CONCEPTUAL AND PRELIMINARY DESIGN OF AN UNMANNED AERIAL VEHICLE USING MACHINE LEARNING

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ABSTRACT

In this study, the relations between design parameters of an unmanned aerial vehicle (UAV) are obtained using machine learning (ML) algorithms by fitting the requirements to existing data followed by conceptual and preliminary design. The data available for 250 UAVs are collected and 17 design parameters are used to train the ML algorithm among which 5 features are determined as input variables and the remaining 12 are considered to be output. The output results are then estimated by the ML algorithm in a sequential manner concerning a new model for each output that is predicted.

INTRODUCTION

The importance and usage areas of Unmanned Aerial Vehicles (UAV) are increasing day by day. Nowadays UAVs with different design features are being utilized in many civil and military applications such as surveillance, reconnaissance, cargo, agriculture, imaging, fire fighting, etc. This emphasizes the role of UAV design and mission compatibility more than ever. Through the design process of an unmanned aerial vehicle, known design steps consisting of conceptual, preliminary and detailed design are followed as seen in Figure 1 [Raymer, 1992]. As in aircraft design, historical data has substantial importance in order to determine the requirements and designing a UAV [Gundlach, 2011]. During the design phase, many parameters are determined by looking at existing UAVs while there are many design configurations to be decided independently. Some of the methods in the literature that are used to facilitate the complex design process leading to more suitable designs are examined below.

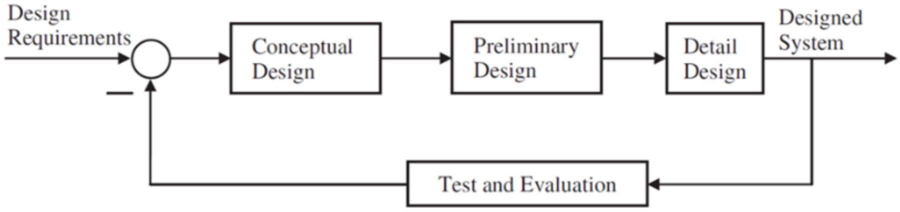

Figure 1: UAV design stages scheme

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Ruben E. Perez et al. tried to improve the aircraft design by using the Genetic Algorithm and Penalty Function with design optimization variables given in a certain interval [Perez, 2000]. Their work showed that Genetic Algorithm as a Machine Learning application gives good results for conceptual design of an aircraft. Yousef Azabi et al. have tried to develop the Aegis UAV geometry using the stochastic multi-objective optimization, combined with an Artificial Neural Network (ANN) [Azabi, 2019]. According to the results of their work, the optimization method they used resulted in a better aerodynamically design result for the Aegis UAV. There exist plenty of applications of Machine learning on aerodynamic design in the literature. In the study of Karali et al., a nonlinear aerodynamic model for UAVs has been developed [Karali, 2020]. They trained the model with a dataset consisting of 22,000 UAVs they created by using non-linear lifting line tool. As a result of this study, the model was able to quickly estimate the aerodynamic performance parameters of different wing-tail configurations and was found to be effective for design optimization. In addition, many examples of machine learning applications in the fields of aerodynamic design, computational fluid dynamics (CFD), and fluid mechanics have been examined in the literature [Brunton, 2020].

Neufeld et. al. used Genetic Algorithm and Data Mining for UAV Conceptual Design [Neufeld, 2005], inspiring the subject of the current study. They have implemented machine learning that decides various configurations using Decision Tree. They simulated a UAV which is designed by the model using the X-Plane® software. Although the full access to the detailed information on the database and results of this study is not possible, it provided a seminal perspective in the use of machine learning for UAV Conceptual Design. Looking at existing studies in the literature and the application areas of machine learning, it is seen that a machine learning application that can give better design results is basically constructed on historical data.

In this study, the conceptual design of a UAV is carried out using a Multilayer perceptron (MLP) machine learning algorithm which is created and taught using the database including design parameters of available existing UAVs. MLP is one of the classes of feedforward artificial neural networks (ANN). MLP comprises at least three layers of nodes: an input layer, a hidden layer, and an output layer. A well-trained MLP can fully perform any complex nonlinear functions, therefore a fully connected MLP is often an excellent choice for the most common classification or regression problems [Zhu, 2019]. With the use of well-known classification strategies in data mining and statistics [Zhang, 2018; Shateri, 2020; Song, 2015, Shateri, 2020], different k, c, and several estimators values are assigned to different test samples for K nearest neighbor (KNN), Support Vector Regression (SVR), and Random Forest (RF) algorithms, respectively, using the cross validation method.

METHOD

Dataset and Software

It is known that machine learning applications yield more accurate results by increasing the amount of data available in the dataset. In this study, a dataset containing the design parameters of the existing UAVs has been prepared from scratch. While doing so, it was decided to use the following design parameters; mission, category, engine location, engine type, wing position, wing type, tail category, maximum take-off weight (MTOW), payload, wingspan, wing area, fuselage length, fuselage height, cruise speed, max speed, ceiling altitude, endurance, and power. An extensive research has been carried out on UAVs according to these design parameters and information on 250 UAVs has been collected using many sources [Hann, 2020; Munson 2005]. As the aim of this study, the conceptual design parameters were estimated with a fewer number of inputs. The selected 6 inputs were determined to cover the general features of the UAV to be designed. Therefore, payload, mission, category, cruise speed, endurance, and ceiling altitude parameters are chosen as input variables. According to the database, there exist different types of tails and in order to reduce this variety, it is decided to categorize tail types into only 4 categories that are shown in Table 1.

Table 1: Tail categories.

	Tail Category			
	TC-1	**TC-2**	**TC-3**	**TC-4**
Tail Type	Conventional Tail	V Tail	Boom	no
	T tail	Inverted V	High Boom Tail	
			Twin Tail	

Looking at the design parameters, it is seen that some of them are numerical parameters while others represent categories. It is thought that the relevant design parameters will provide sufficient perspective for conceptual design. A dataset was created by using above mentioned information. A sample of the dataset is shown in Table 2. Dataset arrangements, model training, and result graphics are made with Python 3.7 in GPU-supported Google Colab. The codes of the classification algorithms that will be explained in detail in the next section are taken from opensource codes in the scikit-learn library and own MLP algorithm code is created by using Keras from the TensorFlow library.

Table 2: Dataset sample.

