}{2} x\, A \qquad (1)$$

L: Lift value.
ρ: Air density.
V: Velocity over airfoil.
A: Wing area.
C_L: C_L is the coefficient at the desired angle of attack. C_L is provided by a surrogate model ANN.

The most important parameter to use when calculating the lift is the Lift Coefficient (C_L). The C_L coefficient contains complex variables and is usually obtained experimentally. The C_L coefficient is a coefficient that depends on the angle of attack, camber and thickness of the wing.

2.2 Artificial Neural Network

Artificial neural networks are information processing systems that mimic the working principle of the human brain in general. Studies on this subject first started with the modelling of the neurons that create the brain. The neural network is formed by the connections of nodes, which are elements that correspond to the brain's neurons (Kose & Oktay, 2021). Nodes are connected by connections, and each connection has a numerical weight that expresses the strength, or in other words, the importance of the input. Weights are the main purpose of long-term memory in ANNs. A neural network learns by repeatedly adjusting these weights (Negnevitsky, 2005).

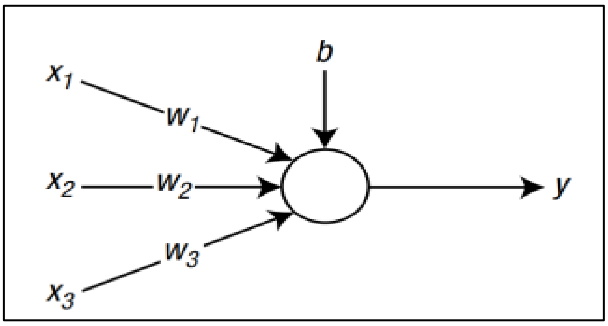

Figure 3. A neural network with 3 inputs and 1 output (Kose & Oktay, 2021)

The x_1, x_2 and x_3 values in Figure 3 are defined as the input values of the network. w_1, w_2, w_3 are also the weights of the input values. y is the output value (Kose & Oktay, 2021).

Hidden layer/layers are a set of neurons located between the input and output layers. It can be in the form of single or multiple layers (Shiruru, 2016).

Within the scope of this study, a surrogate network with 1 Output (C_L) and 1 hidden layer was obtained by training 3 Inputs (Angle, Camber, Thickness) of the wing of the aircraft with the Artificial Neural Network.

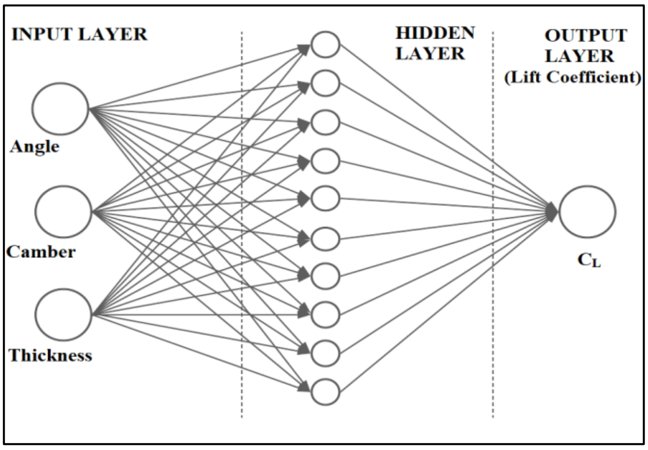

Figure 4. Neural Network Structure

For this article, the learning process in the Artificial Neural Network took place in the following order:

1. Collection of data set: It is the process of collecting data that we will give for our network to learn.
2. Determination of the network structure: The next step is to determine the structure of our network for the subject we want the network to learn. At this stage, it is determined how many inputs there will be, how many hidden layers there will be, how many neurons there will be in the hidden layers, and how many outputs there will be as a result.
3. Determination of the learning parameters of the network: After the completion of the structure of the artificial neural network that we will use for our study, the parameters such as the activation function and the learning rate, which are necessary for the continuation of the learning processes, are determined at this stage.
4. Weight and bias values: These values are given randomly at the beginning by the network itself, and then updated by the network during the learning process and ideal values are determined (Elmas,2018).
5. Giving the dataset to the network for training: After the preparations are complete, the network is ready for the learning process. Data set input and output values are given to start learning.
6. Calculations: Calculation of producing output values suitable for data input values is performed in this step.
7. Comparison of the output values of the network with the actual values: As a result of the comparison, the error of the network is calculated.
8. Change the weights and bias values of the network: In order to reduce the error of the network, the weight and bias values are calculated and updated.

