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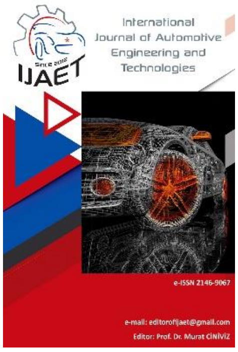

Original Research Article

Modeling the aerodynamic performance of unmanned aerial vehicle (UAV) propellers with multifidelity method

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ABSTRACT

In this study, an artificial neural network (ANN) based method is discussed to determine the aerodynamic performance of propellers used for Unmanned Aerial Vehicles (UAVs). Here, wind tunnel test data was used to obtain data for propellers without test data. First, wind tunnel test data was converted to a specific format using Python and modeling was done using ANN. With this modeling process, it was seen how close the model obtained with artificial neural networks produced results to the data obtained from wind tunnel tests. This study allows for more precise analysis of the aerodynamic performance of UAV propellers and optimization of their design. This approach provided a very accurate modeling of the aerodynamic performance of UAV propellers and took an important step towards determining the performance of propellers without wind tunnel test data. The obtained data constitutes a valuable resource for optimizing the design and performance of UAVs.

Keywords: Unmanned Aerial Vehicles (UAV), Propeller, Artificial Neural Network, Modeling, Internal-Combustion Engine.

1. Introduction

Wind tunnel tests and simulations play an important role in evaluating the design and performance of UAVs. Wind tunnel tests are used to determine the aerodynamic properties of the UAV and optimize its performance. Additionally, thanks to simulations, different flight scenarios can be modeled and the behavior of the UAV can be predicted. One of the important elements affecting the aerodynamic performance of UAVs is propellers. Propellers enable the UAV to stay in the air by converting the power produced by the engine into thrust force. Therefore, the aerodynamic design of propellers must be done carefully, considering factors such as efficiency and noise. During the propeller selection process of unmanned aerial vehicles (UAV), a detailed analysis is made using various methods and techniques. The basis of these analyzes are research and testing methods such as computer-aided design (CAD), fluid dynamics (CFD) analyses, artificial neural networks, machine learning, flight tests and wind tunnel experiments [1]. Artificial neural networks and machine learning techniques are used to predict and optimize propeller performance. These technologies, which have the ability to learn from complex datasets, enable more precise and efficient results in propeller design. Flight tests are important to verify propeller performance in real-world conditions and optimize the design. In these tests, the UAV is flown in different weather conditions and altitudes to evaluate its propeller performance [6]. Finally, wind tunnel tests are also used in the propeller selection process. In these experiments, the aerodynamic properties of UAV propellers are tested in different wind conditions and their performance is evaluated [3]. Integration of these various methods is critical in determining the optimal propeller design and ensuring optimum performance of the UAV. In this study, artificial neural networks and machine learning applications were preferred to determine the aerodynamic behavior of UAV propellers. Technologies such as artificial neural networks and machine learning play an important role in simulations and data analysis. Artificial neural networks are artificial intelligence models capable of learning from complex datasets. Machine learning, on the other hand, is based on the ability of algorithms to learn from datasets and recognize patterns. These technologies are used to obtain more precise results in UAV design and performance analysis and in determining the aerodynamic behavior of propellers. In order to determine the aerodynamic performance of propellers for unmanned aerial vehicles, datasets will be compared using artificial neural networks and methods will be followed to obtain data representing the real environment. The focus is on integrating wind tunnel test data of UAV propellers and thus achieving the closest result to reality.

2. Literature Review

Gamble, investigated the effects of Reynolds number on propeller performance in this study. It was found that the geometric features of the propeller, such as shape, twist, and blade chord, are highly dependent on Reynolds number. In wind tunnel tests, propellers produced by APC, which include glass-filled epoxy for high torsional strength, were used [1].

Figure 1. APC Propeller [1]

Figure 1 shows a propeller belonging to the APC propeller. APC 18x12 and APC 18x8 propellers were tested at 7 different rotation speeds for different Reynolds numbers ranging from 400,000 to 502,000 and 1,080,000 to 1,213,000 respectively. It has been found that efficiency, thrust coefficient, power coefficient and slope increase when the number of Reynolds increases. It was determined that the efficiency of the APC 18x12 propeller increased by 5% by increasing the Reynolds number from 400,000 (1,700 rpm) to 1,155,000 (4850 rpm). It can be seen that the same thrust force is produced at lower speeds as the pitch is reduced while the diameter is kept constant. In other words, as the pitch or pitch/diameter ratio increases, efficiency increases, and the propeller produces thrust at higher advance rates. In conclusion, experimental results show that Reynolds number has a strong effect on small propellers. Therefore, the designer must take the Reynolds number into account.

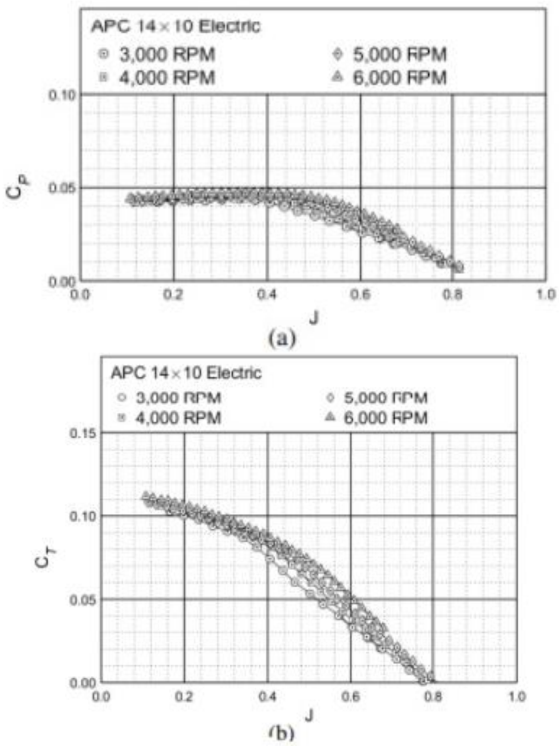

Figure 2. Wind Tunnel performance of APC 14×10 Thin Electric Propeller: (a) Thrust coefficient (Ct), (b) Power coefficient (Cp) [2]

Dantsker and colleagues observed from wind tunnel performance tests that, for a given propeller diameter, as the pitch angle increases, the thrust, power, and efficiency coefficient curves shift upwards and to the right. Figure 2 shows the Ct and Cp values of the 14x10 APC propeller as they vary according to the Advance Ratio from the wind tunnel test results. This observation indicates a trend where, as the advance ratio of a propeller increases, the thrust, power, and efficiency coefficients tend to have higher values, which is an expected general trend. It should be noted that for propellers with high diameter and pitch ratio, the performance curves are incomplete due to the 80 ft/s speed limit set by the propeller balance cover's structural design. Similarly, it is expected that, for a given propeller diameter, increasing the pitch angle will result in higher static (zero-speed) thrust and power coefficients. This study focuses on how propellers behave under different conditions in real-world environments [2]. The Blade Element Momentum (BEM) model is presented and used for performance predictions of sUAS propellers. Several corrections have been proposed for the BEM model to capture the unique characteristics of rotating flow in low Reynolds number propellers. Notably, corrections such as the use of aerodynamic databases produced by XFOIL, stall corrections, Mach corrections, and the inclusion of the model's angular flow components are included. For the specific propeller geometries addressed in this study, the BEM model predictions follow the expected general trends for fixed-pitch propellers. The BEM model has been validated through a series of wind tunnel tests, and positive comparisons have been made between the predicted and measured theoretical trends.

In Figure 3, part (a) presents the relationship between Ct, which likely represents a thrust coefficient, and J across different configurations: "10x5," "10x6," and "10x7." Both analytical (solid lines) and experimental (markers) results are shown for each configuration. The analytical results are represented by continuous lines, with each color indicating a different blade or propeller type. The experimental data, depicted with error bars, generally aligns well with the analytical curves but shows more variance. In part (b), the relationship between Cq, likely a torque coefficient, and J is illustrated for the same configurations. The torque coefficients (Cq) values are lower than those of thrust coefficients (Ct), suggesting that the torque coefficient is smaller in magnitude. While the analytical and experimental trends are similar, the experimental data appears to have a larger error margin. Overall, both graphs demonstrate that the analytical models generally match the experimental data, although there are some discrepancies and variations, indicating that experimental conditions or modeling assumptions may have impacted the results.

