International Journal of Aviation Science and Technology

Research Article

VPSA-Based Transfer Function Identification of Single DoF Copter System

Kübra Çiftçi[1], Muhammed Arif Şen[2], Hasan Huseyin Bilgic[3*]

[1] Sivas University of Science and Technology, Sivas, Turkey
kubraciftci@sivas.edu.tr- 0000-0002-4899-7650

[2] Konya Technical University, Konya, Turkey
masen@ktun.edu.tr- 0000-0002-6081-2102

[3] Necmettin Erbakan University, Konya, Turkey
hhbilgic@erbakan.edu.tr- 0000-0001-6006-8056

Abstract

In this study, an experimental set of a Single-DoF Copter system is created and transfer functions that could model the dynamics of the physical system with high accuracy were investigated. In order to model the dynamics of the physical system with the highest accuracy, the five different transfer functions have been proposed, in which the zero and pole values are determined by optimizing with the Vibrating Particle System Algorithm. Integral Square Error (ISE), Integral Time Square Error (ITSE), Integral Absolute Error (IAE), Integral Time Absolute Error (ITAE) functions, which are widely used in the literature in determining transfer functions, are determined as fitness functions. In order to verify the transfer functions, the responses of the transfer functions and the experimental system response are presented comparatively, and their suitability was evaluated. It has been observed that the proposed method is successful in defining the transfer function of the experimental system, and the compatibility of the obtained transfer functions with the system response is between 75.407% and 98.612% accuracy.

Keywords

VPSA
System Identification
Transfer Function
Single-dof Copter

Time Scale of Article

Received 28 September 2023
Revised until 2 December 2023
Accepted 5 December 2023
Online date 30 December 2023

1. Introduction

Helicopters are systems that attract the attention of researchers working in the field of control due to their relatively complex structure, the multitude of parameters that need to be controlled, and their exposure to external environmental noise. These systems are frequently preferred systems because they do not need a runway for landing and take-off. Creating mathematical models of helicopters and similar systems with minimum error is directly related to the precise control of these systems. Models created by assuming linear system elements often do not converge accurately with experimental results. The reasons for this can be listed as non-linear system elements being considered linear at certain intervals, noises and disturbances in the system and the environment. The methods used to obtain the correct model that describes the system behaviour are examined in two parts. The first of these is modelling using the system's equations of motion (Pehlivan and Akuner 2020). Another is system identification methods based on experimental data (Saengphet et al. 2017).

Creating mathematical models of systems using equations of motion can often be complex and challenging. At the same time, the model obtained as a result of the mathematical modelling process may not be similar to the real system behaviour. In such cases,

*: Corresponding Author Hasan Huseyin Bilgic, hhbilgic@erbakan.edu.tr
DOI: 10.23890/IJAST.vm04is02.0204

various system identification methods are used (Hoffer et al. 2014; Geluardi et al. 2018; Somov et al. 2021; Özcan and Caferov 2022). System identification methods, which are important sub-fields of control engineering, provide convenience in obtaining linear models such as transfer function and state space model of systems. Some of the advantages of this method are that it can be applied to linear or non-linear systems, saves time and often shows successful results. This method is based on the data set obtained from the system to be modelled. The data set to be used is created by applying appropriate input values and collecting system outputs. According to the existence of the data set and the system model, system identification studies are examined in three basic categories: black box, gray box and white box. Among these, the black box system identification method is frequently encountered in the literature (Bogdanski and Best 2017). With this method, only the data set of the system to be modelled is available during the modelling process.

Fidan and Erkan used the black box system identification method in the system identification of the boost converter. First, input and output data were obtained through experimental studies and then three different transfer functions were obtained with Matlab/System Identification toolbox. Among these transfer functions, a transfer function with one zero and four poles with a performance value of 87.26% was selected. In order to verify this model, the system was simulated on Simulink environment and similar results were obtained. After the system identification, PI (proportional integral) controller based on Particle Swarm Optimization algorithm was designed (Fidan and Erkan 2023). Similarly, in the study conducted by Özden et al., linear black box modelling methods were used to model an air heating system. In the study where ARX (auto regressive with exogeneous inputs), ARMAX (auto regressive moving average with exogenous variable models) and OE (output error) modelling methods were used, models with various structures were obtained using analysis methods. As a result of examining models under various performance criteria, it was observed that the best result was the ARMAX model (Tugal et al. 2010).

