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Research Article

Parameter Estimation of BLDC Motors by SVM for UAV Propulsion Systems

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Abstract

In today's world of the globalizing 21st century, in Industry 4.0 technologies that bring together informatics enterprises and industry, unmanned aerial vehicles (UAVs), whose importance is increasing day by day, are used extensively in military, civil, and scientific projects. For this reason, it is of great importance that the UAV motors that power the control system are used with high efficiency and safety. In this study, the data obtained from the brushless direct current motor (BLDC) and the related flight control system, which is an important equipment of UAVs, were analyzed in Matlab SIMULINK using SVM (Support Vector Machine), KNN (K-Nearest Neighbors), decision trees, least-square approximation methods. According to the input parameters of the BLDC motor, the torque value at which the system can reach maximum efficiency has been estimated using the cross-validation method. In the light of the analysis, an cubic SVM-based parameter estimation method with a 98% accuracy rate, has been developed, which significantly improves BLDC motor’s efficiency. When the data BLDC motor was analyzed in Matlab SIMULINK, for cubic SVM algorithm RMSE value was estimated 0.010215, R-squared value 0.010215, R-squared value 0.99, MSE value 0.000104, MAE value 0.008187. For this reason, it was determined that it would be more appropriate to use the cubic SVM algorithm in parameter estimation for BLDC motors of UAVs.

Keywords: Brushless DC Motor, Support Vector Machine, Unmanned Aerial Vehicle, Parameter Estimation.

İnsansız Hava Aracı Tahrik Sistemleri İçin SVM ile BLDC Motorların Parametre Kestirimi

Öz

Küreselleşen 21. yüzyılın günümüz dünyasında bilişim işletmeleri ile sanayiyi buluşturan Endüstri 4.0 teknolojilerinde önemi her geçen gün artan insansız hava araçları (İHA) askeri, sivil ve bilimsel projelerde yoğun olarak kullanılmaktadır. Bu nedenle kontrol sistemine güç veren İHA motorlarının yüksek verim ve güvenlikle kullanılması büyük önem taşımaktadır. Bu çalışmada, İHA'ların önemli bir ekipmanı olan fırçasız doğru akım motoru (BLDC) ve ilgili uçuş kontrol sisteminden elde edilen veriler, SVM (Destek Vektör Makineleri), KNN (En Yakın Komşu), karar ağaçları, en küçük kareler yaklaşımı yöntemleri kullanılarak Matlab SIMULINK ortamında analiz edilmiştir. BLDC motorun giriş parametrelerine göre sistemin maksimum verime ulaşabileceği tork değeri çapraz doğrulama yöntemi kullanılarak tahmin edilmiştir. Analizler ışığında, BLDC motorun verimini önemli ölçüde artıran, %98 doğruluk oranına sahip kübik SVM tabanlı bir parametre tahmin yöntemi geliştirilmiştir. BLDC motor verileri Matlab SIMULINK'te analiz edildiğinde, cubic SVM algoritması için RMSE değeri 0.010215, R^2 değeri 0.99, MSE değeri 0.000104, MAE değeri 0.008187 olarak tahmin edilmiştir. Bu nedenle İHA'ların BLDC motorları için parametre tahmininde kübik SVM algoritmasının kullanılmasının daha uygun olacağı belirlenmiştir.

Anahtar Kelimeler: Fırçasız Doğru Akım Motoru, Destek Vektör Makineleri, İnsansız Hava Aracı, Parametre Kestirimi.

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1. Introduction

UAVs, which are an important part of the rapidly developing world technologies, facilitate the development of many sectors in the national and international arena and also have a very important effect on the economies and defenses of the world countries [1]. With the increasing number of unmanned airline networks and developing unmanned aerial vehicle technology, many applications such as military reconnaissance, scientific observation [2], fire fighting, and freight transportation have become faster, safer, and more economical. Air transportation is often preferred because it is a more advantageous method than other transportation methods, especially in terms of safety, speed, and comfort.

A large number of researchers, including structural concepts, mathematical models, simulation calculations, etc. investigated polyphase motors [3-9]. Other of the researchers worked on double-winding motor, permanent magnet brushless DC motor, switched resistance motor [10-11], asynchronous motor [12-13], induction motor [14-15]. These motors differ from BLDC motors in design and performance criteria [16]. In this study, BLDC motor which are an important part of the power control system of UAVs worked on.