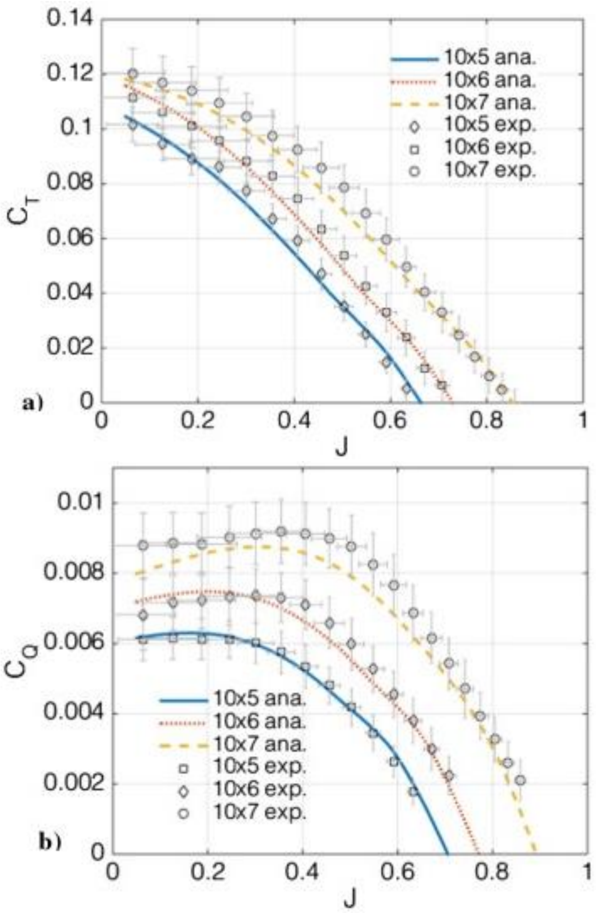

Figure 3. Figure Analytical and experimental (a) thrust coefficients (Ct), (b) torque coefficients (Cq) for APC Propeller [3]

McCrink and colleagues found similar results in their full-power tests to those reported in previous studies on small-scale propellers. A new constant Reynolds number test was introduced to demonstrate the scaling effects on propeller efficiency. Comparisons between experimental and model-based performance measurements highlight the importance of including Reynolds number dependence in the analysis of small-scale thrust systems. The presented and validated BEM model is highly useful for propeller design for sUAS, especially since the operating Reynolds numbers of these propellers are low, where viscous effects are predominantly significant. Additionally, the general power model for sUAS thrust systems enables high-fidelity vehicle performance predictions for sUAS and determination of vehicle performance during flight tests and routine operations [3].

In his study, Bağçe, determined the performance of mini aircraft propellers through static and dynamic tests. A propeller testing setup was designed and assembled to evaluate the static performance of the propellers. This setup was also placed inside a wind tunnel. In the static tests, thrust, power, and efficiency values for four different Turbotek propellers were obtained as a function of propeller rotational speed. These data were compared with the calculation results from Turbotek, Computational Fluid Dynamics (CFD) analysis, and the static test results. In the dynamic tests, the variation of thrust coefficient, power coefficient, and efficiency values of these four Turbotek propellers as a function of advance ratio was obtained. The experimental results were compared with the analytical and CFD results provided by Turbotek, and the experimental results were found to be successful [4].

Demirhan analyzed the fuel consumption performance of a commercial aircraft using an artificial neural network model. The data were modeled using a feedforward neural network and trained with high-accuracy simulation data (operational flight plans). Subsequently, real flight data from the Quick Access Recorder (QAR) were used to adjust the model's hyperparameters. Ten models with the least errors were selected and tested with a portion of the QAR data. After a statistical comparison among these ten models, the best model was chosen. Finally, a classification process for flights with fuel consumption prediction errors exceeding the three-sigma limit was described. Although the model was created using only five key parameters (takeoff weight, air distance, average cruise Mach number, altitude parameter, and fuel mileage deviation), it demonstrated a high level of accuracy. Additionally, the study proposes an additional method for identifying abnormal fuel consumption [5].

In Figure 4, a propeller motor setup within a wind tunnel is shown. This setup is used to test the aerodynamic performance of the propeller. The large fan at the end of the tunnel generates airflow through the tunnel, allowing for analysis of the propeller's effects. Most UAVs use propellers operating at low Reynolds numbers ranging from 50,000 to 100,000. Although sufficient data for these propellers are lacking, the performance of propellers for larger aircraft is well-documented. Therefore, in this study, tests were conducted at the University of Illinois, Urbana-Champaign, where the performance of 79 propellers with diameters ranging from 9 to 11 inches was determined, and static thrust measurements were taken. The subsonic wind tunnel at the University of Illinois, Urbana-Champaign, is reported to have a rectangular cross-section of 2.8 x 4.0 ft (0.853 x 1.219 m) and a maximum flow speed of 160 mph (71.53 m/s) [6].

Figure 4. Wind Tunnel Used for Propeller Testing [6]

Whitmore and colleagues (2012) revisit and enhance the classical first-order design tool known as the Blade Element Momentum (BEM) theory. Blade element theory analyzes a propeller blade by dividing it into segments and evaluating each element individually. In Figure 5, the relationship between the advance ratio and both the thrust coefficient and the power coefficient is shown. In part (a), the thrust coefficient is compared across test data, Analytical BEM, and Nonlinear BEM models. The test data, displayed with error bars, generally aligns well with both models, though there is a slight divergence at higher advance ratios. In part (b), the power coefficient is similarly compared, indicating good agreement between the test data and both models. However, slight discrepancies appear as the advance ratio increases. Overall, both graphs demonstrate that the Analytical and Nonlinear BEM models accurately capture the trends in the test data, with minor deviations at higher advance ratios. However, blade element theory alone lacks the capability to predict the inflow velocity required to complete the flow field of the propeller. By combining blade element and momentum theories, a combined low-order prediction tool known as the Blade Element Momentum (BEM) theory is created. The BEM theory uses momentum theory to calculate the local induced velocity and incorporates this information into the blade element model. The conventional method used to close the nonlinear BEM equations involves a small local angle of attack and assumptions of low local induced drag across all sections as proposed by McCormick. McCormick also assumes that the amount of local induced drag negligibly reduces the local propeller thrust coefficient. While these assumptions allow for a closed-form solution, they are known to be inaccurate at high advance ratios and for the inner radius of the blade. This paper presents a nonlinear solution method that avoids these flawed and simplifying assumptions and offers a general improvement over known analytical methods for the BEM model. Calculations using two BEM solution methods are compared with wind tunnel test data collected for a small radio-controlled (RC) aircraft propeller. The solution methods are compared, and it is shown that the traditional linear solution predicts propeller performance with high accuracy, especially at high advance ratios [7].