In the study by Altan and Hacıoğlu, a linear Output Error identification method was used to create the transfer function of the three-axis gimbal system on the UAV (Unmanned Aerial Vehicles). After creating the required data set for the process, the data was divided into two parts to be used in modelling and validation processes. For the transfer function obtained with an accuracy rate of 91.46%, validations were made under disturbance effects and it was predicted that it would make a great contribution to the control of the system (Altan and Hacioglu 2017).

Okçu and Leblebicioğlu were approached a new model with the closed loop system identification method in order to verify the existing mathematical model for a helicopter. In their study, a flight simulation was made using the nonlinear equations of motion of the system and the obtained data was used as input data for the system identification process. The frequency responses of the system were examined. Since it was observed that linear and non-linear models show similar results, it was predicted that these responses would be similar to the frequency responses of the linear model. Simulations were carried out in SAS (Stability Augmentation System) model, which is the simplest autopilot mode. As a result of the simulations performed in the study in which CIO (combined input-output) and direct approach were used, it was observed that the frequency responses of the model obtained using the CIO approach and the current model were similar (Doğa Okcu and Leblebicioğlu 2022).

In the study conducted by Salameh et al., system identification was carried out by collecting data on the hovering situation of a quadcopter. SISO (single-input single-output) and MIMO (multiple-input multiple-output) models were determined through the system identification process using the ARX model. The results obtained showed that the system identification method can be used in modelling quadcopters in the hovering (Salameh et al. 2015).

Machine learning-based system identification methods are increasingly used. Artificial Neural Network-based system identification methods can be given as examples of these methods (Fahmi Pairan et al. 2020). System identification method based on metaheuristic optimization algorithms is also another method used. A system identification process for a quadrotor was carried out using metaheuristic methods by Oliveira et al. In the study where Particle Swarm Optimization algorithm, Adaptive Particle Swarm Optimization algorithm and Cuckoo Optimization algorithm were used, a NARX (non-linear autoregressive exogenous) model was used for each state variable. The found models were compared using various performance criteria. The results obtained showed that metaheuristic optimization algorithms gave successful results for this process (de Oliveira et al. 2019). Similarly in the study by Zaloğlu et al., the system identification process was carried out using the existing data set for an experimental setup based on measuring air temperature. Five different metaheuristic optimization algorithms were used to determine the transfer functions for the system identification. These algorithms were evaluated for various performance criteria and it was observed that the Artificial Ecosystem-Based optimization algorithm gave better results. When the results obtained were examined, it was determined that metaheuristic optimization algorithms were successful in system identification applications (Zaloğlu et al. 2023).

In this study, an experimental setup of a Single DoF Copter system was designed and prototyped. Then transfer functions that would ideally meet the system dynamics were investigated. A metaheuristic optimization algorithm was used to determine appropriate transfer functions. Fitness functions with different structures were used and the results were presented comparatively. In the introduction section, recent relevant literature studies are given. In the second section, the experimental setup and the methodology of the study are explained. In the results and discussion section, research results showing the performance of the proposed transfer function are presented. In the conclusion, the findings were evaluated and suggestions for further studies were stated.

2. Method

2.1. Experimental Setup

Interest in research on UAVs, which have many uses in our lives such as exploration, surveillance, agricultural spraying, transportation, photography and video shooting, is increasing day by day. At the same time, interest in helicopters and drones, which are vertical take-off and landing systems that eliminate the need for runways, is increasing due to their superior features compared to aircraft. The Single DoF helicopter system, which is an example of these systems, is frequently encountered in the literature (Ťapák and Huba 2018).