	1	2	3	4	5	6	7	8	9	10
Name	Delair UX11	OM UAV Systems Eagle Eye	Aeromapper Avm	Bramor C4EYE	Lockheed Martin Stalker XE	Orlan 10	Warrior Gull 24	UAV Factory Penguin B	Qods Mohajer-2	Wulung
Category	MİNİ	MİCRO	CR	SR	MR	MRE	LALE	LALE	CR	SR
Mission	commercial	commercial	commercial	commercial	commercial	tactical	cargo	commercial	tactical	tactical
Engine Location	back	back	front	back	front	front	front	back	back	back
Engine Type	electrical	piston	piston	electrical	electrical	piston	piston	piston	piston	piston
Wing Position	mid	high	high	mid	high	high	high	high	high	high
Wing Type	delta	tapered	straight	delta	straight	straight	straight	straight	straight	straight
Tail Category	TC-4	TC-1	TC-2	TC-4	TC-1	TC-1	TC-1	TC-2	TC-3	TC-1
Tail Type	no	C	V	no	T	C	T	inverted V	HBT	T
MTOW [kg]	1,5	1,81	2	4,5	10,9	15	18	21,5	85	125
Payload [kg]	1,5	0,5	0,7	0,5	2,5	6	6	10	15	35
Wingspan [m]	1,1	2	2,14	2,3	3,7	3,1	2,7	3,3	3,8	6,34
Fuselage Length [m]	0,5	1,05	1	0,96	2,5	2,5	2,2	2,27	2,91	4,42
Fuselage Height [m]	0,2	0,08	0,4	0,1	0,6	0,7	1	0,9	1	1,48
Cruise Speed [m/s]	15	13,9	16,7	16	15,6	30	30	22	150	30,9
Max speed [m/s]	18	16,5	21	22	20,1	42	38	36	200	51,4
Ceiling Altitude [m]	6000	3000	3500	5000	3700	5000	4000	5000	3350	1700
Endurance [h]	1	0,83	3	3	8	16	20	20	1,5	4
Power [kW]	0,2	0,29	0,2	0,5	0,8	2,00	3,00	1,86	18,64	16,4

MLP Models for Regression Predictions

As a result of many trials, it has been observed that it is not efficient to take all the outputs simultaneously. Therefore, a new model was assigned for each output. The inputs to be used for each model were used as 6 target inputs and outputs of previous models. 7 different models were created for a total of 7 regression outputs. For regression estimations, two different models were used: Multi Layer Perceptron (MLP) and Decision Tree Regression (DT). Then, the most successful one was selected for each above mentioned 7 models and the result of this model was given as an input to the next model. The outcomes are given in the results section. MLP is a subgroup of Feed-forward Network Functions. The architecture of MLP is in figure left. Hidden layers and neuron counts were determined after HyperTuning [Bishop, 2016]. While creating MLP models, Mean Square Error (MSE) and Leaky-rectified linear unit (Relu) were used as the loss and

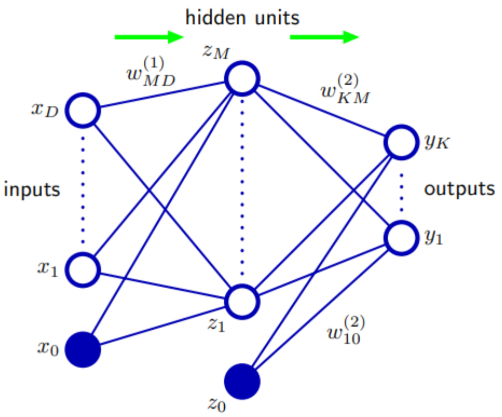


Figure 2: Structure of Multilayer Perceptron.

activation functions, respectively [Calik, 2019]. The training was carried out with 300 iterations and EarlyStopping was used to prevent overfitting [Caruana, 2001]. Finally, Nesterov accelerated adaptive moment (NAdam) was implemented as an optimizer [Dozat, 2016]. As a common practice, the existing database is divided into 70% and 30% for train and test datasets, respectively. StandardScaler and MinMaxScaler were used to scale the inputs. There was no such procedure applied to the outputs. The StandardScaler score of sample x is calculated as [Pedregosa, 2011]:

$$z = (x - u) / s \quad (1)$$

where u is mean of the training samples, s is the standard deviation of the training samples.

The standardized result of x_{scaled} for MinMaxScaler is:

$$x_{scaled} = s * (X_{min} - X_{max}) \quad (2)$$

where X_{min} is the minimum value and X_{max} is maximum value of data.

Hidden layers and neuron counts were determined after HyperTuning. Decision Tree algorithm was called from scikit-learn library [Pedregosa, 2011]. Inputs of above mentioned 7 models are shown in Table 3. It is worth mentioning that because of the lack of data for wing area, during the training of the relevant model (Model 7 in Table 3), the approach was to select a dataset containing only 60 UAVs and in addition to that to use all the outputs from the rest of the models (models 1-6 in Table 3).

Table 3: Inputs and outputs of regression models.

Models	Outputs	Inputs
Model 1	MaxSpeed	Payload, Cruise Speed, Endurance, Category, Mission
Model 2	Maximum Take-Off Weight (MTOW)	Payload, Cruise Speed, Endurance, Category, Mission, Max. Speed
Model 3	WingSpan	Payload, Cruise Speed, Endurance, Category, Mission, Max. Speed, MTOW
Model 4	Power	Payload, Cruise Speed, Endurance, Category, Mission, Max. Speed, MTOW, Wingspan
Model 5	Fuselage Length	Payload, Cruise Speed, Endurance, Category, Mission, Max. Speed, MTOW, Wingspan, Power
Model 6	Fuselage Heigth	Payload, Cruise Speed, Endurance, Category, Mission, Max. Speed, MTOW, Wingspan, Power, Fuselage Length
Model 7	Wing Area	Payload, Cruise Speed, Endurance, Category, Mission, Max. Speed, MTOW, Wingspan, Power, Fuselage Length, Fuselage Height, Wing Position, Engine Location, Engine Type, Wing Type, Tail Category

Models for Classification Predictions

KNN, SVC, DT and RF algorithms were taken from the scikit-learn library and dataset divided into a 70:30 ratio as training and test data for the classification part [Pedregosa, 2011]. SVM error function and KNN probability function is given below [Bishop, 2016]:

$$C \sum_{n=1}^{N} (\xi_n + \hat{\xi}_n) + \frac{1}{2} \|w\|^2 \quad (3)$$

$$p(Ck|x) = \frac{p(x|Ck)p(Ck)}{p(x)} \quad (4)$$

Where w is an error function, C is the inverse regularization parameter, ξ is continuous one dimension parameter and p is probability.

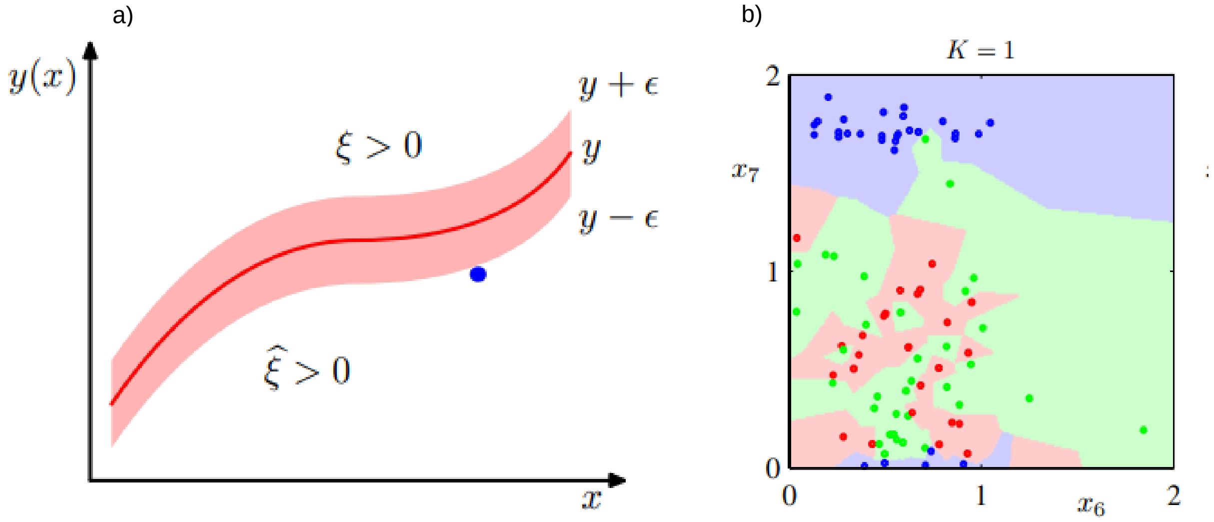


Figure 3: a) SVM with regression curve tube, b) KNN class example while K=1.