BLDC motors in UAVs, it is more preferred than brushed motors. BLDC motors are also extensively used in diverse industrial applications [17], engineering, and robotic practices [18]. By virtue of their high efficiency, smaller size compared to other motors and higher momentum (requires less copper), silent operations, little heating, no need for maintenance, and much longer life than other motors BLDC motors can be considered as a good choice [3-4].

BLDC motors generally are defined by reliability, high efficiency [19], and a wide range of pace inside the performance criteria of other motors. Regardless of the distinction between fixed-wing and rotary propeller in UAVs, BLDC motors are used to provide effective power, especially in using batteries.

It is of great importance to select the input values of the flight control system equipment and especially the components used in the motor system to ensure maximum flight safety and performance in UAVs. Systems designed without selecting input values that will maximize efficiency cause loss of time, money, and lack of trust. For this reason, the control system should be designed by estimating the torque value according to input parameters of the UAV motors, which form the basis of the flight control system, in a way to maximize efficiency.

SVM is one of the supervised learning algorithms used classification and regression analysis of medium-dimensional data sets. Apart from SVM, there are many analysis methods used by researchers such as KNN, ANN, decision trees, random trees in testing data sets [8]. The success rates of the tested data sets differ according to the analysis method used. Choosing the appropriate analysis method for the problem is very important in increasing the success rate of the estimation algorithm developed on the system.

In this study, the data set in the implementation of the established model for the UAV's BLDC motor were analyzed in Matlab SIMULINK using SVM, KNN, and decision tree algorithms. According to the analysis results, with a 98% success rate, SVM was more successful than other algorithms used. For this reason, the SVM algorithm has been examined thoroughly in the materials and methodology part, and the success of SVM in previous studies has been included.

$[1000]_{mxn}$ size data of UAVs' BLDC motor with 10 parameters obtained from the data set were analyzed in Matlab SIMULINK. In the analysis, it was determined that the two most important parameters affecting efficiency in the flight control system are the input voltage and torque. In the SVM method, the data were estimated with a 98% confidence rate, in the least-squares approach, the data were estimated with a 95% confidence rate. In this way, the value of the torque parameter defined will be easily determined, and more efficient and safer systems will be designed.

2. Material and Methods

In this section, first of all, the formulation and mathematical model of the BLDC motor are explained. Then, the efficiency and data set of systems containing BLDC motors are presented. Finally, using this data set, the torque value that the system can reach maximum efficiency according to the input parameters of the BLDC motor is estimated using the SVM-based cross-validation method.

2.1. Mathematical Formulation and Modeling of Brushless DC motor

System dynamics are examined in detail in the reference. This section will focus on the mathematical model and equations of the designed system. A three-phase synchronous motor equation (7) can be contrasted and analyzed with the design modeling of a BLDC motor. If the voltage equation of the UAVs' BLDC motor is explained by equation 3 [18].

$$V_a = L\,\frac{dI_a}{dt} + R.\,I_a + e_a \tag{1}$$

$$V_b = L\,\frac{dI_b}{dt} + R.\,I_b + e_b \tag{2}$$

$$V_c = L\,\frac{dI_c}{dt} + R.\,I_c + e_c \tag{3}$$

If equations (1), (2), and (3) are rewritten in the form below,

$$\begin{bmatrix} V_a \\ V_b \\ V_c \end{bmatrix} = \begin{bmatrix} R & 0 & 0 \\ 0 & R & 0 \\ 0 & 0 & R \end{bmatrix}\begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} + \begin{bmatrix} L_a & L_{ab} & L_{ac} \\ L_{ba} & L_b & L_{bc} \\ L_{ca} & L_{cb} & L_c \end{bmatrix} p \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} + \begin{bmatrix} e_a \\ e_b \\ e_c \end{bmatrix} \tag{4}$$

In equation number 4, if phase winding resistances are equal, iron losses are neglectable and sags are considered to be unsaturated,

$$L_a = L_b = L_c = L \tag{5}$$

$$L_{ba} = L_{bc} = L_{ca} = M = 0 \tag{6}$$

$$\begin{bmatrix} V_a \\ V_b \\ V_c \end{bmatrix} = R \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} + L_p \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} + \begin{bmatrix} e_a \\ e_b \\ e_c \end{bmatrix} + \begin{bmatrix} V_n \\ V_n \\ V_n \end{bmatrix} \tag{7}$$

(8), (9) and (10) equations contain torque equations.

$$T_e = \frac{e_a\, i_a + e_b i_b + e_c i_c}{W_r} \tag{8}$$

$$T_e = T_L + J\frac{dw}{dt} + Bw \tag{9}$$

$$T_e = K_t\, I \tag{10}$$

The output power is given by this equation.