The system used in this study consists of a rotor that is jointed so that it can move circularly on a planar platform and a brushless motor connected to the end of the rotor. In the system shown in Figure 1; Arduino Uno is used as a microcontroller, and the necessary thrust is provided by a brushless DC (direct current) motor. The power supply of the system is provided by a 12V DC power supply, and the angular position of the rotor is measured with a 10K Potentiometer. Additionally, a 30A ESC (electronic speed controller) connected to the microcontroller is used to produce constant impulse. The system works in real-time with Matlab/Simulink via Arduino Uno.

Figure 2 presents the connection diagram of the system elements. The shaft jointed with the rotor is supported on the chassis with the help of bearings. The shaft and potentiometer are linked. The microcontroller communicates with the PC and all inputs and outputs of the system are read in real time through the block diagrams of the system created in the Simulink environment. Analog signals generated on the potentiometer by the movement of the shaft are converted into angle values and recorded. The step input applied to the system is transmitted to the ESC as PWM (pulse width modulation) signals and a constant impulse value is applied to the system. The experimental data obtained was used to define the transfer functions. Step input of 8.75 V was applied to the motor. Data on the time-dependent angular position of the beam was collected with sample time of 0.02.

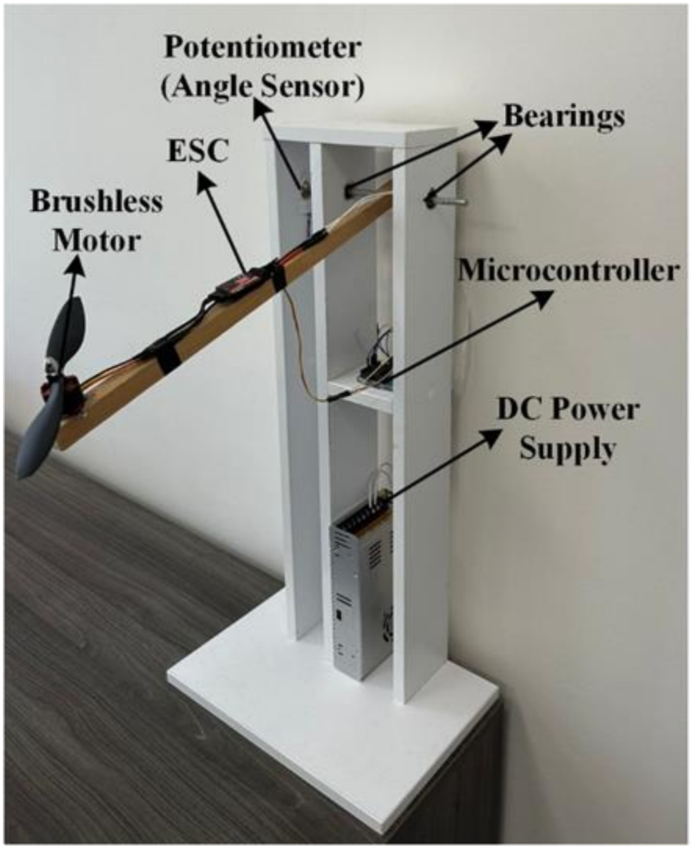

Fig. 1. The experimental setup of single DoF copter

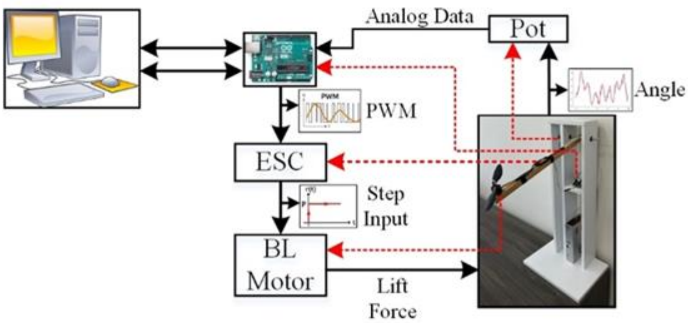

Fig. 2. The system elements and connection diagram

2.2. System Identification

The models designed as a result of modelling studies for systems must be similar to the experimental system behaviour. Otherwise, development studies with the system are unlikely to be successful. Therefore, the modelling process should be done accurately and completely. It is often not possible to obtain exact models of systems with equations of motion. Moreover, the model response may not match the experimental response. In such cases, the system identification method, which is an experimental method, is often preferred (Wei et al. 2017; Ivler et al. 2021; Simmons 2021). There are many examples in the literature of the use of the system identification method in creating models of difficult and complex systems such as aircrafts, helicopters and quadcopters (Geluardi et al. 2018; Yu et al. 2020; Ebrahimi and Barzamini 2021).