Parameters in models were optimized to increase accuracy by using for-loops which include an available range of parameters. Stratify - which is an addon to skitlearn library - was used so that the number of samples in the classes in test data and train data were directly proportional [Fernandes, 2018]. MLP was not included in the comparison. It is because of the fact that MLP models focus on a large number of data in the dataset and therefore they tend to predict the class with the highest number of data in the dataset. Since the data in our dataset is not evenly distributed, MLP models seem not to be appropriate.

Models Evaluations

To evaluate the regression models, their performance was compared based on MSE and R^2 values. As in classification, accuracy value and cross validation score values in scikit-learn library were used. Mean Square Error (MSE) and R^2 were obtained by using the formulas given below [Kobayashi, 2000]:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_{predicted} - Y_{actual}\right)^2 \tag{5}$$

$$R^2 = \frac{\sum_{i=1}^{n}(Y_{predicted} - Y_{actual})^2}{\sum_{i=1}^{n}(Y_{predicted} - Y_{mean})^2} \tag{6}$$

where n is the number of test data, $Y_{predicted}$ is output of models, Y_{actual} is the real value of test data, and Y_{mean} is the average of Y_{actual} values.

RESULTS

Model Results

Table 4 shows MSE and R^2 values for the models used in regression estimation. Comparing DT and MLP seems to give better results for MLP in each model. According to the values listed in the table, the average of R^2 values is about 90%, suggesting that the results are substantial. The table also shows the models and the number of related neurons that were used for training. While many neurons were required for the wing area model (Model 7), a comparably small number of those was sufficient for MTOW model (Model 2). MSE values in some models are due to the fact that the outputs are either not scaled or the scalers are different. The low accuracy in fuselage height could be due to the low accuracy of data for some of the UAVs in the dataset, where the landing gear is included in the total height, while in others is not. The actual results are compared with the predictions in the test data for each model and it is presented in Appendix A.

Table 4: Regression models results. Outputs are given in Table 3.

Models	MLP					Decision Tree	
	Number of Hidden Layers	Total Neurons	Scaler	R2	MSE	R2	MSE
Model 1	6	38	StandardScaler	**0,9827**	**171,7**	0,9296	700,84
Model 2	6	33	StandardScaler	**0,8961**	**1750**	0,5089	8272
Model 3	5	75	StandardScaler	**0,8611**	**0,76**	0,7418	1,412
Model 4	6	87	MinMaxScaler	**0,9518**	**13,74**	0,9233	21,88
Model 5	5	81	StandardScaler	**0,9087**	**0,137**	0,8515	0,2223
Model 6	5	81	StandardScaler	**0,8195**	**0,04**	0,5821	0,093
Model 7	21	175	StandardScaler	**0,9309**	**0,196**	0,4509	1,55

Classification models seem to have low accuracy according to the classification results that are listed in Table 5. This is due to the fact that the geometric parameters are not taken into account in the preliminary design stage and are subject to change during the analysis and are not finalized. The engine location model has the highest accuracy in classification models. Although RF model has higher accuracy for 3 classification models, only DT models were used for them because otherwise, they may lead to unclassified results. Since tail type accuracy is low, only those configurations of tail were chosen that were believed to be relevant to each other.

Table 5: Classification models results.

Model Numbers	Classification	Models			
Model 8	Wing Position	**DT**	RF	KN	SVR
	Accuracy	**0,74**	0,69	0,66	0,67
	Cross Validation	**0,72**	0,69	0,61	0,67
	Standart Deviation	**0,08**	0,11	0,05	0,09
Model 9	Engine Location	DT	**RF**	KN	SVR
	Accuracy	0,62	**0,72**	0,6	0,62
	Cross Validation	0,59	**0,65**	0,59	0,58
	Standart Deviation	0,04	**0,05**	0,1	0,11
Model 10	Engine Type	DT	**RF**	KN	SVR
	Accuracy	0,85	**0,89**	0,84	0,85
	Cross Validation	0,79	**0,88**	0,84	0,86
	Standart Deviation	0,08	**0,06**	0,08	0,08
Model 11	Wing Type	DT	**RF**	KN	SVR
	Accuracy	0,8	**0,84**	0,76	0,78
	Cross Validation	0,72	**0,8**	0,69	0,75
	Standart Deviation	0,14	**0,14**	0,1	0,11
Model 12	Tail Category	**DT**	RF	KN	SVR
	Accuracy	**0,69**	0,65	0,52	0,42
	Cross Validation	**0,55**	0,47	0,46	0,4
	Standart Deviation	**0,05**	0,08	0,1	0,1

Table 6: Confusion classification matrix.

		Predicted				
Model 8 (Wing Position)	Actual		High	Mid	Low	
		High	**48**	3	3	
		Mid	3	**4**	1	
		Low	8	1	**4**	
Model 9 (Engine Location)	Actual		Back	Front		
		Back	**36**	9		
		Front	12	**18**		
Model 10 (Engine Type)	Actual		Electrical	Internal C.		
		Electrical	**22**	5		
		Internal C.	3	**45**		
Model 11 (Wing Type)	Actual		Delta	Straight	Tapered	
		Delta	**5**	12	0	
		Straight	1	**50**	0	
		Tapered	0	5	**2**	
Model 12 (Tail Category)	Actual		TC-1	TC-2	TC-3	TC-4
		TC-1	**22**	13	1	1
		TC-2	2	**10**	1	0
		TC-3	0	1	**14**	1
		TC-4	1	1	1	**6**

Table 6 shows the confusion classification matrix wherein the columns represent the models predictions and rows show the actual values of the dataset. Looking at the results, it is seen that no model made a choice in only one class. In addition, it has been observed that the error distributions are not concentrated in one class. Therefore, it can be thought that although the accuracy rates of the models are low, models could properly find a relation between the data in the dataset. It is observed that the accuracy of the low class prediction is very low in wing position and most of the predictions in the wing position model are of straight type.

Test Results

Models were tested using input parameters determined for 10 different UAV designs out of which, 3 test outputs are shown in Table 7 and the rest are given in Appendix B. Design parameters of a similar UAV are also given in order to compare with the results.

The next step after obtaining the output values is to select the airfoil for the wing and tail. During the calculations, values of zero-lift drag coefficient (c_{d_0}) were chosen between 0.01-0.05 in accordance with the literature as well as the characteristics of the current UAV to be designed [Raymer, 1992]. For a steady state flight it is assumed that lift is equal to the weight, therefore - using the formulas given below - lift (equation 3) and induced drag (equation 4) coefficients as well as drag force (equation 5) and required power (equation 6) can be calculated. While determining stall speed, the maximum lift coefficient ($c_{l_{max}}$) that the airfoil can provide has been taken into consideration. Airfoil selection was made in accordance with the c_l value required for the stall speed determined here.