$$P = T_e\, W_r \tag{11}$$

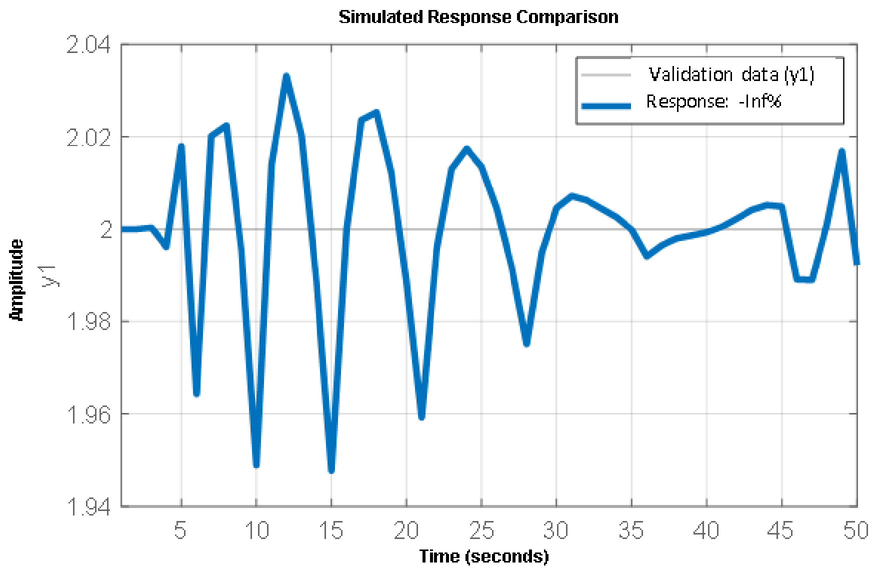

Figure 1. Parametric model evaluation - state-space model fit.

Figure 1 shows the frequency response of the data set obtained as a result of the experiment against time. $[1000]_{mxn}$ size of data referenced were analyzed in Matlab SIMULINK and an estimation graph was drawn in time and frequency axis. In Figure 1, the x-axis time shows the y-axis frequency. The gray solid line represents the verification of the estimated data and the blue line represents the system response. When the figure is examined, the responses of the estimated data against the frequency and the verification of the data can be easily observed in a 50-second sampling period.

2.2. Efficiency of Systems Containing BLDC Motors

The first step in improving the performance of systems [2], containing BLDC motors is to comprehend efficiency. In a brushless system, two fundamental efficiencies are mentioned, namely motor efficiency and propeller efficiency. In this study, to focus on motor efficiency, it will be said that the larger the propeller, the higher the efficiency of the motor. BLDC motor has a high efficiency when rotating at high speed with relatively low torque. Heating increases and performance decreases in motors operated with high torque. In addition to these, a larger, more efficient propeller is often more profitable than using a gearbox that causes heat losses. In this section, the factors affecting the efficiency of a BLDC motor will be determined and expressed with the help of mathematical equations. Especially for UAV designers, this information includes important strategies to maximize flight performance and portable payload capacity.

$$\text{Motor efficiency} = \text{Mechanical power} / \text{Electrical power} \tag{12}$$

$$\text{Mechanical power} = \text{Torque} * \text{RPM} \tag{13}$$

$$\text{Electrical power} = \text{Current} * \text{Voltage} \tag{14}$$

$$\text{Electrical power} = \text{Mechanical power} + \text{Heat losses} \tag{15}$$

$$\text{Heat losses} = \text{R} * \text{Current} \tag{16}$$

$$\text{Electrical power} = \text{Torque} * \text{RPM} + \text{R} * \text{Current}^2 \tag{17}$$

$$\text{Torque} * \text{RPM} + \text{R} * \text{Current}^2 = \text{Current} * \text{Voltage} \tag{18}$$

When the mathematical equations regarding the efficiency of the BLDC motor are examined, it is seen that torque and voltage are important parameters for the performance of the motor. As a result of the analysis made in Matlab SIMULINK, it was determined that the two parameters that affect the efficiency most for this system are torque and input voltage. It is clear that the results found support mathematical equations.

The data set used in this study was taken from Matlab SIMULINK's database [20]. The data set includes data on BLDC motors, one of the most used motor types in rotary and fixed-wing UAVs [21-22]. The data were analyzed in Matlab SIMULINK using SVM, KNN, and decision trees, and least square approximation algorithms. Since the highest accuracy rate is acquired with the SVM method, only the SVM algorithm is included in the methods section.