Hang Zhu and colleagues (2021) present an analysis of a model to calculate the requirements and aerodynamic performance of propellers for rotorcraft unmanned aerial vehicles (UAVs). Based on blade element momentum theory, the aerodynamic forces on a blade element are examined and utilized. The symbolic NACA0012 airfoil model is used as an example to validate the model's accuracy. An experimental system designed and constructed to test the aerodynamic

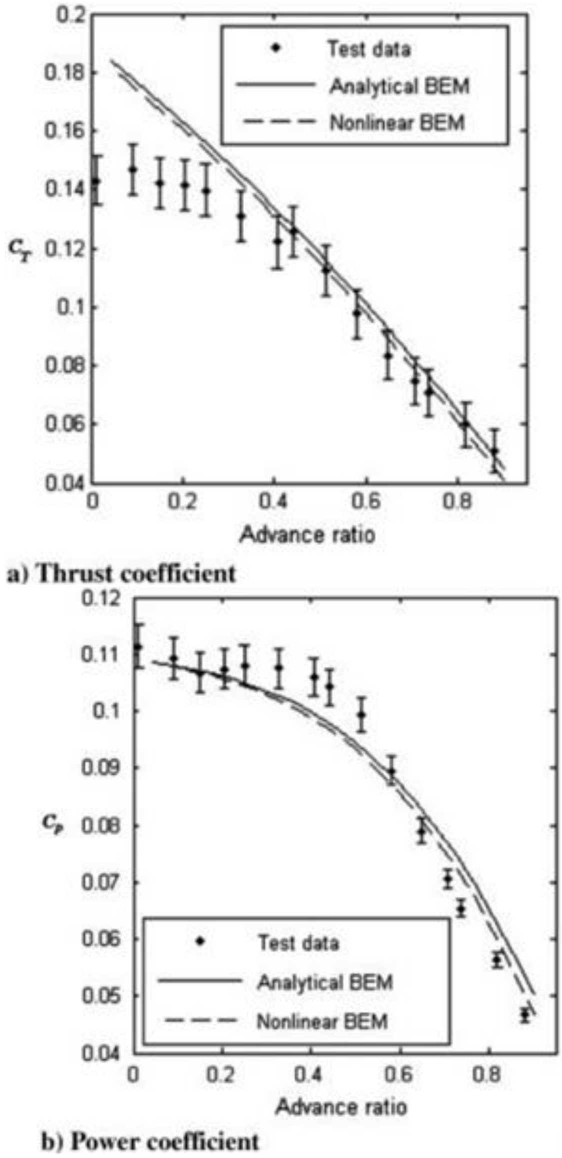

Figure 5. Comparisons of a) Thrust Coefficient (Ct) and b) Power Coefficient (Cp) for the APC 8x8 Thin Electric Propeller [7]

performance of propellers is used to evaluate six different types of APC propellers. Additionally, data processing software is developed to perform single-step calculations of three propeller parameters (airfoil drag power, induced velocity, and efficiency) for plotting aerodynamic graphs. The results of the experiment show that the thrust and torque of the propeller increase with rotational speed, propeller diameter, and pitch. The newly developed system and software provide more precise torque measurements and greater stability under current experimental conditions. Experimental data, including propeller speed, thrust, and torque, are used to analyze the aerodynamic performance of APC propellers. The chosen propeller type for the experiment is one of the most commonly used for UAVs, making the experimental data more convincing for assisting in propeller selection for UAVs [8].

In their 2021 study, Zbigniew Czy and colleagues investigate the impact of propeller geometry on the aerodynamic performance of propellers. In Figure 6, the Thrust/Power ratio is shown for different PWM ratios. One of the factors affecting propeller performance is the propeller pitch. This parameter indicates the distance a propeller will advance during one rotation. The key aspect is to determine the pitch at which the propeller performance is optimal. In this study, the aerodynamic performance of propellers with different pitches is tested using a wind tunnel, and experimental results are obtained. The tests were conducted in a subsonic wind tunnel. As a result of the study, the values of dimensionless coefficients for thrust force, torque, power, efficiency, and thrust-to-power ratio were calculated. The results allow for the selection of the most suitable solution when these coefficients are used as criteria. It is shown that there is a decrease in the force produced per unit power at higher airflow speeds; however, high-pitch propellers were observed to perform better at higher airflow speed ranges [9].

Onay and colleagues (2012) compared the design, analytical-based analysis results, and performance test results of two propellers intended for unmanned aerial vehicles (UAVs). In Figure 7, the comparison of results obtained through BEM and experimental methods for the XOAR 26x12 propeller is shown. Dynamic tests of the two UAV propellers were conducted in a wind tunnel and compared with the results of the Blade Element Momentum (BEM) analysis. The study revealed that the results obtained from Computational Fluid Dynamics (CFD) closely matched the BEM analysis results. This indicates that the BEM analysis method can be used for propeller optimization [10].

In their 2024 study, Xiaojing Wu and colleagues investigated the efficiency of electric propulsion systems used in unmanned aerial vehicles (UAVs).

The study highlights the conflict between accuracy and design efficiency in optimization designs when using Computational Fluid Dynamics (CFD) and Propeller Theory methods. To address this, the study introduces a high-accuracy artificial neural network-based optimization framework for electric aircraft propellers.

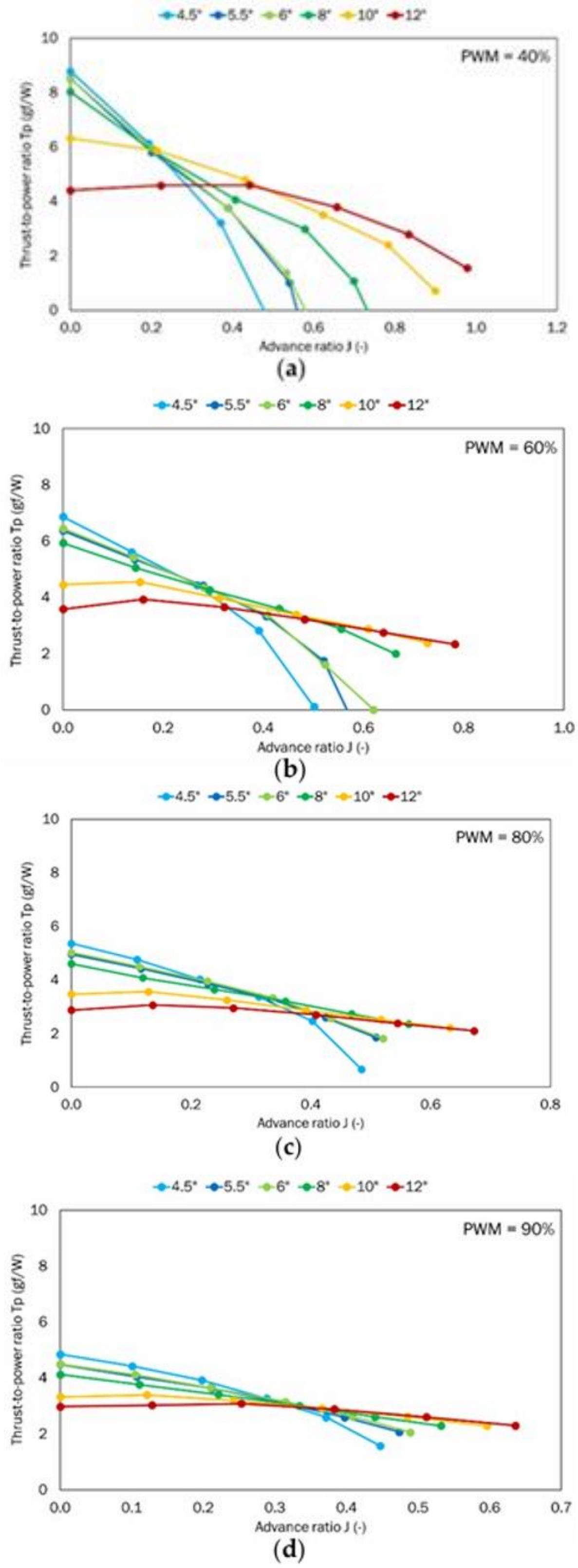

Figure 6. Thrust-to-Power Ratio as a Function of Advance Ratio for the Tested Propeller Set at Different PWM Values: (a) 40%; (b) 60%; (c) 80%; (d) 90% [9].

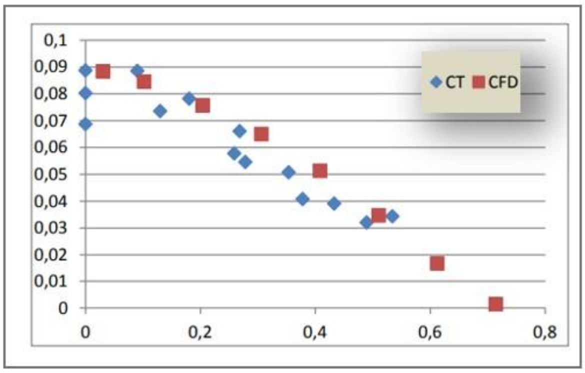

Figure 7. Comparison of Thrust Coefficient (Ct) Values Obtained Experimentally and with the Blade Element Momentum (BEM) Analysis Method for the XOAR 26x16 Propeller [10]

This method is based on high-accuracy CFD numerical simulations and combines low-order Blade Element Momentum Theory (BEMT) knowledge with fewer CFD simulations to achieve higher model accuracy. This method improves the propeller's cruising efficiency from a point of 82.3% designed by CFD and BEMT to 87.1% using the newly employed method. It has been shown that this method offers advantages in optimization effectiveness and efficiency compared to single-order optimization approaches [11].