The maximum speed obtained by the maximum power approximates some designs for a UAV while there might be some cases that are far overpredicted by the approach. An example of calculations for test UAVs is given in Appendix C. When the airfoil selection is made, the fuselage as well as the wings and control surfaces, can be drawn in CAD software in accordance with the outputs. Comparison of output UAVs and similar existing ones are shown in figure 2. These solid models are given as simple representational pictures and the final design can be improved using the same outputs.

Table 7: Design parameter results of Test-1, Test-2 and, Test-3 UAVs.

		AeroVironment Wasp AE-RQ 12A	Test-1	IDS IA-17	Test-2	UAV Factory Penguin C	Test-3
INPUT	Category	MİCRO	MİCRO	SR	SR	LALE	LALE
	Mission	commercial	commercial	commercial	commercial	commercial	commercial
	Payload [kg]	0,2	0,2	2,5	2,5	7	7
	Cruise Speed [m/s]	10,30	10,30	37	37	22	22
	Ceiling Altitude [m]	500	500	4500	4500	5000	5000
	Endurance [h]	0,8	0,8	5	5	20	20
OUTPUT	MTOW [kg]	1,3	2,47	27,5	22,87	23	25,62
	Wingspan [m]	1,02	1,25	2,8	2,91	3,3	3,40
	Fuselage Length [m	0,76	0,99	1,27	1,43	2,286	1,82
	Fuselage Height [m]	0,2	0,26	0,22	0,37	0,201168	0,64
	Max speed [m/s]	23,20	23,59	44,4	43,58	36	34,57
	Stall speed [m/s]	Unknown	9,00	Unknown	20,00	Unknown	18,00
	Wing Area [m2]	Unknown	0,26	Unknown	0,90	0,79	0,68
	AR	Unknown	6,10	Unknown	9,41	13,78481013	17,08
	W/S	Unknown	95,00	Unknown	250,00	Unknown	370,00
	Power [kW]	0,2	0,49	1,8	1,96	1,86	1,73
	Engine Location	front	front	back	back	back	back
	Engine Type	electrical	electrical	piston	piston	piston	piston
	Wing Position	low	high	mid	mid	high	high
	Wing Type	tapered	tapered	delta	delta	straight	straight
	Tail Category	TC-1	TC-1	TC-4	TC-4	TC-2	TC-2
	Tail Type	C	C	no	no	inverted V	inverted V
	Airfoil	Unknown	Selig s1223	Unknown	NACA 63412	Unknown	Selig s1223

$$cl = \frac{W}{0,5*\rho*V^2*S} \tag{7}$$

$$cd_i = \frac{cl^2}{\pi*e*AR} \tag{8}$$

$$D = cd_0 + cd_i \tag{9}$$

$$P = D * V \tag{10}$$

DISCUSSION

When similar existing UAVs are compared with the results obtained as outputs of the ML algorithm, it is predictable to get a general similarity in terms of design parameters. These values are considered to be sufficient for the phase of the conceptual design of UAVs. Considering that the current study is based on a limited number of training populations while keeping such different and mostly independent parameters, it will not be exaggerative to consider this method to be efficient. To get more reliable results it is recommended to create an independent dataset for each category of UAVs. However, it is often difficult to obtain all the characteristics of UAVs due to either commercial or military concerns which is the biggest obstacle in the current study. By creating such separated datasets, it is probable to get more stable results for each model. Due to the nature of MLP which can be fixed to the local minimums, different weights in each training model can result. To avoid this and to use MLP more efficiently, 7 samples were selected to cover the entire data. Among the trained models the ones that made the most accurate predictions for these 7 samples were selected. In addition, this method was found to be helpful in reducing the margin of error that increases sequentially. The high error value of the previous model has been reduced in the later models. Further customized models can be created by increasing the number of these 7 samples or selecting samples in different UAV categories.

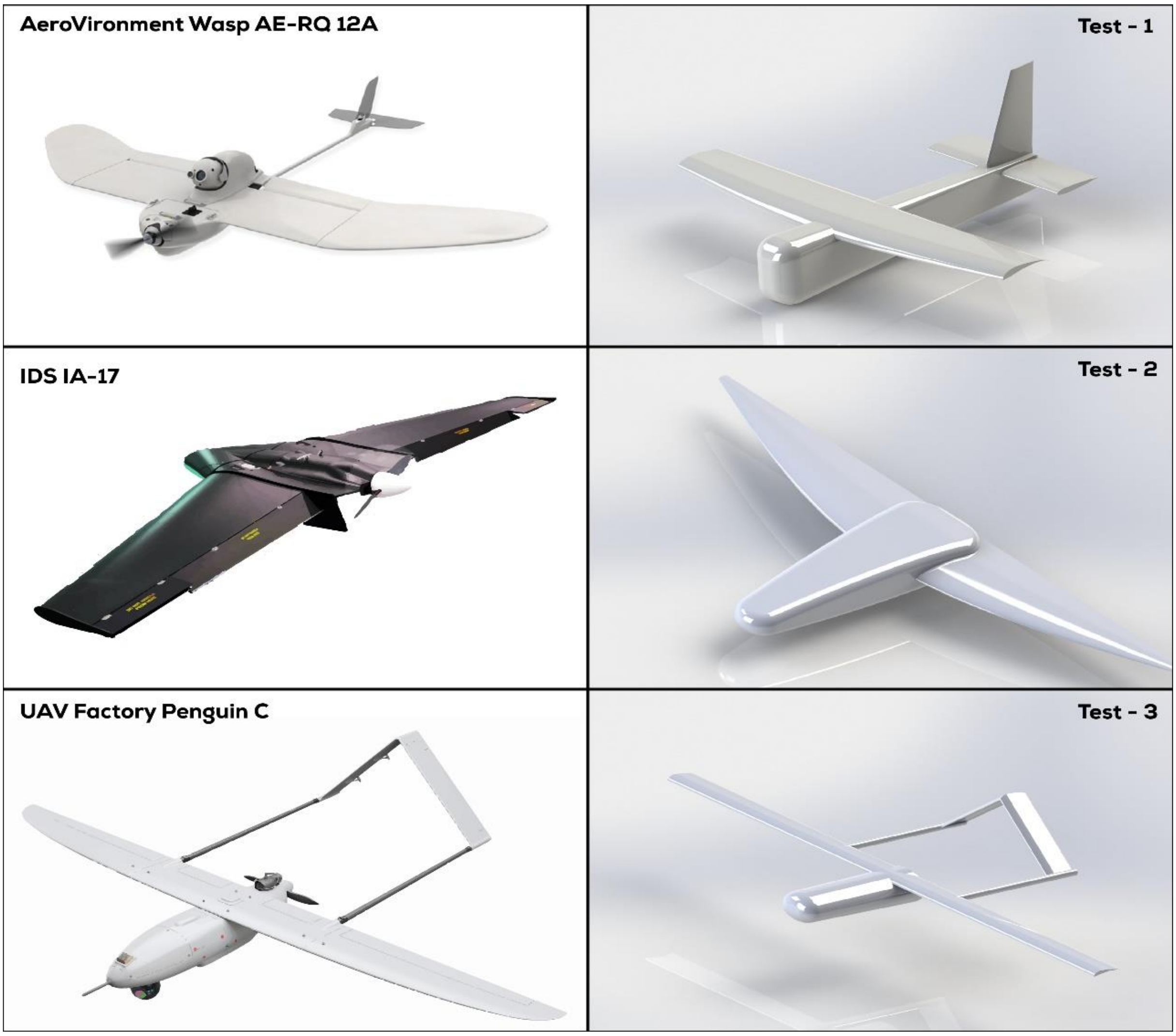


Figure 4: Solid models of chosen UAVs and test results.