2.3. Support Vector Machine Algorithm

Support Vector Machine (SVM) algorithm is a supervised machine learning theory used by many researchers to do robust estimation [8]. Today, it is frequently used in many areas, especially to analyze medium-dimensional data sets. The theoretical statement of the SVM algorithm is as follows. For the analyzed parameters,

$$T = \{(x_i, y_i) \text{ I } i = 1,2,\ldots, n\} \tag{19}$$

the n-dimensional characteristic vectors in the real number field x_i and y_i, $x_i \in X$ and $y_i \in \{-1, +1\}$.When the analyzed data set is expressed with a linear relationship, can be used the linear equation in below,

$$w^T x + b = 0 \tag{20}$$

$$w = (w_1; w_2; \ldots; w_d) \tag{21}$$

where w is the hyperplane, b is the distance between the origin and the hyperplane. For this reason, the distance from the hyperplane to any point x can be expressed as follows [23].

$$\gamma = \frac{|\omega^T x + b|}{\|\omega\|} \tag{22}$$

In this study, it is clearly seen that SVM's advantages such as analyzing medium sized data sets, providing a high success rate, and creating multi-directional estimation and decision making functions are valid in this study as in other studies [8], [17], [24-25].

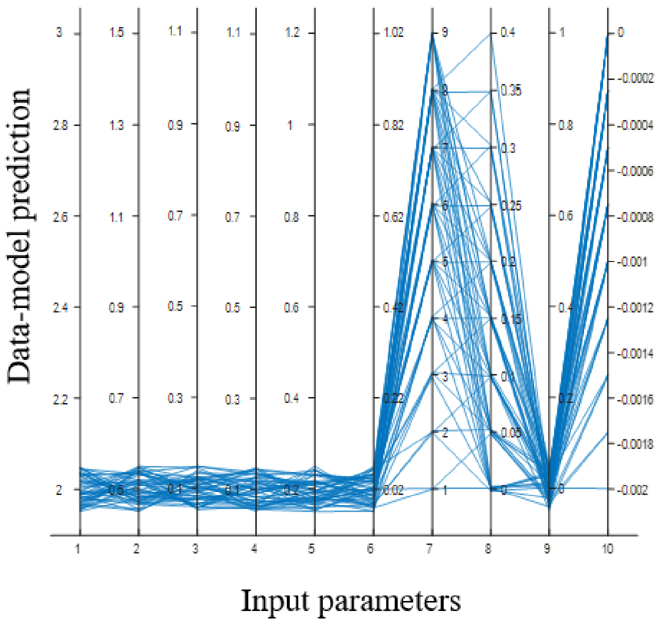

Figure 2. Parallel coordinates plot using SVM algorithm.

Figure 2 involves the analysis of the data and prediction model procures from the simulation in Matlab Simulink parallel coordinates application using the SVM algorithm. It can be seen as there are 10 parallel lines for 10 input parameters analyzed in the system. When the parallel coordinates plot is analyzed, an inference can be made on how the input parameters of the designed system affect the efficiency. It can be seen from the figure that the data are collected on the 7th and 8th parameters. Parameter 7th is the input voltage, parameter 8th is torque. For this reason, the necessary calculations should be made by taking these parameters as a reference while designing and the values of other elements should be selected. As a matter of fact, in this study, the torque parameter was taken as the response in the estimation made in Matlab SIMULINK.

$[1000]_{mxn}$ size of data with 10 parameters belonging to the BLDC motor of the UAV were analyzed in Matlab SIMULINK using SVM, KNN, and decision trees algorithms. The data set were trained using SVM algorithms. The accuracy rates of SVM algorithms are as in Table 1.

Table 1. Accuracy rates of SVM (Support Vector Machine) algorithms based estimation

SVM Algorithm Types	Accuracy Rates
Quadratic SVM	98%
Cubic SVM	98%
Fine Gaussian SVM	90%
Medium Gaussian SVM	88%
Coarse Gaussian SVM	80%

The data set was trained using K-Nearest Neighbors (KNN) algorithms in Matlab SIMULINK. The accuracy rates of KNN algorithms are as follows: fine KNN 94%, medium KNN 88%, coarse KNN 80%, cosine KNN 89%, cubic KNN 92%, weighted KNN 84%.

The data set were trained using decision tree algorithms in Matlab SIMULINK. The accuracy rates of decision tree algorithms are as follows: fine tree 88%, medium tree 88%, coarse tree 80%.