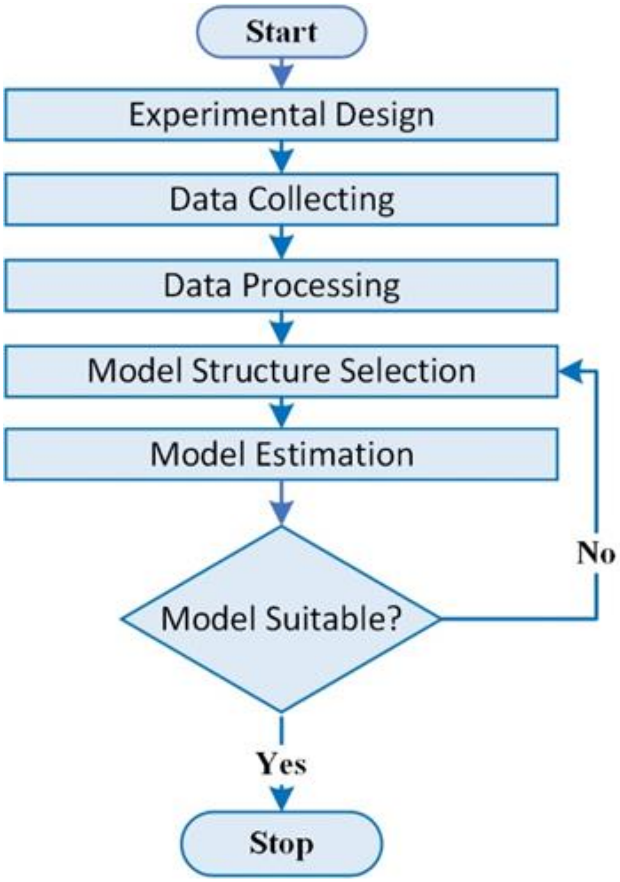

Fig. 3. The stages of system identification

In system identification methods, the process is performed with the experimental data set obtained for the system to be modelled. Obtaining the data set completely and appropriately affects the success of the system identification process significantly. In this part, the input signal to be applied to the system must be selected correctly. In input signal selection, which is one of the most important steps in the system identification process, step functions, PRBS (pseudo random binary sequence) and sinusoidal signals are frequently preferred (Sanatel 2020), (Sayll et al. 2023).

System identification methods are examined under three sections according to the known states of the system model. The first of these sections is white box definition, where the system model is fully known (Nugroho and Akmeliawati 2018). Another is the grey box system identification method, in which the model is determined with the data set in cases where the equations expressing the system are known but the parameters are unknown (Yuan and Katupitiya 2011). The last one is the black box system identification method, which is a modelling process performed using only the data set without any information about the system (Fidan et al. 2022). By using the system identification method, models such as the transfer unction of the system and the state-space model can be obtained more easily and accurately.

2.3. Vibrating Particle System Algorithm

Vibrating Particle System algorithm, one of the metaheuristic search algorithms, is based on the single degree of freedom vibration motion of damped systems. VPSA is a Physics-Based algorithm that is among meta-heuristics algorithms. Thanks to its inspired by the free vibration of under-damping systems, it can be used for solve complex problems including real-world different types of data (Almufti 2022).The flow chart of the algorithm is given in Figure 4.