CONCLUSION

This study was conducted with the idea of making UAV design efficient using machine learning algorithms. Initially, a dataset consisting of 17 different parameters of 250 UAVs was created. All models were trained by selecting 5 input parameters and the relevant outputs of the sequential training process. Various improvements were made to the dataset as well as models to increase the accuracy of the approach. Determined targets were transferred to previously trained models and the algorithm was tested on 10 different cases. These results were visualized adhering to methods in the literature. The resulting solid models were compared with existing UAVs. Recommendations have been made to propose more efficient and reliable models in the future.

REFERENCES

Azabi, Y., Savvaris, A., & Kipouros, T. (2019). Artificial Intelligence to Enhance Aerodynamic Shape Optimisation of the Aegis UAV. *Machine Learning and Knowledge Extraction*, *1*(2), 552–574. https://doi.org/10.3390/make1020033

Bishop, C. (2016). *Pattern recognition and machine learning*. SPRINGER-VERLAG NEW YORK.

Brunton, S. L., Noack, B. R., & Koumoutsakos, P. (2020). Machine Learning for Fluid Mechanics. *Annual Review of Fluid Mechanics*, *52*, 477–508. https://doi.org/10.1146/annurev-fluid-010719-060214

Calik, N., Belen, M. A., & Mahouti, P. (2020). Deep learning base modified MLP model for precise scattering parameter prediction of capacitive feed antenna. *International Journal of Numerical Modelling: Electronic Networks, Devices and Fields*, *33*(2). https://doi.org/10.1002/jnm.2682

Caruana, R., Lawrence, S., & Giles, L. (2001a). Overfitting in neural nets: Backpropagation, conjugate gradient, and early stopping. *Advances in Neural Information Processing Systems*, *January 2000*.

Caruana, R., Lawrence, S., & Giles, L. (2001b). Overfitting in neural nets: Backpropagation, conjugate gradient, and early stopping. *Advances in Neural Information Processing Systems*.

Dozat, T. (2016). Incorporating Nesterov Momentum into Adam. *ICLR Workshop*, *1*, 2013–2016.

Fernandes, D. D., Matuck, G. R., Montini, D. A., Dias, L. A. V., & Montini, A. A. (2018). A Stratified Sampling Algorithm for Artificial Neural Networks. *Advances in Intelligent Systems and Computing*, *738*, 275–283. https://doi.org/10.1007/978-3-319-77028-4_38

Gundlach, J. (2011). Designing Unmanned Aircraft Systems: A Comprehensive Approach. In *Aurora Flight Sciences*.

Hann, R., & Wallisch, J. (2020, October 1). *UAV Database*. DataverseNO. https://dataverse.no/dataset.xhtml?persistentId=doi%3A10.18710%2FL41IGQ

Munson, K., Jane's Unmanned Aerial Vehicles and Targets, Jane's Information Group, 2005.

Karali, H., Demirezen, M. U., Yukselen, M. A., & Inalhan, G. (2020). Design of a deep learning based nonlinear aerodynamic surrogate model for uavs. *AIAA Scitech 2020 Forum*, *1 PartF*(January), 1–14. https://doi.org/10.2514/6.2020-1288

Kobayashi, K., & Salam, M. U. (2000). Comparing simulated and measured values using mean squared deviation and its components. *Agronomy Journal*, *92*(2), 345–352. https://doi.org/10.2134/agronj2000.922345x

Neufeld, D. J., & Chung, J. (2005). Unmanned aerial vehicle conceptual design using a genetic algorithm, and data mining. *Collection of Technical Papers - InfoTech at Aerospace: Advancing Contemporary Aerospace Technologies and Their Integration*, *3*(September), 1273–1297. https://doi.org/10.2514/6.2005-7051

Perez, R. E., Chung, J., & Behdinan, K. (2000). *AIAA-2000-4938 AIRCRAFT CONCEPTUAL DESIGN USING GENETIC ALGORITHMS Ruben E. Perez,* Joon Chung,. c*.

Raymer. (1992). *D. Raymer - Aircraft Design. A Conceptual Approach (1992).pdf* (p. 745).

Scikit-learn: Machine Learning in Python, Pedregosa *et al.*, JMLR 12, pp. 2825-2830, 2011.

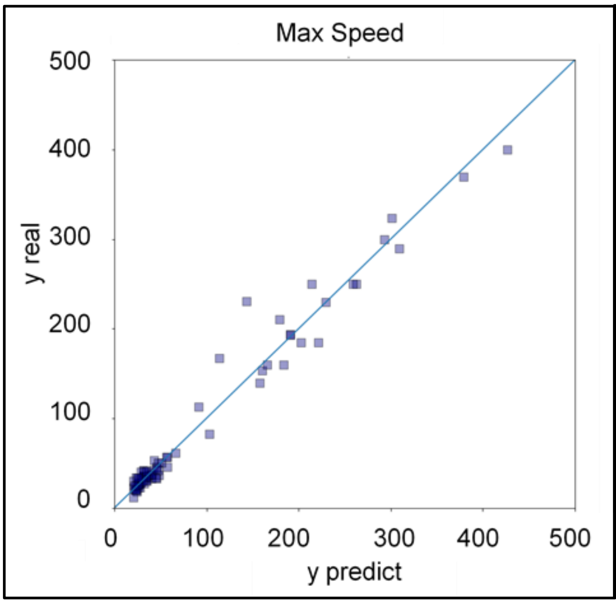
Shateri, M., Sobhanigavgani, Z., Alinasab, A., Varamesh, A., Hemmati-Sarapardeh, A., Mosavi, A., & Shamshirband, S. S. (2020). Comparative analysis of machine learning models for nanofluids viscosity assessment. *Nanomaterials*, *10*(9), 1–22. https://doi.org/10.3390/nano10091767

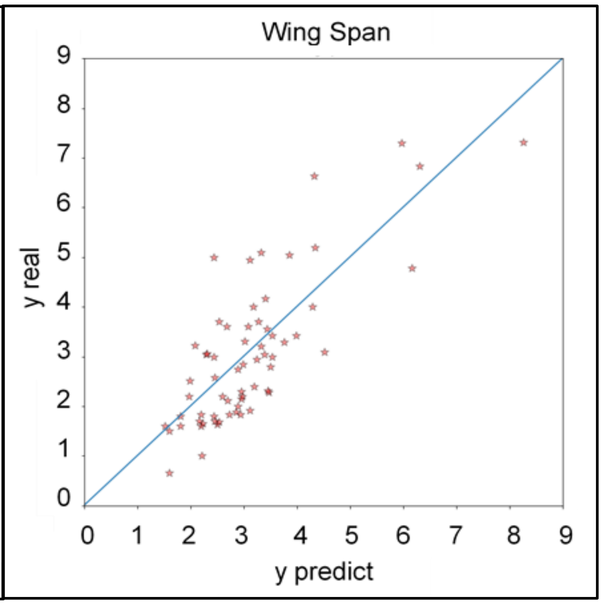
Song, Y. Y., & Lu, Y. (2015). Decision tree methods: applications for classification and prediction. *Shanghai Archives of Psychiatry*, *27*(2), 130–135. https://doi.org/10.11919/j.issn.1002-0829.215044