3. Applications

Obtaining a Wind Tunnel Data Set

Propeller tests were conducted in the UIUC low-turbulence subsonic wind tunnel. The wind tunnel is an open-return type with a 7.5:1 contraction ratio. Here, many variable sizes and pitches of the APC propeller were tested. These tests were carried out by changing many parameters such as RPM and Speed of the propellers. As a result of these tests, UIUC has compiled the wind tunnel test results into a test data set and shared it with the companies using this propeller.

Artificial Neural Network Model

The Artificial Neural Network (ANN) model is a model generally used in the fields of machine learning and artificial intelligence. ANN is a computational model inspired by the functioning of biological neural networks and is used to solve various complex problems. In this study, the artificial neural network (ANN) model will be established with wind tunnel data. Here, the artificial neural network model will be taught wind tunnel test data of propellers of different sizes and different pitch combinations, and as a model output, it will be aimed to predict propeller combinations without wind tunnel test data with the help of the wind tunnel test data model. Here, while the model is being established, changes will be made to the model according to the state of learning the test data of the model, and the most optimum artificial neural network model will be found.

Creating Wind Tunnel Models

Thrust coefficients (Ct) and Power coefficients (Cp) values were arranged before creating the model according to the variable RPMs in different propeller diameters and pitch combinations in the Wind Tunnel data set. This data Set is divided into Ct/Cp for "Sport" type propeller wind tunnel and Ct/Cp for "Thin Electric" type propeller wind tunnel. Before creating wind tunnel models, the data will be examined and the necessary data editing procedures for the models have been carried out. For the use of APC propellers in the modeling of propellers with variable diameter and pitch combinations tested in the wind tunnel, there are actual test data in the wind tunnel regarding 30 different diameter and pitch combinations of the "Sport" propeller type propellers between 1000 RPM and 10000 RPM. In addition, there are actual test data performed in the wind tunnel on propellers of the "Thin Electric" propeller type, in the range of 1000 RPM and 10000 RPM, in 34 different diameter and pitch combinations. These data are arranged so that the "Sport" and "Thin Electric" type propeller data are side by side in the format "RPM J V Ct Ct_Predited Cp Cp_Predicted Typed p".

APC Propeller Sport Type Data Set Ct (Thrust Coefficient) Prediction Model Creation

With the wind tunnel data set, first a model will be created using the wind tunnel data set for the "Sport" type propeller. Before creating the model, the independent variables to be used in the training process of the model were determined. These variables are the X_train dataset. "RPM J Predicted_Ct Diameter Pitch V" values will be used for the x_train data set. These values are the features given as input to the model and help the model estimate the Ct value for the wind tunnel by using these features. The reason why these values were chosen as x_train is that these values are the main factors that determine propeller performance. RPM (number of revolutions), J (advance coefficient), Diameter (diameter), Pitch (pitch) and V (speed) are important features that directly affect the performance of the propeller. It is important for the model to learn these factors that determine the estimated Ct value. Y_train training set is the dependent variable that the model tries to learn during the training process. So, Ct will be used for y_train. While determining the hyperparameters of the model, different combinations were used, and the models were tested. In this way, the parameters were finalized by trial-and-error method. The hyperparameters used for the Wind Tunnel "Sport" type propeller Ct prediction model are as follows:

- 5 Layers
- 1 Input Layer, 3 Layers, 1 Output Layer
- Batch Size 16
- 1000 Epochs,
- 256 Neurons in layers except Output Layer
- Mean Squared Error (MSE) Loss Function
- ReLU Activation Function
- Adam Optimization Algorithm
- Standard Scaler
- Validation (X_test, y_test)
- Test Size 1%

With these determined parameters, the artificial neural network (ANN) model for the wind tunnel was trained.

For the artificial neural network (ANN) model created for wind tunnel Ct prediction, the number of layers and the number of neurons in the layer were adjusted to be the most optimum values at which the model would perform best, based on previous studies and trial and error method. According to the created model "Epochs" values, the point at which the model performs best will be determined. Accordingly, the “Epochs” value will be determined.

When the loss function and R2 performances of the models are examined according to 2 different "Epochs" values, Model 1 has lower loss function performance and R2 score. This shows that Model 1 performs better. When evaluating the number of "Epochs", it is seen that there is no need for more "Epochs" values since the performance of the model is quite good for 1000 "Epochs".

Table 1. Wind Tunnel “Sport” Ct Sequential Model Structure

Wind Tunnel “Sport” Ct Sequential Model		
Layer (type)	**Output Shape**	**Parameter**
Dense	252	1764
Dropout	252	0
Dense	168	42504
Dropout	168	0
Dense	84	14196
Dropout	84	0
Dense	42	3570
Dropout	42	0
Dense	1	43
Total Parameter = 62077		Trainable Parameter = 62077

Table 2. Comparison of model performances according to Wind Tunnel Ct Forecast Model “Epoch” Values according to Loss functions and R2 method

Model No	**1**	**2**
Model Type	Wind Tunnel “Sport” Ct Forecast Model	Wind Tunnel “Sport” Ct Forecast Model
Epochs	1000	2000
MAE	0.032211390	0.056139356
MSE	0.001689722	0.0077393565
RMSE	0.17947532	0.2369374517
R^2	0.99833180	0.993742881

When the Loss-Validation Loss graphs are examined in Figure 8, it is seen that the Loss and Validation Loss values overlap at 1000 "Epochs". In this case, it appears that the model is not overfit. The fact that the loss values encountered during the training of the model are low and stable shows that the model works well in both the training and validation phases. This helps predict that the model can give good results against new data. When the graphics are evaluated, model 1 will be preferred for the wind tunnel Ct prediction model since the model performance shows good performance for 1000 "Epochs" value. Model 1 will be trained with the wind tunnel data set.

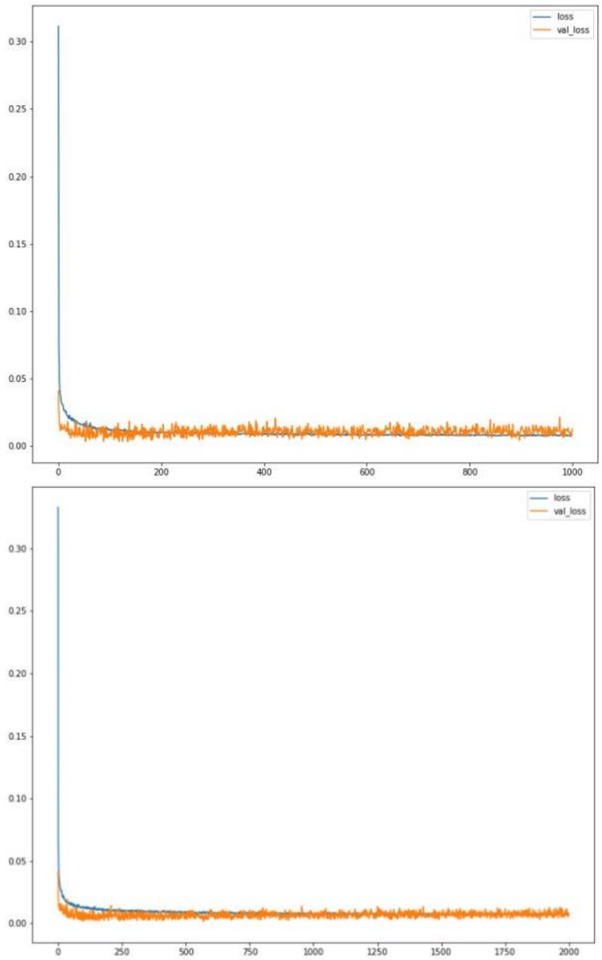

Figure 8. Wind Tunnel “Sport” Type Propeller Ct Forecast Model (top) 1000 “Epoch” and (bottom) 2000 “Epoch” (Blue - Loss, Orange - Validation Loss)

APC Propeller Sport Type Data Set Ct (Thrust Coefficient) Prediction Model Training and Outputs

After the hyper parameters and “Epochs” value determined for the wind tunnel Ct prediction model, the artificial neural network (ANN) model was trained with the data set.