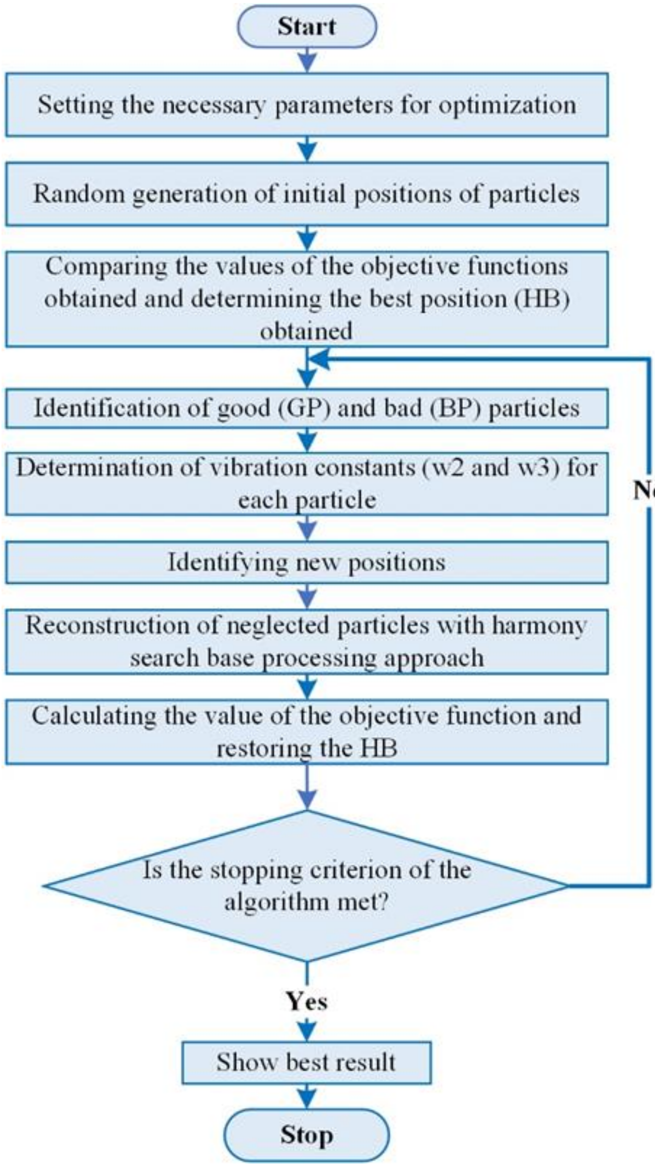

Fig. 4. VPSA flowchart(Kaveh et al. 2017)

For this population-based algorithm, which is based on the motion of vibrating particles, initially the number of iterations, the number of vibrating particles, α, w_1, w_2, w_3, p parameters are determined. Then the initial positions of the particles are determined randomly and the value of the objective function is calculated for each particle. The weights w_1, w_2 and w_3, which are the parameters set at the beginning, represent the importance of the HB (best position), GP (good particle) and BP (bad particle) equilibrium positions, respectively. Determining these equilibrium positions created by using these weights is the next step of the algorithm. In this section, a function called the descending function (D) is defined to show the effect of damping ratio, which is one of the most important factors affecting the vibration motion, on the motion.

The equation for this function is given in Equation 1. One of the initial parameters of the algorithm, α, refers to the constant used in the definition of the descending function. With the definition of this function, the new positions of the particles are determined. In the determination of these new positions, it is checked whether the BP position will be neglected by using the p parameter, which is one of the initial parameters. This control is done by accepting the w_3 parameter as zero if the p parameter is less than the randomly generated number. The equations for determining the new position of the particles are given in Equation 2.

$$D = \left(\frac{Number\ of\ iterations}{Maximum\ Number\ of\ Iterations}\right)^{-\alpha} \quad (1)$$

$$NP = w_1[D.A.rand1 + HB] + w_2[D.A.rand2 + GP] + w_3[D.A.rand3 + BP]$$

$$A = w_1(HB - PP) + w_2(GP - PP) + w_3(BP - PP) \quad (2)$$

w_1+w_2+w_(3)=1

NP in Equation 2 represents the new position of the particle, PP represents the current position of the particle.