Foilsim online interface developed by NASA (https://www.grc.nasa.gov/www/k-12/airplane/foilsime.htm l). Angle of attack(degree), camber(%) and thickness(%) inputs in Foilsim online interface are in the range of 0-20 for each. These values can be integer or decimal values between 0-20. The C_L dataset used in this study was collected directly by entering the angle of attack, camber and thickness values into the Foilsim online interface. The data set consists of 20x20x20=8000 C_L values by entering integer values between 0-20 (starting from 1-1-1 to 20-20-20) for each of the angle of attack, camber and thickness values. MATLAB program and Java awt Robot were used to collect 8000 pieces of data. Robot is an application that does the work that the user will do. In other words, the robot moves the mouse and presses the buttons instead of user. It also presses keys from the keyboard. This robot is used for various purposes. In this study, the Robot enters the angle of attack, camber and thickness values from 1-1-1 to 20-20-20 in the Foilsim online interface and saves the C_L value obtained for each value into an array. Angle of attack, camber and thickness values starts and increases one by one 1-1-1, 1-1-2, 1-1-3 … 1-1-20 ------ 1-2-1, 1-2-2, 1-2-3 … 1-20-20 ------ 2-1-1, 2-1-2, 2-1-3 … 20-20-20 and ends 20-20-20. An artificial neural network with 3 inputs and 1 output was trained with 8000 C_L datasets collected, and it was turned into a structure that automatically calculates the C_L value when the angle of attack, camber and thickness value is entered. For the network, 80% (6400) of the 8000 pieces of data were used for training and 20% (1600) for testing, and high success training was carried out with 5-fold cross validation.

Artificial neural networks are divided into two as forward and feedback artificial neural networks according to the way neurons are connected to each other. A feedforward neural network consists of layers and connections and communication are from input to output direction. In feedback artificial neural networks, there is a bilateral communication between the input layer and the hidden layer, and between the output and the hidden layers (Elmas, 2018).

In feed-forward neural networks, neurons are in the form of regular layers from input to output. There is only a connection from one layer to the next layers. The information sent with the data set coming to the input of the artificial neural network is transmitted to the hidden layer or layers without any change. Hidden layers transmit the information transmitted to them from the input layer to the next layer (Öztürk & Şahin, 2018).The feed forward artificial neural network is very involved in engineering studies and scientific studies, so the feed forward Artificial Neural Network was preferred in this study. (Du, He and Martins, 2021; Khurana, Winarto and Sinha, 2009; Li, Cai and Qu, 2019).

In artificial neural network algorithms, the behavior of the algorithms is controlled by hyperparameters. These hyperparameters cannot be determined by learning algorithms (Goodfellow, Bengio and Courville, 2016), they must be created by the designer who created the network.

The number of hidden layers and neurons causes the complexity of the network to increase. If the model is complex, it can be a serious waste of time, and while there is no problem in the training data, serious problems may occur in the test data. Considering these situations, the network with fewer layers and number of neurons was preferred in this study. Activation functions are used in ANN to process an input value and convert it to an output value that feeds it as input to the next layer. There are various activation functions. In this study, the Sigmoid activation function was preferred.

In this study, MATLAB R2019a numerical computing environment was used to create the ANN model. Levenberg-Marquadt Algorithm (Du, He and Martins, 2021), which is the default and frequently used for feed forward networks, is used in regression problems.

Table 1. Parameters and their values in the artificial neural network

Parameter	Value
Number of layers	1
Number of neurons	10
Learning rate	0.005
Activation function	logsig
Backpropagation Algorithm	trainlm

The information including the termination criteria of the network is decided by evaluating the criteria given in Table 2. If we want to use a certain time constraint in the training of our network, the time parameter is used. There is no time limit in this study. Another parameter is the number of iterations. The training ends when the limit iteration number that we will use in the training of our network is reached.The next parameter is the training ends when the reaches the desired minimum gradient value.Training ends when the network reaches the desired minimum performance.