When the "Predictions-Real Values" graph in Figure 9 is examined, it is seen that the graph shows a linear relationship. This shows that the model's predictions are quite close to the actual values and the performance of the model is very good. The fact that the points are regularly distributed around the ideal line shows the consistency of the model predictions and that the model has learned the data set well in general. Using an artificial neural network (ANN) model, the performance of the model was evaluated with the data set.

When the performance of the wind tunnel “Sport” Ct prediction model is examined, it is seen that the performance of the model is almost the same as the real data set. Here, it is predicted that the predicted performance of the model is good and that it will make a good prediction for different propeller combinations.

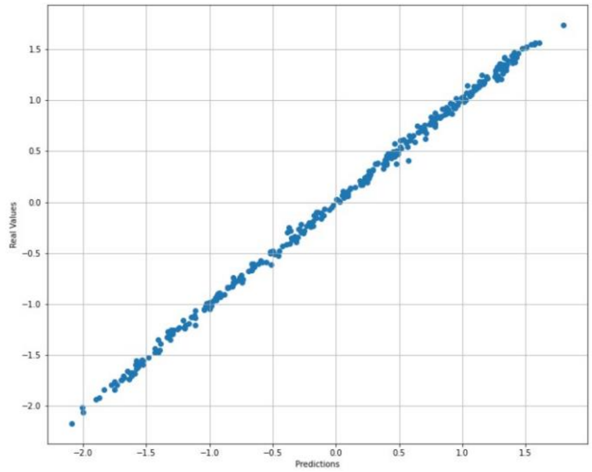

Figure 9. Wind Tunnel “Sport” Ct Forecast Model Predictions-Real Values

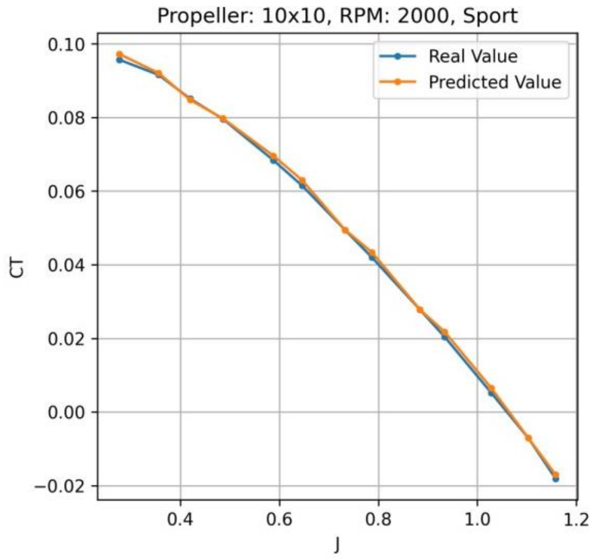

Figure 10. Wind Tunnel “Sport” Type Propeller Ct Forecast Model 10x10 Propeller 2000 RPM Model Performance

APC Propeller Sport Type Data Set Cp (Power Coefficient) Prediction Model Creation

Wind tunnel data set was used to create the wind tunnel “Sport” Cp prediction model. While creating the model and determining the model parameters, the previously created wind tunnel model was taken as reference. The hyperparameters used for the Wind Tunnel "Sport" type propeller Cp prediction model are as follows:

- 5 Layers
- 1 Input Layer, 3 Layers, 1 Output Layer

- Batch Size 4
- 500 Epochs,
- 256 Neurons in layers except Output Layer
- Mean Squared Error (MSE) Loss Function
- ReLU Activation Function
- Adam Optimization Algorithm
- Standard Scaler
- Validation (X_test, y_test)
- Test Size 1%

The determined parameters were determined based on the variables according to the prediction performance of the model and the Loss-Validation Loss graph. A neural network (ANN) model was trained according to these hyperparameters

Table 3. Wind Tunnel "Sport" CP Sequential Model Structure

Wing Tunnel "Sport" Cp Sequential Model		
Layer (type)	Output Shape	Parameter
Dense	252	1764
Dropout	252	0
Dense	168	42504
Dropout	168	0
Dense	84	14196
Dropout	84	0
Dense	42	3570
Dropout	42	0
Dense	1	43
Total Parameter = 62077		Trainable Parameter = 62077

The artificial neural network (ANN) model structure created for wind tunnel Cp prediction was created based on previous models. In order for the model to give the best performance, different "Epochs" values were tested for the established model structure.

Models trained with different "Epochs" values were examined. Among these Examined models, Model 1 has the lowest MSE and the highest R2. This shows that Model 1 performs better than other models. Since the models performed very well according to the examined "Epochs" values, the number of "Epochs" was limited to 2000 for comparison. When the Loss-Validation Loss graphs of the models for different "Epochs" values are examined, it appears that the graphs show almost similar behavior. Although the Loss and validation Loss values of the graph with an

Table 4. Comparison of model performances according to Wind Tunnel Cp Forecast Model "Epoch" Values according to Loss functions and R2 method

Model No	**1**	**2**	**3**
Model Type	Wind Tunnel "Sport" Ct Forecast Model	Wind Tunnel "Sport" Ct Forecast Model	Wind Tunnel "Sport" Cp Forecast Model
Epochs	500	1000	2000
MAE	0.03589336	0.05087223	0.043748091
MSE	0.002298777	0.00520541	0.00403422
RMSE	0.189455449	0.225548752	0.20916044
R^2	0.997517669	0.99659612	0.996350194

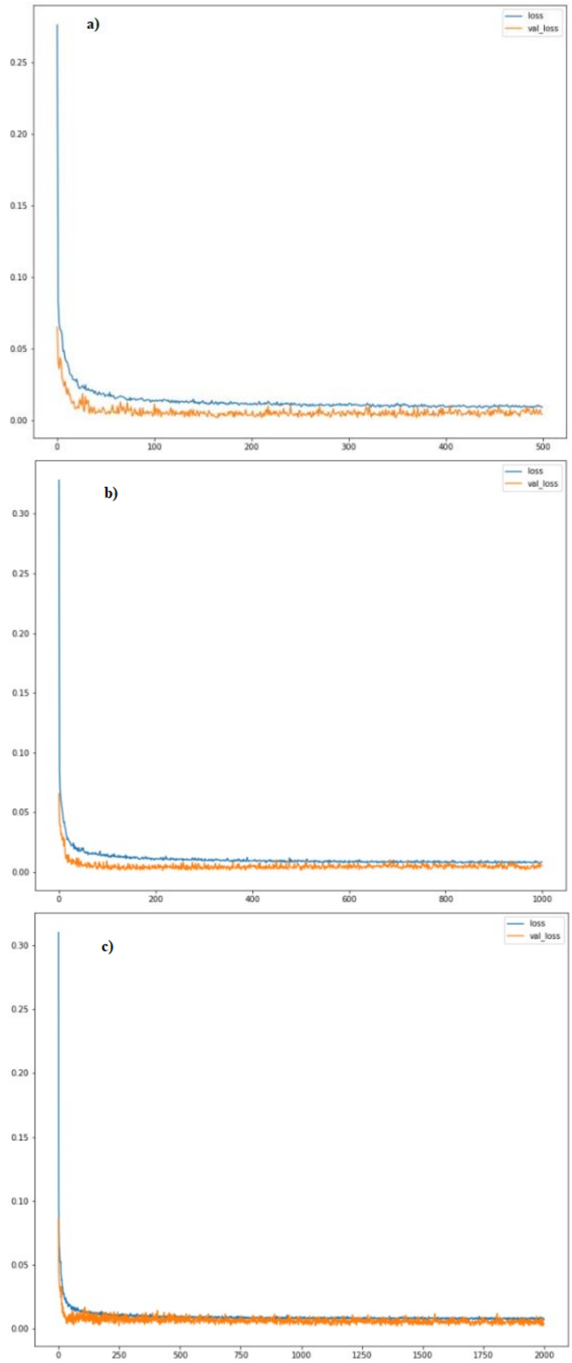

Figure 11. Wind Tunnel "Sport" Type Propeller Cp Prediction Model a) 500 "Epoch" and b) 1000 "Epoch" c) 2000 "Epoch" (Blue - Loss, Orange - Validation Loss)

"Epochs" value of 500 in Figure 11 do not overlap completely, this does not matter in terms of the performance of the model. Because the loss and validation loss values do not overlap, it generally indicates that the model can generalize well and is not overfitting. This shows that the model does not overfit the training data and can perform well with new data. When the Loss-Validation Loss graphs are examined, as well as the loss function performances and R2 results of the models, it can be seen that the model that performs well is Model 1, Model 1 will be trained for the wind tunnel "Sport" Cp prediction model.