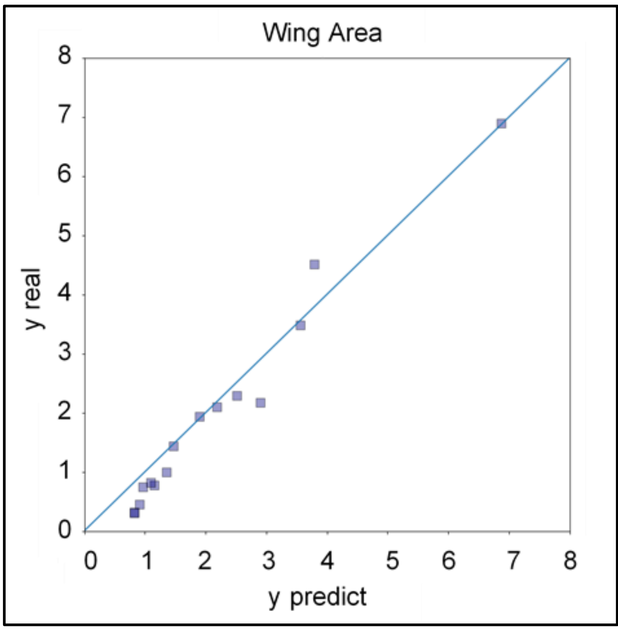
Zhang, S., Li, X., Zong, M., Zhu, X., Wang, R., Zhang, S., Zong, M., & Zhu, X. (2017). IEEE TRANSACTIONS ON NEURAL NETWORKS AND LEARNING SYSTEMS 1 Efficient kNN Classification With Different Numbers of Nearest Neighbors. *Ieee Transactions on Neural Networks and Learning Systems*, 1–12. http://ieeexplore.ieee.org.

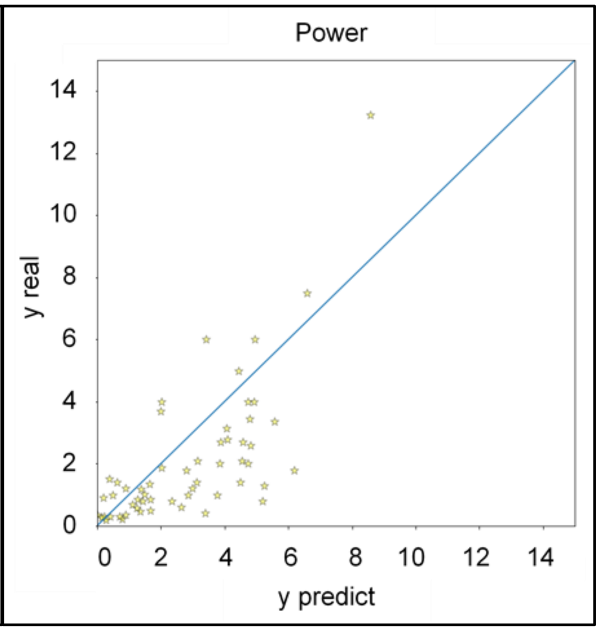
Zhu, Y. H., & Luo, Y. Z. (2019). Fast evaluation of low-thrust transfers via multilayer perceptions. *Journal of Guidance, Control, and Dynamics*, *42*(12), 2627–2637. https://doi.org/10.2514/1.G004080