Table 2. The stopping criteria used for the Neural network

Parameter	Value
Iteration	1000
Performance	1e-06
Gradient	1e-07
Time	No time constraint was used.

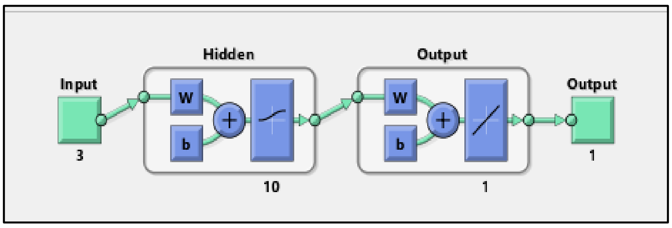

Figure 5. Artificial Neural Network structure

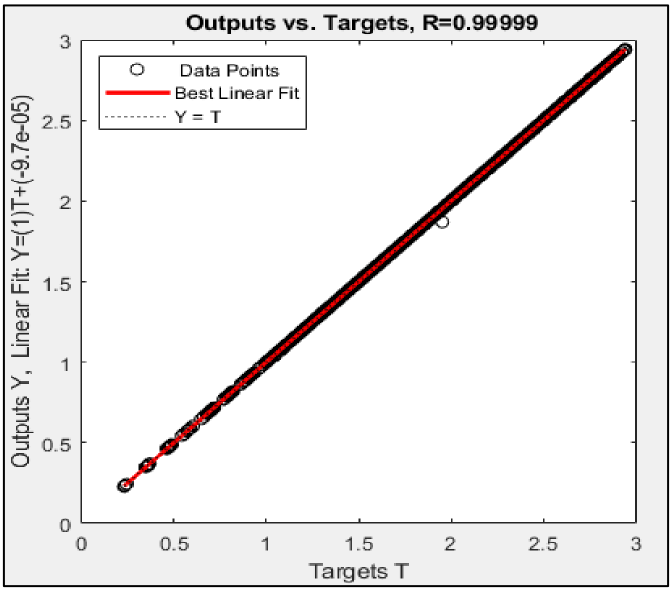

Figure 6. First fold performance

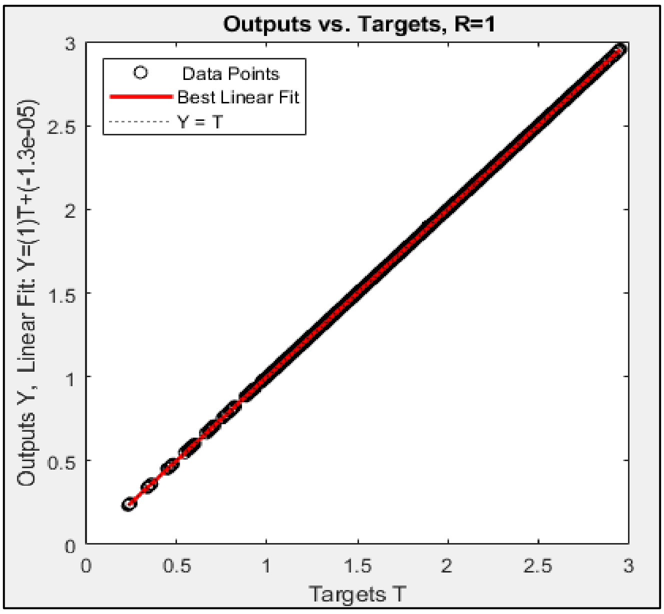

Figure 7. Second fold performance

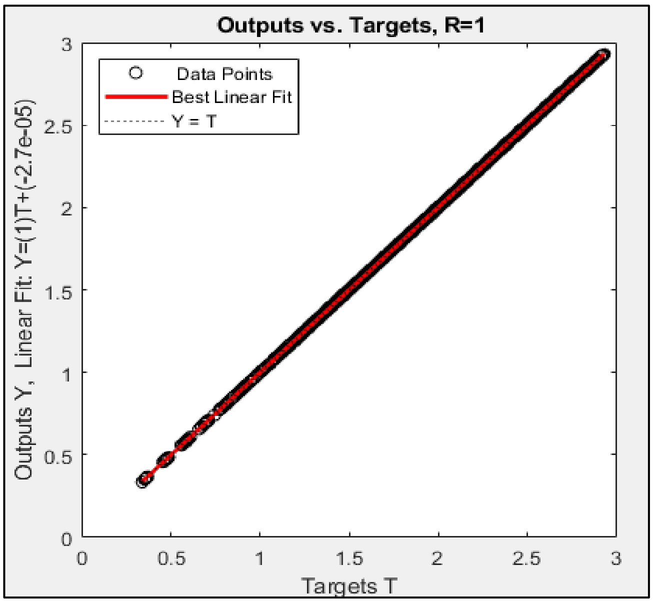

Figure 9. Fourth fold performance

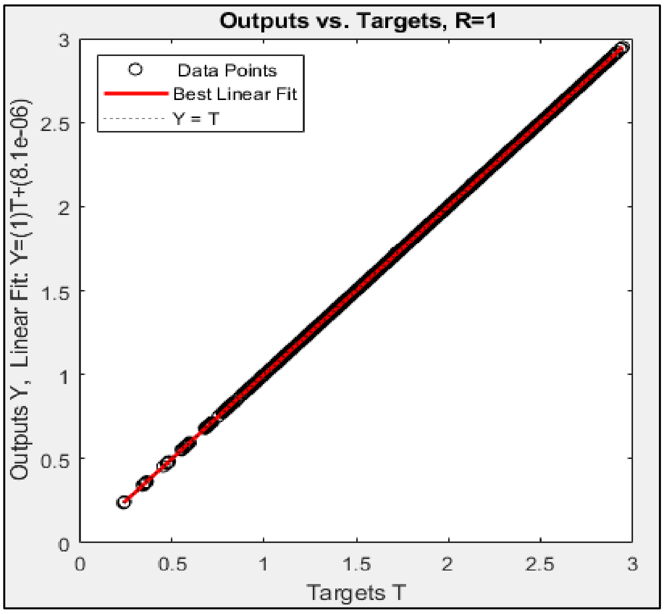

Figure 8. Third fold performance

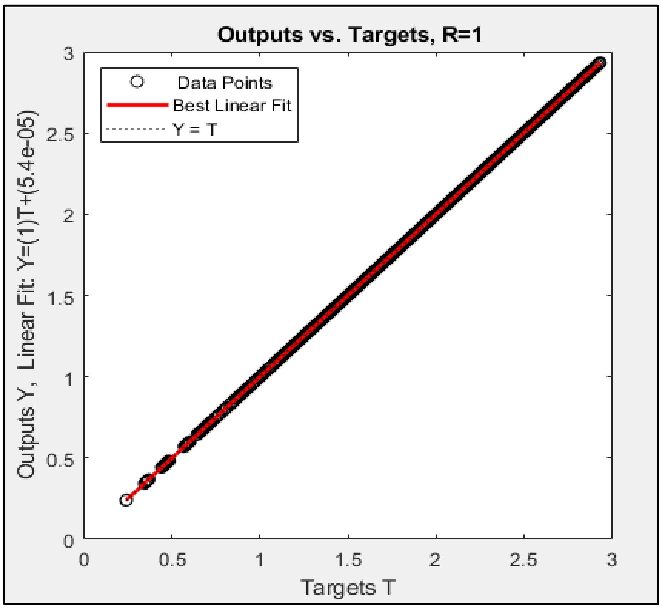

Figure 10. Fifth fold performance

2.3 Optimization

Optimization is defined as a technology that enables reaching certain goals by using the resources available in a system in the most efficient way. Optimization is used to accelerate the decision-making process and increase decision quality. It is used in the effective, accurate, and real-time solution of real-life problems (Türkay,2021).

Since most of the optimization problems in daily life are too complex to be developed when trying to solve with mathematical formulas from known methods, the solution may take a very long time and the predicted result may not be achieved. For this reason, heuristic methods have been developed as a solution to the problem and it has been tried to reach the best result that can be obtained (Gülcü & Kuzucuoğlu, 2006). Optimization is the process of finding the best solution for an identified problem or improvement.

2.4 Artificial Bee Colony Algorithm (ABC)

Artificial bee colony algorithm is an optimization algorithm inspired by the methods used by bees when searching for food by taking the unique intelligent behavior of honey bee swarms as an example. This algorithm, based on swarm intelligence, is used to solve optimization problems based on the behavior of bees moving in swarms in finding food (Küçüksille & Tokmak, 2011).