APC Propeller Sport Type Data Set Cp (Power Coefficient) Prediction Model Training and Outputs

The Cp prediction model, which will be created using the wind tunnel data set, was trained with the artificial neural network (ANN) model data set after the determined hyperparameters and "Epochs" value.

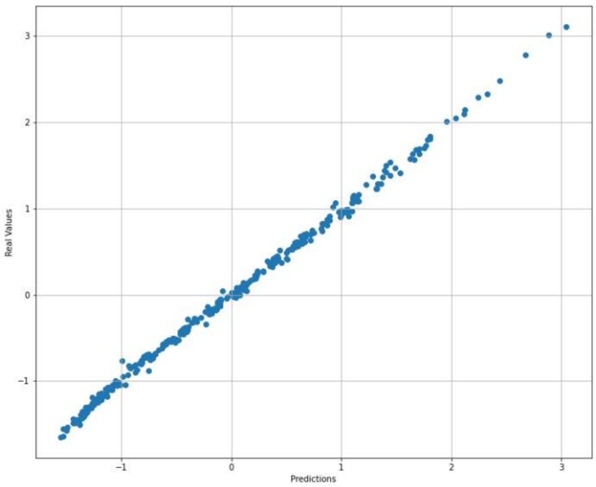

Figure 12. Wind Tunnel "Sport" CP Forecast Model Predictions-Real Values

When the Predictions-Real Values graph in Figure 12 is examined, it shows that the model and its predictions are consistent according to the behavior of the points in the graph, and that the model has learned the data set well in general. With the model trained with the wind tunnel data set, the performance of the model was examined according to propeller and RPM values in different combinations.

When the prediction ability of the model is examined, it is seen that the Cp predictions make a close prediction to the values in the data set according to the variable J (Advance ratio) values.

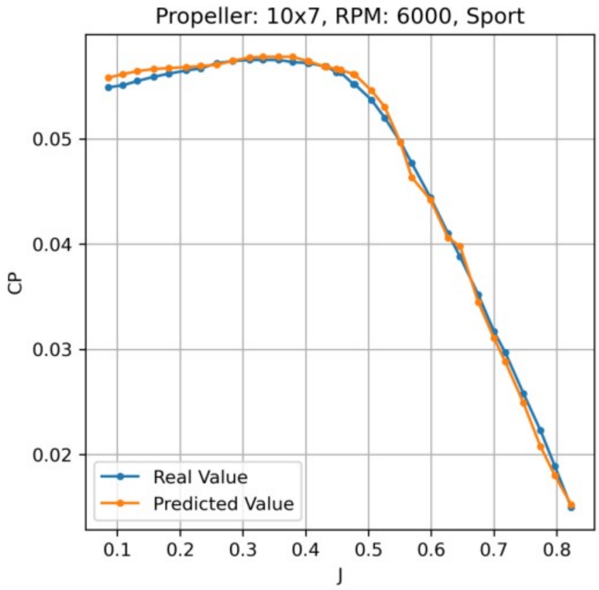

Figure 13. Wind Tunnel "Sport" Type Propeller CP Forecast Model 10x7 Propeller 6000 RPM Model Performance

APC Propeller Thin Electrical Type Data Set Ct (Thrust Coefficient) Prediction Model Creation

While creating the "Thin Electric" type propeller Ct prediction model, wind tunnel data set was initially used. Previous wind tunnel models were taken as a basis in the process of establishing the model and determining its parameters. The initial hyperparameters determined for the "Thin Electric" type propeller Ct prediction model are as follows:

- 5 Layers
- 1 Input Layer, 3 Layers, 1 Output Layer
- Batch Size 4
- 500 Epochs,
- 256 Neurons in layers except Output Layer
- Mean Absolute Error (MAE) Loss Function
- ReLU Activation Function
- Adam Optimization Algorithm
- Standard Scaler
- Validation (X_test, y_test)
- Test Size 1%

Artificial neural network (ANN) model structure will be established with the determined parameters. According to these parameters, the artificial neural network (ANN) model will be trained. Parameters can be changed according to the performance of the model.

Table 5. Wind Tunnel "Thin Electric" Ct Sequential Model Structure

Wing Tunnel "Thin Electric" Ct Sequential Model		
Layer (type)	Output Shape	Parameter
Dense	252	1764
Dropout	252	0
Dense	168	42504
Dropout	168	0
Dense	84	14196
Dropout	84	0
Dense	42	3570
Dropout	42	0
Dense	1	43
Total Parameter = 62077		Trainable Parameter = 62077

The model structure was determined by reference to previous models. It has been observed that models previously trained in this determined structure showed high prediction performance. The number of "Epochs" that would give the best performance with this model structure was determined by trial and error method.

Table 6. Comparison of model performances according to Wind Tunnel "Thin Electric" Ct Estimation Model "Epoch" Values according to Loss functions and R2 method

Model No	**1**	**2**
Model Type	Wind Tunnel "Thin Electric" Ct Forecast Model	Wind Tunnel "Thin Electric" Ct Forecast Model
Epochs	500	1000
MAE	0.03377714	0.04106794
MSE	0.0018278	0.00286244
RMSE	0.18378559	0.20265226
R^2	0.99827756	0.9974655550

The performance of models trained according to different "Epochs" values was compared. When comparing between two models, the model with lower error values is generally considered better. Therefore, in this case, it can be seen that the MAE, MSE, RMSE and R values of Model 1, which has a value of 500 epochs, are lower. Since the model learned the data set with good performance even at low Epochs numbers, there was no need for high Epochs values.

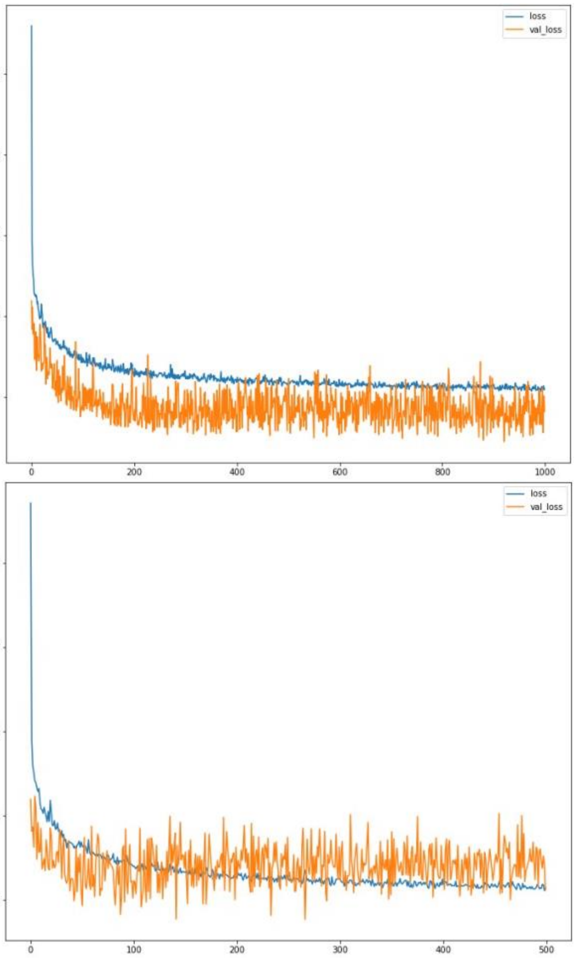

Figure 14. Wind Tunnel "Thin Electric" type propeller Ct Prediction Model (left) 500 "Epoch" and (right) 1000 "Epoch" (Blue - Loss, Orange - Validation Loss)

When the Loss-Validation Loss graphs are examined, it appears that the Loss values and Validation Loss values show similar behavior. Although these behaviors are not very stable compared to other models, the data set learning performance of the models is quite good. When the graph of the model with an "Epochs" value of 500 is examined in Figure 14, it is seen that the model generally shows a good learning performance during the training process and there is no overfitting problem. Since the difference between training and validation losses is small, it can be said that the model generalizes well to both training data and unvalidated data. However, the fluctuation of training loss indicates that the learning rate may be too high, or some training examples are forced by the model. But in general, it seems that the predicted performance of the model will be good. Model 1, that is, the model with an "Epochs" value of 500, will be preferred for training with the data set.