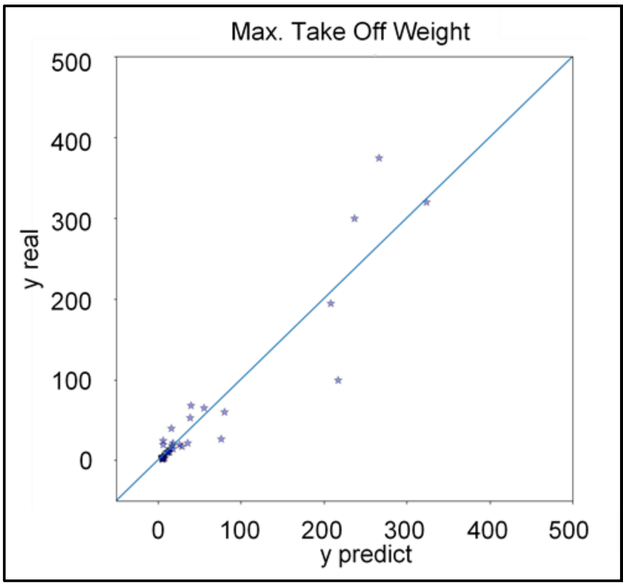
APPENDIX – A

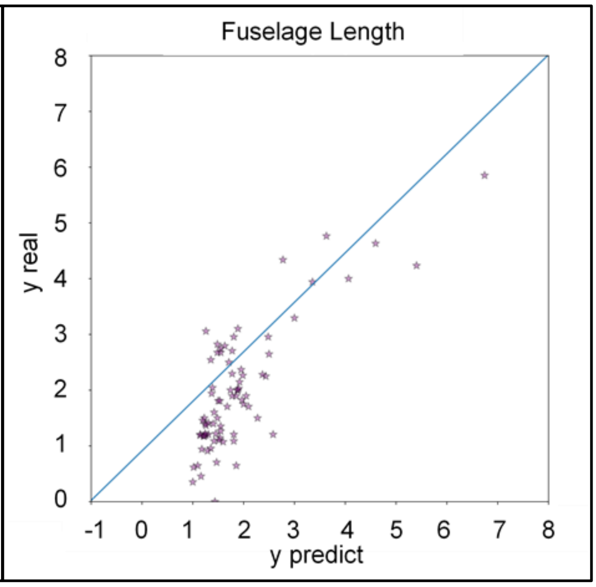

Max Speed
y real
y predict
0
100
200
300
400
500


Wing Span
y real
y predict
0
1
2
3
4
5
6
7
8
9


Wing Area
y real
y predict
0
1
2
3
4
5
6
7
8


Power
y real
y predict
0
2
4
6
8
10
12
14


Max. Take Off Weight
y real
y predict
0
100
200
300
400
500


Fuselage Length
y real
y predict
-1
0
1
2
3
4
5
6
7
8

APPENDIX - B

		NRL Sender	Test-4	Delair DT26M	Test-5	Boeing Insitu RQ-21 Blackjack	Test-6	Aeronautics Defense Orbiter 3	Test-7	EADS 3 Sigma Alkyon	Test-8	IDS Hornet Mk5	Test-9	UTS GSAT-200	Test-10
INPUT	Category	MİNİ	MİNİ	CR	CR	MRE	MRE	MR	MR	CR	CR	CR	CR	MİNİ	MİNİ
	Mission	commercial	commercial	tactical	tactical	tactical	tactical	experimenta	experimenta	target	target	target	target	target	target
	Payload [kg]	1,13	1,13	2	2	17	17	5,5	5,5	14	14	20	20	4	4
	Cruise Speed [m/s]	26,00	26,00	16	16	31	31	30	30	42,00	42,00	89,00	89,00	45,00	45,00
	Ceiling Altitude [m]	500	500	3000	3000	5900	5900	5486	5486	4000	4000	1500	1500	2000	2000
	Endurance [h]	2	2	2,25	2,25	16	16	7	7	1,5	1,5	2,5	2,5	0,6	0,6
OUTPUT	MTOW [kg]	4,54	6,72	15	13,59	61	55,79	30	26,20	50	51,01	60,00	88,84	14,00	16,89
	Wingspan [m]	1,22	2,08	3,3	2,42	4,9	4,71	4,4	4,15	2,06	2,20	2,92	3,78	2,21	1,99
	Fuselage Length [m]	1,22	1,52	1,6	1,38	2,5	2,26	1	1,38	2,15	2,13	2,64	3,28	1,80	1,82
	Fuselage Height [m]	0,31	0,30	0,5	0,51	0,6	0,69	0,4	0,53	0,21	0,36	0,46	0,95	0,43	0,45
	Max speed [m/s]	46,39	46,36	19	26,93	46	44,81	36	36,36	69,44	73,65	106,67	87,72	53,33	58,45
	Wing Area [m2]	Unknown	0,68	Unknown	0,38	Unknown	1,59	Unknown	1,39	0,83	1,37	3,09	2,76	0,99	0,58
	AR	Unknown	6,42	Unknown	15,38	Unknown	13,97	Unknown	12,42	5,11	3,53	2,76	5,19	4,96	6,84
	Power [kW]	0,3	2,17	1	0,88	6	4,78	2	1,55	8,6	8,25	33,60	35,24	5,20	3,22
	Engine Location	front	front	front	front	back	back	back	back	back	back	front	back	front	front
	Engine Type	electrical	electrical	electrical	piston	piston	piston	electrical	electrical	piston	piston	piston	piston	piston	piston
	Wing Position	high	high	high	high	high	high	high	high	low	low	high	high	high	high
	Wing Type	straight	straight	straight	straight	straight	straight	straight	straight	delta	delta	delta	delta	delta	tapered
	Tail Category	TC-2	TC-2	TC-2	TC-1	TC-3	TC-3	TC-4	TC-4	TC-3	TC-4	TC-1	TC-2	TC-1	TC-1
	Tail Type	V	V	V	C	HBT	HBT	no	no	TT	no	C	V	C	C

APPENDIX - C

Test-1

W (N)	W/S (N/m2)	V∞ (m/s)	λ - taper ratio	Croot (m)	Ctip (m)	b (m)	S (m2)	ρ (kg/m3)	CL	AR	e	π	Cd0	Cdi	Cd	D (N)	P (N*m/s)
24,27	94,16	1,00	0,70	0,24	0,17	1,25	0,26	1,23	153,73	6,10	0,80	3,14	0,05	1541,23	1541,28	243,32	243,32
24,27	94,16	2,00	0,70	0,24	0,17	1,25	0,26	1,23	38,43	6,10	0,80	3,14	0,05	96,33	96,38	60,86	121,72
24,27	94,16	3,00	0,70	0,24	0,17	1,25	0,26	1,23	17,08	6,10	0,80	3,14	0,05	19,03	19,08	27,11	81,32
24,27	94,16	4,00	0,70	0,24	0,17	1,25	0,26	1,23	9,61	6,10	0,80	3,14	0,05	6,02	6,07	15,33	61,33
24,27	94,16	5,00	0,70	0,24	0,17	1,25	0,26	1,23	6,15	6,10	0,80	3,14	0,05	2,47	2,52	9,93	49,65
24,27	94,16	6,00	0,70	0,24	0,17	1,25	0,26	1,23	4,27	6,10	0,80	3,14	0,05	1,19	1,24	7,04	42,26
24,27	94,16	7,00	0,70	0,24	0,17	1,25	0,26	1,23	3,14	6,10	0,80	3,14	0,05	0,64	0,69	5,35	37,47
24,27	94,16	8,00	0,70	0,24	0,17	1,25	0,26	1,23	2,40	6,10	0,80	3,14	0,05	0,38	0,43	4,31	34,46
24,27	94,16	9,00	0,70	0,24	0,17	1,25	0,26	1,23	1,90	6,10	0,80	3,14	0,05	0,23	0,28	3,64	32,79
24,27	94,16	10,00	0,70	0,24	0,17	1,25	0,26	1,23	1,54	6,10	0,80	3,14	0,05	0,15	0,20	3,22	32,23
24,27	94,16	15,00	0,70	0,24	0,17	1,25	0,26	1,23	0,68	6,10	0,80	3,14	0,05	0,03	0,08	2,86	42,86
24,27	94,16	20,00	0,70	0,24	0,17	1,25	0,26	1,23	0,38	6,10	0,80	3,14	0,05	0,01	0,06	3,77	75,31
24,27	94,16	25,00	0,70	0,24	0,17	1,25	0,26	1,23	0,25	6,10	0,80	3,14	0,05	0,00	0,05	5,32	133,07
24,27	94,16	30,00	0,70	0,24	0,17	1,25	0,26	1,23	0,17	6,10	0,80	3,14	0,05	0,00	0,05	7,37	221,24
24,27	94,16	35,00	0,70	0,24	0,17	1,25	0,26	1,23	0,13	6,10	0,80	3,14	0,05	0,00	0,05	9,87	345,39
24,27	94,16	36,00	0,70	0,24	0,17	1,25	0,26	1,23	0,12	6,10	0,80	3,14	0,05	0,00	0,05	10,42	375,04
24,27	94,16	37,00	0,70	0,24	0,17	1,25	0,26	1,23	0,11	6,10	0,80	3,14	0,05	0,00	0,05	10,98	406,41
24,27	94,16	38,00	0,70	0,24	0,17	1,25	0,26	1,23	0,11	6,10	0,80	3,14	0,05	0,00	0,05	11,57	439,54
24,27	94,16	39,00	0,70	0,24	0,17	1,25	0,26	1,23	0,10	6,10	0,80	3,14	0,05	0,00	0,05	12,17	474,48
24,27	94,16	40,00	0,70	0,24	0,17	1,25	0,26	1,23	0,10	6,10	0,80	3,14	0,05	0,00	0,05	12,78	511,27