First of all, brief information about the food source search behavior of real bees is given.Foraging behavior of bees. The most important factor that ensures the continuation of the life of bee colonies is the food source. The important factors in this process are the resources accumulated in the hive, the feed sources that can be found in the environment, and the interactions of the bees. The bee leaves the hive and the food search continues randomly. If a food source is found and there is less food in this source, they start to look for a new food or they start to turn to other sources according to the information they receive from other bees (Küçüksille & Tokmak, 2011)

Akay used a grouping related to the search for food by bees in her study and explained this in her study(Akay,2009).

Food Sources: They are the sources that bees go to find food. The value of a food source has been defined, for the sake of simplicity, as its wealth. This value can be attributed to factors such as the type of source, distance from the nest, amount of nectar.

Worker bees with specific duties: This worker bee is concerned with bringing the food collected from the predetermined source to the hive.

Worker bees with uncertain duties: These bees are in charge of searching for food sources(scout bees and onlooker bees). The scout bee randomly searches for resources. The onlooker bee waits in the hive, watches the attendant bees, and directs the information from these bees to new sources.

Bees share information about the quality and location of the food source in the dance area. While one of the bees dances, the other touches it with its antenna and receives information from it. The distance between the bee and the hive, the condition of the food, the weather conditions are the factors affecting the dance (Kaya & Eke, 2020).

According to the distance from the source to the hive, there is a circular tail and quivering dance. The trembling dance provides the balance between the amount of nectar and the ability to bring food. This dance is a form of dance that is provided without giving the direction and distance to the source 50-100 meters away. It is understood that the number of repetitions in a wide area from 10 meters to 100 kilometers gives the distance information and the angle between the sun and the food source is 45 degree by making a dance similar to the number 8 (Kaya & Eke, 2020).

In the Artificial Bee Colony Algorithm, the foraging process of bee colonies is modeled and some assumptions are made.There are three different types of bees in the ABC Algorithm: scout bee, worker bee, and onlooker bee. There is one worker bee for each food source. The number of worker bees is equal to the number of onlooker bees. In case of depletion of resources, worker bees turn into scout bees and scout bees go to search for new sources. Thus, when the resources are depleted, the worker bees abandoning those resources is defined as negative feedback. The search for new resources by scout bees is defined as randomness oscillation. The number of emerging scout bees is determined by the limit parameter.

In the ABC Algorithm, the position of a food source corresponds to a solution. The nectar richness of the food source is defined through the objective function of the solution. The amount of nectar from the sources indicates the quality of the results, and the locations of the food sources represent the probability results of optimization. Worker bees search for food sources and share information about these sources with onlooker bees. Onlooker bees also tend more towards rich food sources with the information they receive from worker bees. Thus, onlooker bees show positive feedback. The ABC algorithm first starts with the production of food sources and positions suitable for these food sources (Karaboga & Akay, 2009).

Basic stages of Artificial Bee Colony Algorithm:

- Creation of food source areas,
- Repeat,
  - ✓ Sending worker bees to food sources
  - ✓ and calculating the amount of nectar
  - ✓ Calculation of probability values according to information sharing from employed bees,
  - ✓ Onlooker bees choose food source areas according to their probability values,
  - ✓ Criteria for leaving the resource: Limit and number of scout bee production,
  - ✓ Control: Maximum loop.

The stages of the ABC Algorithm are as follows.

Stage 1 : The algorithm starts by generating a random food source positions. This process starts by generating random values between the lower and upper limits of each parameter. $i= 1...N, j=1...M$, N is the number of food sources, M is the number of parameters to be optimized, x_j^{min}, lower bound of j.parameter, x_j^{max} is the upper limit of the j.parameter. In addition, at the initial stage, each resource has an $error_i$ value that expresses the number of failures to develop.