APC Propeller Thin Electric Type Data Set Ct (Thrust Coefficient) Prediction Model Training and Outputs

The model will be trained using the wind tunnel data set using the created model structure and the determined hyperparameters. After the artificial neural network (ANN) model is trained with the training data set, the performance of the model will be examined.

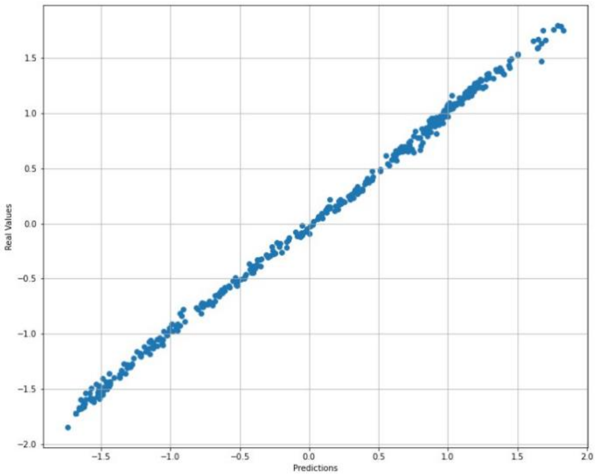

Figure 15. Wind Tunnel "Thin Electric" Ct Forecast Model Predictions-Real Values Graph

When you look at the Predictions-Real Values graph in Figure 15, you can see that there is a clear linear relationship in the graph. This indicates that the predictions of the model are very close to the real values and the performance of the model is quite good and the model performs well in learning the data set. The prediction performance of the artificial neural network (ANN) model trained with the data set was examined.

Model prediction performance is very close to real data. The model performance output shows that the model can predict well both the propeller combinations in the data set and the propeller combinations not in the data set

APC Propeller Thin Electrical Type Data Set Cp (Power Coefficient) Prediction Model Creation

While creating the wind tunnel "Thin Electric" Cp prediction model, previous wind tunnel prediction models were taken as reference. Wind tunnel "Thin Electric" data set was used as the data set. For the wind tunnel "Thin Electric" Cp artificial neural network (ANN) prediction model, the following hyperparameters were determined for the model.

- 5 Layers
- 1 Input Layer, 3 Layers, 1 Output Layer
- Batch Size 16
- 1000 Epochs,
- 256 Neurons in layers except Output Layer
- Mean Absolute Error (MAE)Loss Function
- ReLU Activation Function
- Adam Optimization Algorithm
- Standard Scaler
- Validation (X_test, y_test)
- Test Size 1%

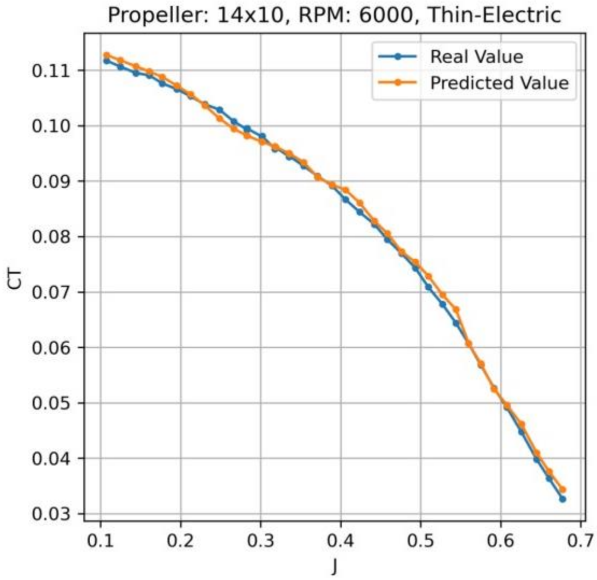

Figure 16. Wind Tunnel "Thin Electric" Type Propeller Ct Forecast Model 14x10 Propeller 6000 RPM Model Performance

Artificial neural network (ANN) model structure will be established according to the determined parameters. This model structure was created based on the structure of artificial neural network (ANN) models created with previously good performing simulation and wind tunnel data sets.

It has been observed that the number of layers and neurons is sufficient for previously created artificial neural network (ANN) models. Therefore, there was no need for more layers and number of neurons in the wind tunnel "Thin Electric" Cp prediction model structure. With the created model structure, the model will be trained with different "Epochs" values. "Epochs" values will be determined by trial and error method according to the prediction performance of the model.

Table 7. Wind Tunnel “Thin Electric” Cp Sequential Model Structure

Wind Tunnel “Thin Electric” Cp Sequential Model		
Layer (type)	Output Shape	Parameter
Dense	252	1764
Dropout	252	0
Dense	168	42504
Dropout	168	0
Dense	84	14196
Dropout	84	0
Dense	42	3570
Dropout	42	0
Dense	1	43
Total Parameter = 62077		Trainable Parameter = 62077

Table 8. Comparison of model performances according to Wind Tunnel Cp Forecast Model “Epoch” Values according to Loss functions and R2 method

Model No	**1**	**2**
Model Type	Wind Tunnel “Thin Electric” Cp Forecast Model	Wind Tunnel “Thin Electric” Cp Forecast Model
Epochs	500	1000
MAE	0.0309182	0.030591069
MSE	0.00173574	0.00196366
RMSE	0.17498080	0.17490302
R^2	0.99818197	0.99820711

With the created model structure, the performance of the model was examined for different "Epochs" values. It is seen that the model performs well when training the model with a low number of "Epochs". So there is no need for more Epochs values. In Figures 17 and 18, the models trained with 500 and 1000 "Epochs" values are compared. When these two models are examined, it is seen that the models perform very close to each other when the loss function performance and R2 score are examined. Although the R2 performance of the 2nd model is very close, it is higher, so the 2nd model was preferred to train the prediction model.

Loss-Validation When the loss graphs are examined, it is seen that the graph of the 2nd model shows a generally good learning performance in the process of learning the data set. 2. When the Loss-Validation Loss graph of the model is examined, it is seen that the Loss and Validation Loss values do not increase, so there is no overfitting problem. Since the difference between the training and validation losses of the model is small, it can be said that the model generalizes well to both training data and unvalidated data. Considering the loss function performance, R2 score and Loss-Validation Loss graph for the wind tunnel “Thin Electric” Cp prediction model, it was decided to train the 2nd Model, which has a value of 1000 “Epochs”, with the data set and use it as the prediction model.