For estimation in Matlab SIMULINK analysis armature resistance, armature rated current, armature inductance, armature voltage, moment of inertia, sliding mode parameters, input voltage, sampling period, frequency of carrier parameters were used. The torque parameter was taken as a response. 70% of the estimated data using the cross-validation method was used in training, 15% of the remaining data was used for the test, and 15% for the validation of the model. Cross-validation 10 folds are selected in the analysis. When the accuracy rates of the methods are evaluated, it is clearly seen that SVM algorithm provides superiority over other methods with a 98% accuracy rate. Since the highest accuracy rate in the estimation analyses was obtained with quadratic SVM and cubic SVM, detailed analyzes of these two methods were performed in Matlab SIMULINK.

Table 2. SVM (Support Vector Machine) based estimation analyzes results

SVM Algorithms	RMSE	R^2	MSE	MAE
Quadratic SVM	0.085505	0.99	0.000073	0.007670
Cubic SVM	0.010215	0.99	0.000104	0.008187
Fine Gaussian SVM	0.029292	0.93	0.000858	0.016089
Medium Gaussian SVM	0.016326	0.98	0.000267	0.010274
Coarse Gaussian SVM	0.053390	0.75	0.002851	0.043672

Table 2 contains RMSE (Root Mean Square Error), R^2 (Coefficient of Determination, MSE (Mean Squared Error), MAE (Mean Absolute Error) results of SVM methods used for estimation in Matlab SIMULINK. R^2 is the decision coefficient based on the accuracy of the model. RMSE, MSE, and MAE are the criteria showing the error rate. For a successful estimation, the value of R^2 is desired to be as close to 1 as possible. The values of RMSE, R^2, MSE , MAE are also desired to be as close to 0 as possible [26]. For the determined time t, the error in the time series p_t observed and predicted in the time interval r_t is defined as,

$$e_t = r_t - p_t \quad (23)$$

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n} e_t^2 \quad (24)$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_t^2} \quad (25)$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |e_t| \quad (26)$$

As a result of the simulation, for cubic SVM was found as RMSE value 0.010215, R^2 value 0.99, MSE value 0.000104, MAE value 0.008187, accuracy rate 98%, for quadratic SVM was found as RMSE value 0.085505, R^2 value 0.99, MSE value 0.000073, MAE value 0.007670, accuracy rate 98%. When Matlab SIMULINK analysis results were evaluated, it was determined that the most successful parameter estimation was made with cubic SVM.

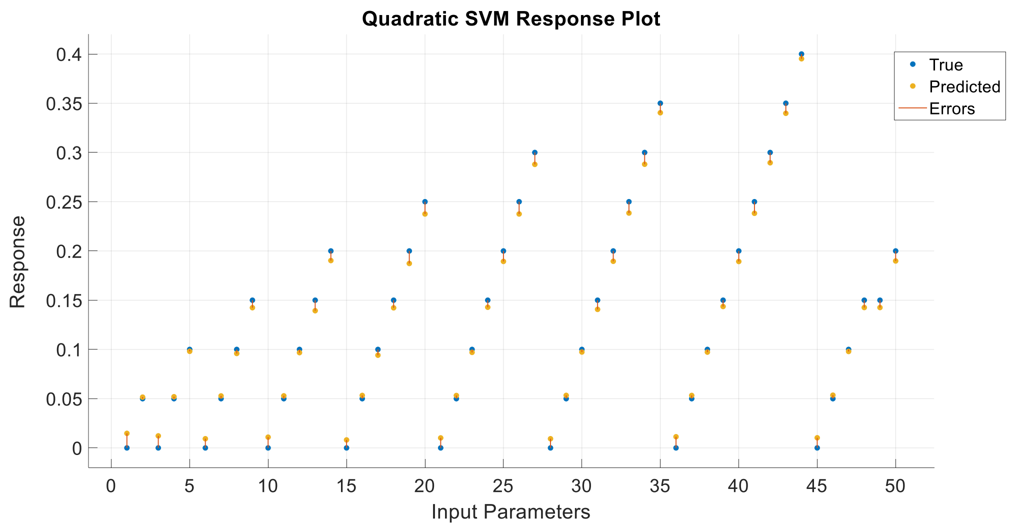

Figure 3. Quadratic SVM response plot.

In Figure 3, with the quadratic SVM method, the torque parameter on the y axis is taken as a response against the input parameters on the x-axis. The graph contains the true, predicted, and errors information of the parameter estimated by this method. When the figure created in Matlab

SIMULINK was examined, an estimation with 98% accuracy rate was obtained by using quadratic SVM.