$$x_{ij} = x_j^{min} + rand(0,1)(x_j^{max} - x_j^{min}) \qquad (2)$$

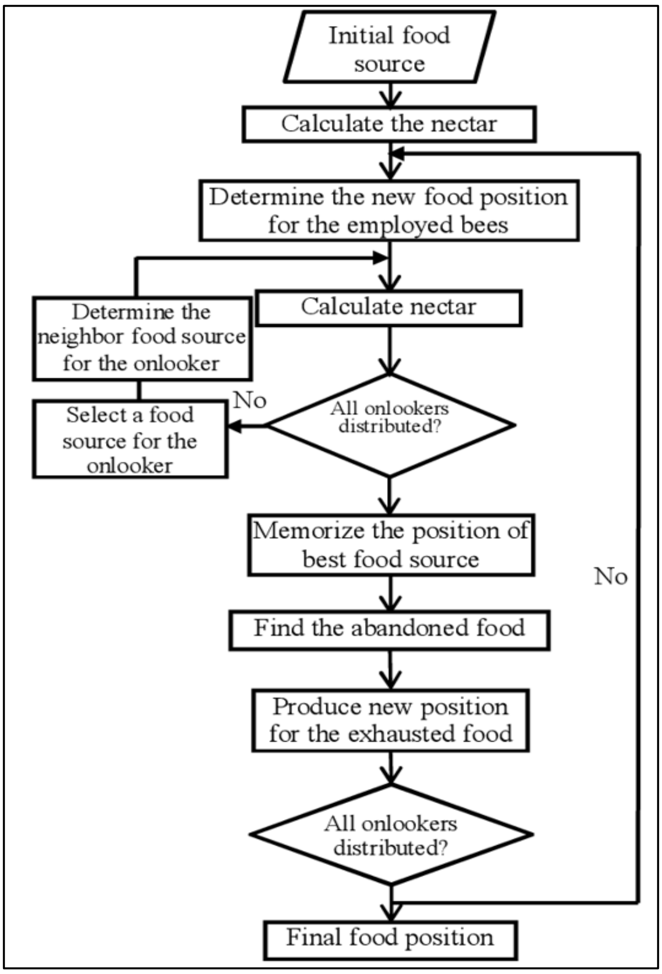

Figure 11. ABC Algorithm Flowchart (Akay, 2009)

Stage 2: The worker bee determines a new food source in the vicinity of the food source it works with and evaluates the quality of this source. If the new resource is more valuable, it memorizes the new resource. The determination of the new resource is provided by Equation 3.

$$v_{ij} = x_{ij} + \emptyset_{ij}(x_{ij} - x_{kj}) \qquad (3)$$

In case the v_{ij} value produced by this process exceeds the lower-upper limits previously specified, it is shifted to the lower and upper limit values of the j.parameter using Equation 4.

$$v_{ij} = \begin{cases} x_j^{min}, & v_{ij} < x_j^{min} \\ v_{ij}, & v_j^{min} \le v_{ij} \le x_j^{max} \\ x_j^{min}, & v_{ij} > x_j^{max} \end{cases} \quad (4)$$

The parameter vector *vi* produced in the bounds range represents a new resource. By calculating the quality of this new resource, the fitness value of the new resource is calculated.. The fitness value of the solution is calculated by substituting a cost value of this resource in *f(vi)*. *fi* is the cost value of the *vi* resource (solution).

$$fitness_i = \begin{cases} 1/(1+f_i), & f_i \ge 0 \\ 1+abs(f_i), & f_i < 0 \end{cases} \quad (5)$$

A selection process is applied according to the fitness value between x_i and v_i. If the new v_i solution is better, the bee responsible for it deletes the location of the old source from its memory and assigns the location of the v_i source to the memory. If this did not happen, the bee responsible for it would continue to go to the *xi* resource, and since the solution could not be developed, the $error_i$ related to the x_i resource would increase by one, and when it was developed, the counter would be reset.

Stage 3: The onlooker bee chooses a source with probability proportional to the nectar amounts of the food sources, benefiting from the information shared through dance. This selection process using probability is done by using the fitness values corresponding to the nectar amounts in the algorithm. The selection process based on the fitness values is done by the Roulette wheel method. The angle of each slice of the wheel is proportional to its fitness value. In other words, the ratio of the fitness value of a resource to the sum of the fitness value of all resources gives the relative probability of choosing that resource relative to other resources. In the formula below, SN represents the number of employed bees.

$$p_i = \frac{fitness_i}{\sum_{i=1}^{SN} fitness_i} \quad (6)$$

Stage 4: After calculating the probability values in the algorithm, the selection is made according to the Roulette wheel and a random number is generated for each source within the range of [0,1]. Afterward, the p_i value is generated, if it is greater than this number, onlooker bees such as employed bees use Equation 3 to generate a new solution in this source region.