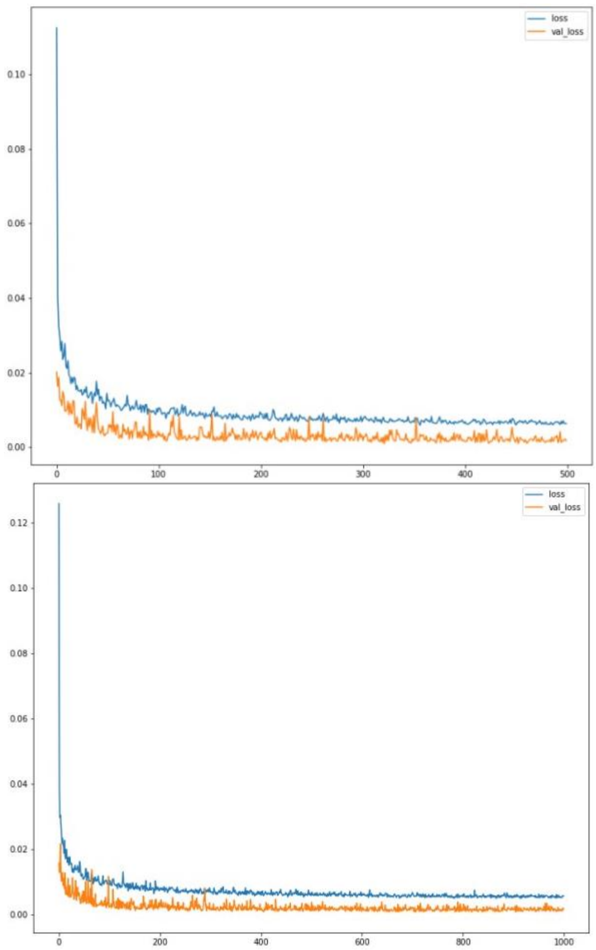

Figure 17. Wind Tunnel “Thin Electric” Type Propeller Cp Prediction Model (left) 500 “Epoch” and (right) 1000 “Epoch” (Blue - Loss, Orange - Validation Loss)

APC Propeller Thin Electric Type Data Set Cp (Power Coefficient) Prediction Model Training and Outputs

After the hyperparameters and "Epochs" value of the model were determined, the model was trained with the wind tunnel data set. After the artificial neural network (ANN) model was trained, the prediction performance of the model was examined.

When the Predictions-Real Values graph in Figure 18 is examined, it is seen that there is a linear and linear relationship between the prediction and real values.

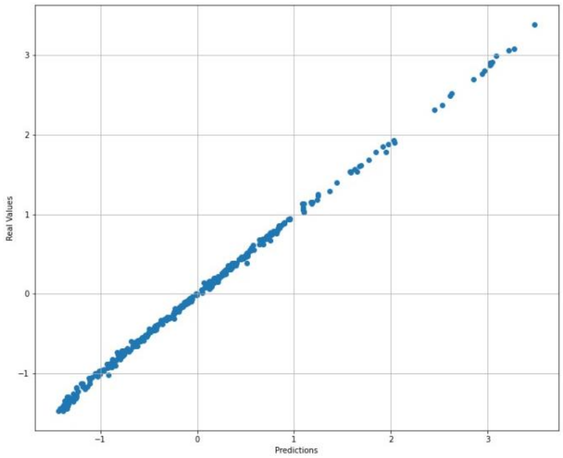

Figure 18. Wind Tunnel "Thin Electric" Cp Forecast Model Predictions-Real Values Graph

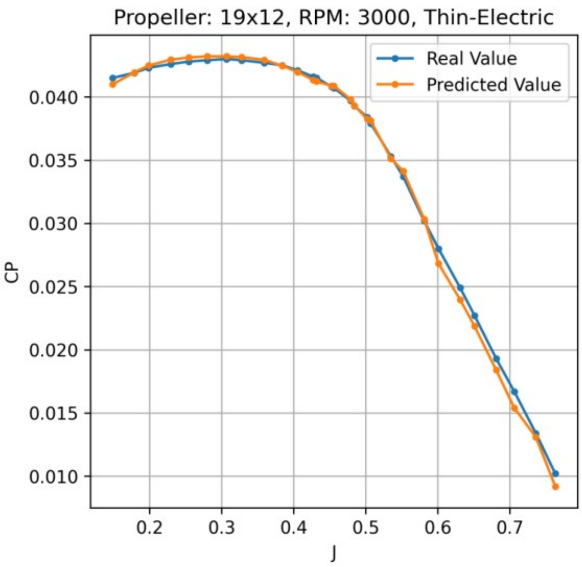

Figure 19. Wind Tunnel "Thin Electric" Type Propeller Cp Forecast Model 19x12 Propeller 3000 RPM Model Performance

This relationship shows that the model has a good performance in learning the data set well. The prediction performance of the artificial neural network (ANN) model trained with the data set was examined.

When the prediction performance of the model is examined, it is seen that it performs well between the real data and the predicted data according to different RPM values and different propeller combinations. The performance of the model in predicting the real data in the data set and the data not in the data set is very good and gives results very close to reality. This model will be used for the wind tunnel "Thin Electric" Cp prediction model.

Comparison of Wind Tunnel Artificial Neural Network Models

Four artificial neural network (ANN) models were created using the wind tunnel data set. These created wind tunnel models will help find Ct (Thrust Coefficient) and Cp (Power Coefficient) for different RPM values of propeller combinations that do not have wind tunnel test data without going to the wind tunnel.

When the four artificial neural network (ANN) models created are examined, it is seen that error metrics such as MAE, MSE and RMSE are at a very low level. These metrics show that the model's predictions are quite close to the actual values. Additionally, the R2 score is very close to 1 in 4 models. This means that the models fit the data set very well and their predictions exactly match the real values.

4. Conclusion

This study explores an approach that utilizes artificial neural networks and machine learning methods to determine the aerodynamic performance of propellers. The primary goal is to estimate the thrust and power values that different propeller combinations will produce without relying on wind tunnel data. The analyses demonstrate that artificial neural networks and machine learning models can accurately model the aerodynamic performance of propeller combinations without wind tunnel data.

Table 9. Artificial Neural Network (ANN) Models for "Sport" and "Thin Electric" type propellers created using the Wind Tunnel dataset and Simulation Forecast dataset

Model type	Epochs	MAE	MSE	RMSE	R^2
Wind Tunnel "Sport" Ct Forecast Model	1000	0.032211390	0.001689722	0.17947532	0.99833180
Wind Tunnel "Sport" Cp Forecast Model	500	0.03589336	0.002298777	0.189455449	0.997517669
Wind Tunnel "Thin Electric" Ct Forecast Model	500	0.03377714	0.0018278	0.18378559	0.99827756
Wind Tunnel "Thin Electric" Cp Estimation Model	1000	0.030591069	0.00196366	0.17490302	0.99820711

This provides a significant advantage by reducing dependence on wind tunnel testing and speeding up the design process. In this study, four different wind tunnel models were created, all of which produced results very close to real-world conditions. The results obtained from the models of propellers with wind tunnel data are very close to the true value of 1, with all four models yielding values that are 99.8% close to the actual value. This indicates how well the models align with reality. These models can accurately predict the thrust (Ct) and power (Cp) coefficient values of propellers without wind tunnel test data. This success is based on the effective use of artificial neural networks and machine learning methods. The results obtained show that these techniques can be successfully applied in the process of modeling the aerodynamic performance of propellers.

5. Suggestions and Evaluations

The artificial neural network models used in this study exhibit similarities to those found in the literature. However, these models can exhibit different behaviors depending on the dataset. Upon examining the models and datasets in the literature, it is observed that the average accuracy rate of the models in this study is 99.9%, which surpasses the accuracy capabilities of all models previously reported in the literature. The findings of this study are significant for accelerating the design process and reducing costs by decreasing reliance on wind tunnel testing. While wind tunnel testing can typically take months, the artificial neural network models used here can provide high-accuracy test data in seconds. Additionally, accurately predicting the thrust and power values of propeller combinations is considered a crucial step in UAV design and optimization. These results suggest that artificial neural networks and machine learning techniques are valuable tools for analyzing and optimizing the aerodynamic performance of propellers.

Nomenclature

UAV : Unmanned Aerial Vehicle
ANN : Artificial Neural Network
CFD : Computational Fluid Dynamics
APC : Propeller Brand
Cp : Power Coefficient
Ct : Thrust Coefficient
BEM : Blade Element Momentum Theory
UAS : Unmanned Aircraft System
CQ : Torque Coefficients
QAR : Quick Access Recorder
RC : Radio Controlled
PWM : Pulse Width Modulation
UIUC : University of Illinois at Urbana-Champaign
MSE : Mean Squared Error Loss Function
MAE : Mean Absolute Error Loss Function
RMSE: Root Mean Squared Error Loss Function
J : Advance Ratio

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