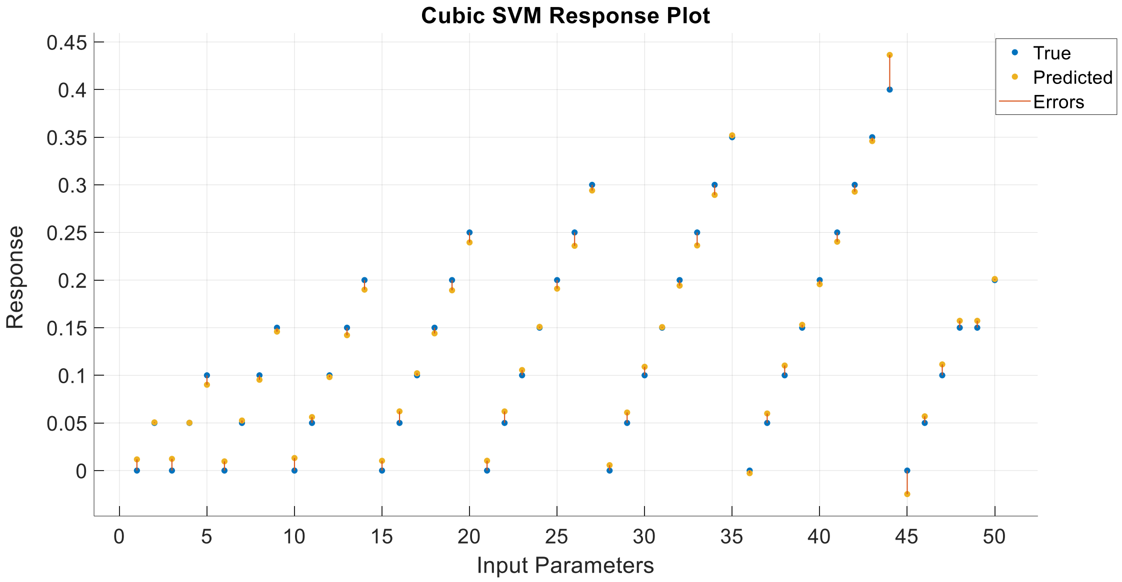

Figure 4. Cubic SVM response plot.

In Figure 4, with the cubic SVM method, the torque parameter on the y axis is taken as a response to the input parameters on the x-axis. The graph contains the true, predicted, and errors information of the parameter estimated by this method. When the figure created in Matlab SIMULINK was examined, an estimation with 98% accuracy rate was obtained by using cubic SVM.

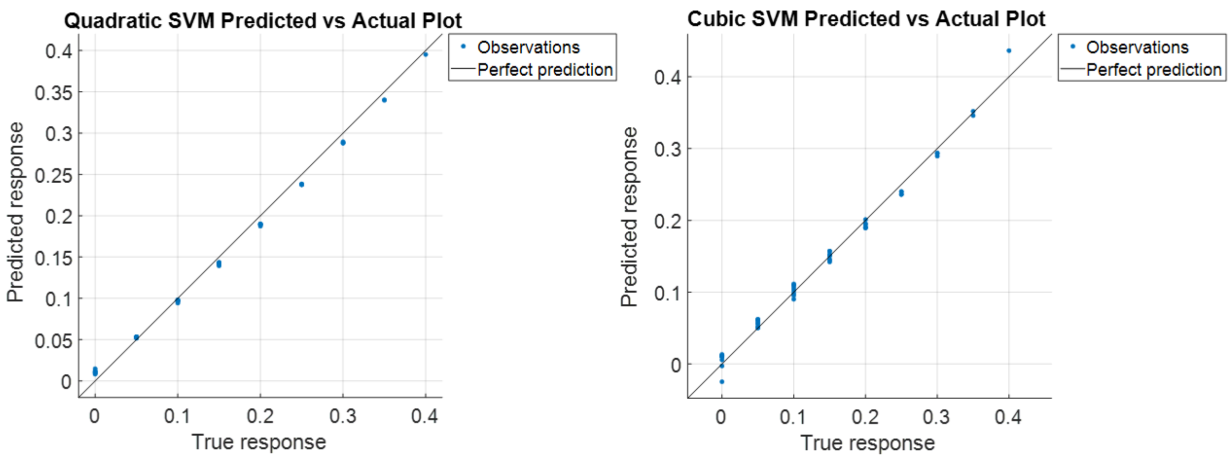

Figure 5. Quadratic SVM predicted vs actual plot - Cubic SVM predicted vs actual plot.