The new solution found is evaluated and its quality is calculated. Then, the compatibility of the new solution with the old solution is compared and it is subjected to a selection process in which the best one is selected. If the new solution found is better, this solution is taken instead of the old solution and the solution error counter error is reset, if the new solution found is not better, the solution failure counter ($error_i$) is increased by one. (Akay, 2009).

Stage 5: It is checked whether the nectar is exhausted at the source. If it is exhausted, it is replaced with a random value generated by Equation 2.

Stage 6: The best solution is kept in memory.

Stage 7: The conditions for termination are checked, and then if these conditions are not met, it must be repeated from Step 2 to Step 6 (Kaya & Eke, 2020).

In this study, after the surrogate model was trained in the artificial neural network, it was used in Equation 1 in the Artificial Bee Colony Algorithm. The most suitable angle, hump and thickness values for the lift value requested by the designer are found by the study prepared with the help of ABC algorithm.In this study, the restrictions in the Artificial Bee Colony Algorithm are given in Table 1. The algorithm was developed in MATLAB 2019a version and tested on a computer with AMD Ryzen 7 4800H Radeon Graphics 2.90 GHz processor, 16.0 GB Ram, 64 Bit Windows 10 Pro Operating system.

Table 3. Optimization constraint

Parameter	Value
Angle(degree)	1-20
Camber(%)	1-20
Thickness(%)	1-20
Air Density(slugs/ft^3)	0.00511844

The optimization constraints in Table 1 depend on Foilsim.

Table 4. Parameter of the optimization algorithm

Parameter	Value
Colony Size (employed bees+onlooker bees).	40
Limit (A food source that could not be improved through trials).	10000
maxCycle (the number of cycles of foraging is stopping criteria).	180
The number of optimised parameters.	5

3. Result and Discussion

28 experiments were carried out by using the network trained with ANN by optimizing in ABC algorithm. In the first stage of these experiments, Angle Camber and Thickness values were found in the constant velocity and fixed wing area. (Experiment 1, Experiment 8, Experiment 15, Exp 22).

Then at the same constant speed and in a different fixed wing area; Camber and Thickness values were kept constant and Angle value was observed (Experiment 2, Experiment 9, Experiment 16, Experiment 23). As a result of the observation, it was determined that there was a **decrease** in Angle values.

In Experiments 3, Experiment 10, Experiment 17, Experiment 24, Angle and Thickness values were kept constant and Camber value was observed. As a result of the observation, it was observed that there was a **decrease** in the Camber value.

In the last experiments of the first stage (Experiment 4, Experiment 11, Experiment 18, Experiment 25), Angle and Camber values were kept constant and Thickness values were observed. As a result of the observation, it was determined that there was a **decrease** in Thickness values.

In the second stage of the experiment; The wing area at the beginning of the first stage was left the same, at a different constant speed, the Camber and Thickness values were kept constant and the Angle value was observed (Experiment 5 Experiment 12 Experiment 19 Experiment 26). As a result of the observation, it was determined that there was an **increase** in Angle values.

Angle and Thickness values were kept constant and Camber values were observed in Experiment 6, Experiment 13, Experiment 20 and Experiment 27.

A **decrease** was observed in Camber values as a result of the experiment. In the last experiments of the second stage, Angle and Camber values were kept constant in Experiment 7 Experiment 14 Experiment 21 Experiment 28 and Thickness value was observed. As a result of the experiment, it was observed that there was a **decrease** in Thickness values.

This study aims to contribute to efficient aircraft design by determining the optimal wing profile by using Foilsim data in optimization.

Table 5: Observation of Angle, Camber and Thickness values. (Entered Lift=8 Ibs).