Test-2

W (N)	W/S (N/m2)	V∞ (m/s)	λ - taper ratio	Croot (m)	Ctip (m)	b (m)	S (m2)	ρ (kg/m3)	CL	AR	e	π	Cd0	Cdi	Cd	D (N)	P (N*m/s)
224,35	249,28	5,00	0,10	0,56	0,06	2,91	0,90	1,23	16,28	9,41	0,80	3,14	0,01	11,20	11,21	154,53	772,64
224,35	249,28	6,00	0,10	0,56	0,06	2,91	0,90	1,23	11,31	9,41	0,80	3,14	0,01	5,40	5,41	107,39	644,36
224,35	249,28	7,00	0,10	0,56	0,06	2,91	0,90	1,23	8,31	9,41	0,80	3,14	0,01	2,92	2,92	79,00	553,00
224,35	249,28	8,00	0,10	0,56	0,06	2,91	0,90	1,23	6,36	9,41	0,80	3,14	0,01	1,71	1,72	60,60	484,81
224,35	249,28	9,00	0,10	0,56	0,06	2,91	0,90	1,23	5,02	9,41	0,80	3,14	0,01	1,07	1,08	48,02	432,15
224,35	249,28	10,00	0,10	0,56	0,06	2,91	0,90	1,23	4,07	9,41	0,80	3,14	0,01	0,70	0,71	39,05	390,45
224,35	249,28	15,00	0,10	0,56	0,06	2,91	0,90	1,23	1,81	9,41	0,80	3,14	0,01	0,14	0,15	18,15	272,25
224,35	249,28	20,00	0,10	0,56	0,06	2,91	0,90	1,23	1,02	9,41	0,80	3,14	0,01	0,04	0,05	11,42	228,30
224,35	249,28	25,00	0,10	0,56	0,06	2,91	0,90	1,23	0,65	9,41	0,80	3,14	0,01	0,02	0,03	8,93	223,32
224,35	249,28	30,00	0,10	0,56	0,06	2,91	0,90	1,23	0,45	9,41	0,80	3,14	0,01	0,01	0,02	8,26	247,75
224,35	249,28	35,00	0,10	0,56	0,06	2,91	0,90	1,23	0,33	9,41	0,80	3,14	0,01	0,00	0,01	8,55	299,38
224,35	249,28	36,00	0,10	0,56	0,06	2,91	0,90	1,23	0,31	9,41	0,80	3,14	0,01	0,00	0,01	8,69	312,99
224,35	249,28	37,00	0,10	0,56	0,06	2,91	0,90	1,23	0,30	9,41	0,80	3,14	0,01	0,00	0,01	8,86	327,72
224,35	249,28	38,00	0,10	0,56	0,06	2,91	0,90	1,23	0,28	9,41	0,80	3,14	0,01	0,00	0,01	9,04	343,58
224,35	249,28	39,00	0,10	0,56	0,06	2,91	0,90	1,23	0,27	9,41	0,80	3,14	0,01	0,00	0,01	9,25	360,58
224,35	249,28	40,00	0,10	0,56	0,06	2,91	0,90	1,23	0,25	9,41	0,80	3,14	0,01	0,00	0,01	9,47	378,75
224,35	249,28	45,00	0,10	0,56	0,06	2,91	0,90	1,23	0,20	9,41	0,80	3,14	0,01	0,00	0,01	10,84	487,65
224,35	249,28	50,00	0,10	0,56	0,06	2,91	0,90	1,23	0,16	9,41	0,80	3,14	0,01	0,00	0,01	12,57	628,46
224,35	249,28	55,00	0,10	0,56	0,06	2,91	0,90	1,23	0,13	9,41	0,80	3,14	0,01	0,00	0,01	14,62	803,90
224,35	249,28	60,00	0,10	0,56	0,06	2,91	0,90	1,23	0,11	9,41	0,80	3,14	0,01	0,00	0,01	16,95	1016,90
224,35	249,28	65,00	0,10	0,56	0,06	2,91	0,90	1,23	0,10	9,41	0,80	3,14	0,01	0,00	0,01	19,55	1270,49
224,35	249,28	70,00	0,10	0,56	0,06	2,91	0,90	1,23	0,08	9,41	0,80	3,14	0,01	0,00	0,01	22,40	1567,78
224,35	249,28	75,00	0,10	0,56	0,06	2,91	0,90	1,23	0,07	9,41	0,80	3,14	0,01	0,00	0,01	25,49	1911,94

Test-3

W (N)	W/S (N/m2)	V∞ (m/s)	λ - taper ratio	Croot (m)	Ctip (m)	b (m)	S (m2)	ρ (kg/m3)	CL	AR	e	π	Cd0	Cdi	Cd	D (N)	P (N*m/s)
251,33	370,70	5,00	1,00	0,20	0,20	3,40	0,68	1,23	24,21	17,08	0,80	3,14	0,05	13,65	13,70	142,27	711,33
251,33	370,70	10,00	1,00	0,20	0,20	3,40	0,68	1,23	6,05	17,08	0,80	3,14	0,05	0,85	0,90	37,51	375,13
251,33	370,70	15,00	1,00	0,20	0,20	3,40	0,68	1,23	2,69	17,08	0,80	3,14	0,05	0,17	0,22	20,42	306,32
251,33	370,70	16,00	1,00	0,20	0,20	3,40	0,68	1,23	2,36	17,08	0,80	3,14	0,05	0,13	0,18	19,16	306,53
251,33	370,70	17,00	1,00	0,20	0,20	3,40	0,68	1,23	2,09	17,08	0,80	3,14	0,05	0,10	0,15	18,26	310,46
251,33	370,70	18,00	1,00	0,20	0,20	3,40	0,68	1,23	1,87	17,08	0,80	3,14	0,05	0,08	0,13	17,66	317,96
251,33	370,70	19,00	1,00	0,20	0,20	3,40	0,68	1,23	1,68	17,08	0,80	3,14	0,05	0,07	0,12	17,31	328,93
251,33	370,70	20,00	1,00	0,20	0,20	3,40	0,68	1,23	1,51	17,08	0,80	3,14	0,05	0,05	0,10	17,16	343,29
251,33	370,70	21,00	1,00	0,20	0,20	3,40	0,68	1,23	1,37	17,08	0,80	3,14	0,05	0,04	0,09	17,19	361,04
251,33	370,70	22,00	1,00	0,20	0,20	3,40	0,68	1,23	1,25	17,08	0,80	3,14	0,05	0,04	0,09	17,37	382,17
251,33	370,70	23,00	1,00	0,20	0,20	3,40	0,68	1,23	1,14	17,08	0,80	3,14	0,05	0,03	0,08	17,68	406,70
251,33	370,70	24,00	1,00	0,20	0,20	3,40	0,68	1,23	1,05	17,08	0,80	3,14	0,05	0,03	0,08	18,11	434,69
251,33	370,70	25,00	1,00	0,20	0,20	3,40	0,68	1,23	0,97	17,08	0,80	3,14	0,05	0,02	0,07	18,65	466,18
251,33	370,70	30,00	1,00	0,20	0,20	3,40	0,68	1,23	0,67	17,08	0,80	3,14	0,05	0,01	0,06	22,62	678,74
251,33	370,70	35,00	1,00	0,20	0,20	3,40	0,68	1,23	0,49	17,08	0,80	3,14	0,05	0,01	0,06	28,33	991,49
251,33	370,70	40,00	1,00	0,20	0,20	3,40	0,68	1,23	0,38	17,08	0,80	3,14	0,05	0,00	0,05	35,44	1417,47
251,33	370,70	41,00	1,00	0,20	0,20	3,40	0,68	1,23	0,36	17,08	0,80	3,14	0,05	0,00	0,05	37,01	1517,49
251,33	370,70	42,00	1,00	0,20	0,20	3,40	0,68	1,23	0,34	17,08	0,80	3,14	0,05	0,00	0,05	38,64	1622,72
251,33	370,70	43,00	1,00	0,20	0,20	3,40	0,68	1,23	0,33	17,08	0,80	3,14	0,05	0,00	0,05	40,31	1733,27
251,33	370,70	44,00	1,00	0,20	0,20	3,40	0,68	1,23	0,31	17,08	0,80	3,14	0,05	0,00	0,05	42,03	1849,28
251,33	370,70	45,00	1,00	0,20	0,20	3,40	0,68	1,23	0,30	17,08	0,80	3,14	0,05	0,00	0,05	43,80	1970,84