Figure 5 shows how close the estimation made with the SVM methods with the highest accuracy rate is to the perfect prediction curve. When the graphics were examined, it was observed that the torque estimation was quite close to the perfect prediction curve for cubic SVM. From Matlab SIMULINK obtained RMSE, R^2, MSE, MAE values support this results.

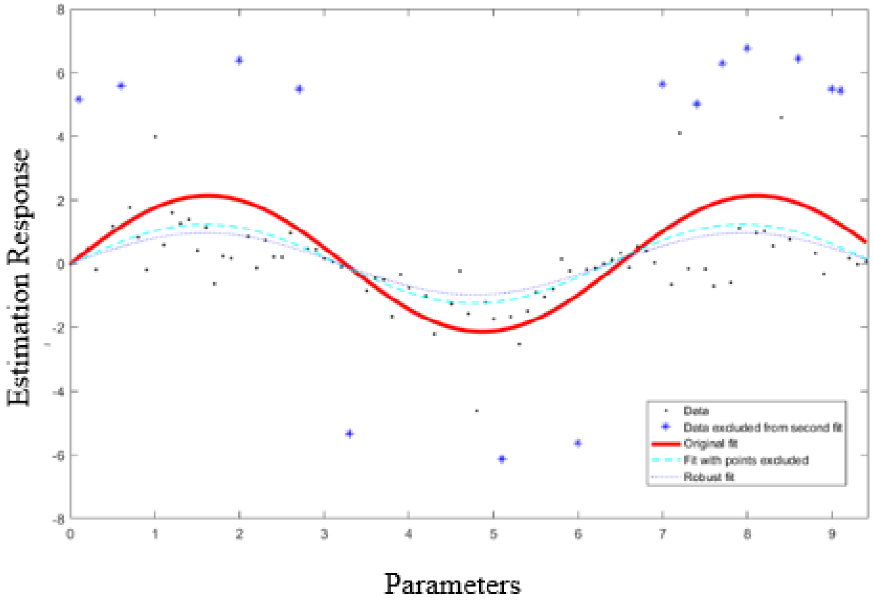

Figure 6. Using least-squares approximations torque parameter estimation.

Figure 6 created in Matlab SIMULINK shows torque parameter estimation using the least-squares approximation method. In the figure, using the experimental results transferred to the Matlab SIMULINK environment, data, data excluded from the second fit, original fit, compliance with excluded points, and robust fit graphs are drawn. When the figure is analyzed, it can be easily seen that the data are estimated at a scale close to the robust fit curve. When all the graphs are drawn were examined, an estimation was made with a 95% confidence rate using the least-squares approach.

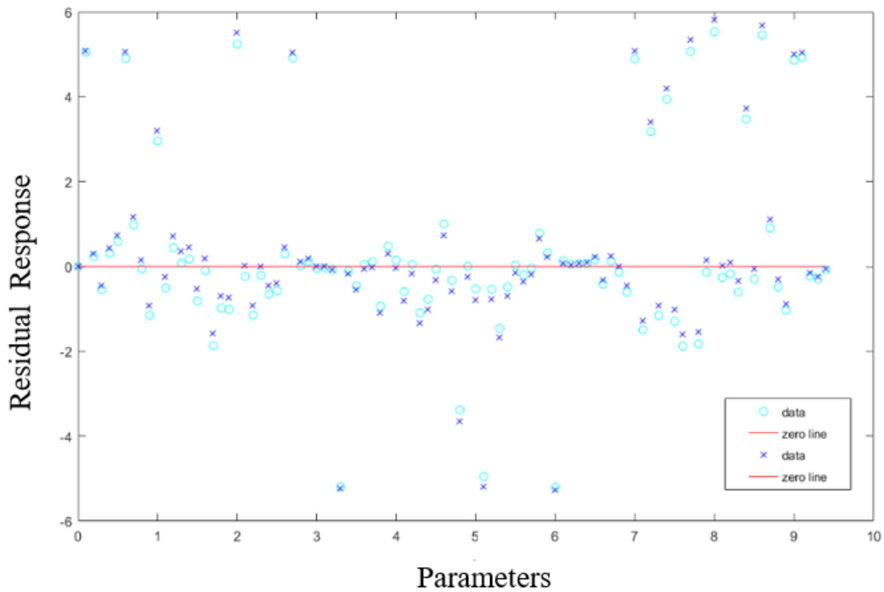

Figure 7. Created in Matlab SIMULINK shows residuals using the least-squares approximation method.