Lift(lbs) (Entered in ABC)	Experiment No	Fixed Speed(mph)	Fixed Wing Area(sqft)	Optimised Angle(°)	Optimised Camber (%)	Optimised Thickness(%)	Foilsim-Real Lift(lbs)
	1	24	2.6	14.1459	8.35663	7.27498	8
	2	24	2.8	9.41287	8.35663	7.27498	8
	3	24	2.8	14.1459	5.66572	7.27498	8
8	4	24	2.8	14.1459	8.35663	1.99969	8
	5	25.4	2.6	17.3841	8.35663	7.27498	8
	6	25.4	2.6	14.1459	6.1912	7.27498	8
	7	25.4	2.6	14.1459	8.35663	1.19178	8

Table 6: Observation of Angle, Camber and Thickness values. (Entered Lift=17 Ibs).

Lift(lbs) (Entered in ABC)	Experiment No	Fixed Speed(mph)	Fixed Wing Area(sqft)	Optimised Angle(°)	Optimised Camber (%)	Optimised Thickness(%)	Foilsim-Real Lift(lbs)
	8	30.4	3.3	12.6009	10.2219	8.22825	17
	9	30.4	3.45	9.80014	10.2219	8.22825	17
	10	30.4	3.45	12.6009	8.41263	8.22825	17
17	11	30.4	3.45	12.6009	10.2219	4.05814	17
	12	31.28	3.3	16.7070	10.2219	8.22825	17
	13	31.28	3.3	12.6009	8.73887	8.22825	17
	14	31.28	3.3	12.6009	10.2219	1.01248	17

Table 7: Observation of Angle, Camber and Thickness values. (Entered Lift= 52 Ibs).

Lift(lbs) (Entered in ABC)	Experiment No	Fixed Speed(mph)	Fixed Wing Area(sqft)	Optimised Angle(°)	Optimised Camber (%)	Optimised Thickness(%)	Foilsim-Real Lift(lbs)
	15	41	4.2	14.6894	19.9987	13.6096	52
	16	41	4.3	9.56763	19.9987	13.6096	52
	17	41	4.3	14.6894	18.9501	13.6096	52
52	18	41	4.3	14.6894	19.9987	2.7278	52
	19	41.8	4.2	16.0302	19.9987	13.6096	52
	20	41.8	4.2	14.6894	18.2971	13.6096	52
	21	41.8	4.2	14.6894	19.9987	1.1346	52

The optimal parameters (angle, camber, thickness, wing area, velocity value) obtained through the ABC Algorithm. The results checked in Foilsim web environment. It has been observed that the Foilsim data and ABC data are very close to each other, and the test results with some values are presented in Table 5, Table 6, Table 7, Table 8.

Table 8: Observation of Angle, Camber and Thickness values. (Entered Lift=157 Ibs).

Lift(lbs) (Entered in ABC)	Experiment No	Fixed Speed(mph)	Fixed Wing Area(sqft)	Optimised Angle(°)	Optimised Camber (%)	Optimised Thickness(%)	Foilsim-Real Lift(lbs)
	22	70.7	4.5	15.0302	17.9987	12.6096	157
	23	70.7	4.65	9.29409	17.9987	12.6096	157
	24	70.7	4.65	15.0302	16.6899	12.6096	157
157	25	70.7	4.65	15.0302	17.9987	1.8696	157
	26	72.1	4.5	16.2354	17.9987	12.6096	157
	27	72.1	4.5	15.0302	16.5710	12.6096	157
	28	72.1	4.5	15.0302	17.9987	1.089009	158

4. Conclusion

In our study, the C_L value was obtained by pre trained ANN, and with this C_L value, the optimum lift value (L) was obtained by ABC optimization algorithm. It is also a current research activity to perform a similar study with the drag coefficient (C_D), and drag value which is complementary to the current study and to obtain the optimum L/D ratio.

Ethical approval

Not applicable.

Nomenclature

ABC = Artificial Bee Colony Algorithm.
ANN = Artificial Neural Network.
CFD = Computational Fluid Dynamics.
D = Drag.
EA = Evolutionary algorithms.
L = Lift.

Symbols

A = Wing Area
C_L = Lift Coefficient
C_D = Drag Coefficient
$error_i$ = Number of failures.
$fitness_i$ = Calculation of the fitness value of the solution.
M = Number of parameters to optimize
N = Number of food sources
ρ = Air Density
p_i = the relative probability of choosing
$Ø_{ij}$ = random value in [-1,1]
SN = represents the number of employed bees
V = Air Speed
x_j^{min} = lower bound of j.parameter
x_j^{max} = upper bound of j.parameter

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