The round symbol in Figure 7 represents the information obtained as a result of the least-squares approximations analyzes, the cross represents the estimated information When this analysis was evaluated, a residuals estimate with 95% accuracy rate was made.

3. Results and Discussion

Unmanned aerial vehicles (UAVs) expand human potential and allow to execute dangerous or difficult duties safely and efficiently, saving time, saving money, and, most crucially, saving lives. In unmanned aerial vehicle technologies, designers are developing methods and algorithms to increase maximum flight safety and performance day by day. Especially in recent times, studies that will increase the flight output of UAVs by consuming less fuel in maximum time have gained popularity. One of the most used motor types in UAV propulsion systems is the brushless DC motor (BLDC). Research articles on this topic and practical applications in the UAV industry support this view.

In this study, parameter estimation has been made using the SVM, KNN, decision tree, and least square approximation algorithms of the BLDC motor used in UAVs. The system's data was estimated in Matlab SIMULINK making use of the 10-fold cross-validation method for maximum efficiency. The important thing this study is to decide when to terminate the training process, to avoid the system's memorization problem, and to create the most effective estimation model based on SVM. For all these, 70% of the data was used for training, 15% for validation, and 15% for testing. Robust estimation curves for the estimation of parameters created using the least-square approximation method in Matlab SIMULINK were drawn with 95% confidence. SVM, KNN, decision tree, and least square approximation methods

$[1000]_{mxn}$ size data belonging to UAVs with 10 parameters were analyzed in Matlab SIMULINK using SVM, KNN, decision trees, and least-squares approximations. The accuracy rates of SVM algorithms are as follows: Quadratic SVM 98%, cubic SVM 98%, fine Gaussian SVM 90%, medium Gaussian SVM 88%, coarse Gaussian SVM 80%. The accuracy rates of KNN algorithms are as follows: fine KNN 94%, medium KNN 88%, coarse KNN 80%, cosine KNN 89%, cubic KNN 92%, weighted KNN 84%. The accuracy rates of decision tree algorithms are as follows: fine tree 88%, medium tree 88%, coarse tree 80%. In this study, it is focused on quadratic SVM and cubic SVM methods that perform the best parameter estimation according to accuracy rates. As a result of the simulation, for cubic SVM was found as RMSE value 0.010215, R^2 value 0.99, MSE value 0.000104, MAE value 0.008187, accuracy rate 98%, for quadratic SVM was found as RMSE value 0.085505, R^2 value 0.99, MSE value 0.000073, MAE value 0.007670, accuracy rate 98%. When the success metrics of all methods were evaluated, it is determined as the method that showed the most successful prediction performance for the BLDC motor of the cubic SVM UAV. When the researchers' articles on the subject are examined in detail, it supports the results obtained in this study that SVM achieved a higher accuracy rate compared to other algorithms in many engineering applications.

In the light of the analysis, it was determined that important two parameters affecting efficiency for the designed system and data are the input voltage and torque. With the SVM-based methodology, the input values of other parameters can be calculated according to the estimated torque value automatically to maximize efficiency. As a result, it is suggested to use the cubic

SVM algorithm, which have the highest accuracy rate with 98% reliability among the algorithms used for machine learning-based parameter estimation. The algorithms and estimation strategy proposed in this study will constitute an important resource in other studies of the BLDC motor of UAVs.

4. Conclusion

In this study, a parameter estimation using SVM, KNN, decision tree, and least square approximation methods was made that notably increases the efficiency of UAV's BLDC motors. When the success metrics of all methods were evaluated, it is determined as the method that showed the most successful prediction performance for the BLDC motor of the cubic SVM UAV. When the researchers' articles on the subject are examined in detail, it supports the results obtained in this study that cubic SVM achieved a higher accuracy rate compared to other algorithms in many engineering applications. In the light of the analysis, it was determined that important two parameters affecting efficiency for the designed system and data are the input voltage and torque. With the SVM-based methodology, the input values of other parameters can be calculated according to the estimated torque value automatically to maximize efficiency. As a result, it is suggested to use the cubic SVM algorithm, which have the highest accuracy rate with 98% reliability among the algorithms used for machine learning-based parameter estimation. The algorithm and estimation strategy proposed in this study will constitute an important resource in other studies of the BLDC motor of UAVs.

Ethics in Publishing

There are no ethical issues regarding the publication of this study.

Author Contributions

HASILCI, B.: conceived and designed the study, scanned the literature, collected the material, implemented the method and wrote the study, determined and interpreted the results. MUMCU, T.V.: scanned the literature, organized the study, analyzed and interpreted the study, evaluated and interpreted the results.

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