In the step before testing the stopping criterion for the algorithm, the particles that violate the boundary are reconstructed by using the harmony search base approach to determine the boundary violations that may occur due to the position change. After this process is done, the stopping criterion is tested and if the criterion is met, the algorithm is completed (Kaveh and Ilchi Ghazaan 2017).

The most important issue in the use of optimization algorithms is the appropriate creation of the fitness function that expresses the problem. There are various fitness functions used in the literature. Examples of these are ISE (integral square error), IAE (integral absolute error), ITAE (integral time absolute error) and ITSE (integral time square error) fitness functions (Gyongyosi 2020).

The IAE fitness function integrates the absolute values of the measured errors. Similarly, the ISE fitness function operates by integrating the squares of the errors. Equations of these fitness functions are given in Equation 3 and Equation 4, respectively.

$$IAE = \int_0^t |e(t)|dt \quad (3)$$

$$ISE = \int_0^t e^2(t)dt \quad (4)$$

The ITAE fitness function is the evaluation of the operations performed in the IAE fitness function with a time constraint. Similarly, the ITSE fitness function operates by evaluating the ISE fitness function with a time constraint. You can see the equations of these functions in Equation 5 and Equation 6, respectively.

$$ITAE = \int_0^t t|e(t)|dt \quad (5)$$

$$ITSE = \int_0^t te^2dt \quad (6)$$

3. Results and Discussion

In this section, the procedures used to create the mathematical model of the designed Single DoF helicopter system are explained. The system identification method was used to determine the appropriate transfer function for the system. First of all, the necessary data was collected by applying unit step input to the system. Afterwards, filtering was applied to these data and the data set was obtained.

The Vibrating Particle System algorithm was used to determine the parameters of the transfer function. The five different transfer function models were defined by varying the number of poles and zeros. The ideal values of the poles and zeros in these transfer functions were determined by four different fitness functions and the ideal values were obtained with the proposed algorithm. The optimizations were made to determine the optimum values of the number of iterations, α, w1, w2, w3, p parameters, which are the initial parameters of the algorithm. In order to find the appropriate values of the parameters, the algorithm was run with different parameter values. As a result of these processes, optimum values were determined. These values were determined as 100, 0.3, 0.2, 0.2, 0.6, 0.2, respectively. The initial parameters of the VPSA was determined according to similar studies used VPSA in the literature. As a result of the optimization processes, the accuracy rates of the transfer functions determined according to the real system behavior were obtained. During this process, the MAPE (mean absolute percentage error) value was used as the performance criterion. The mathematical expression for this performance criterion is given in Equation 7.

$$MAPE = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{e_t}{y_t}\right| \quad (7)$$

The times and accuracy values of the optimization operations performed using four different fitness functions for five different transfer functions are presented by comparing them in Table 1.

Table 1: Comparative optimization results

Transfer Functions	Pole Number	Zero Number	Fitness Function	Transfer Function	Accuracy %	Time
TF-1	p=2	z=0	ISE	$\frac{88.58}{3.25s^2 + 3.35s + 2.46}$	97.410	307.12
			IAE	$\frac{34.05}{0.24s^2 + 1.14s + 0.84}$	92.234	313.12
			ITSE	$\frac{89.90}{1.83s^2 + 3.72s + 2.46}$	95.951	301.42
			ITAE	$\frac{91.38}{2.69s^2 + 4.28s + 2.55}$	93.947	339.1
TF-2	p=2	z=1	ISE	$\frac{0.97s + 81.66}{s^2 + 3.93s + 2.06}$	94.713	297.63
			IAE	$\frac{0.60s + 79.89}{s^2 + 4.53s + 2.35}$	85.105	298.88
			ITSE	$\frac{0.75s + 81.96}{s^2 + 1.85s + 2.15}$	92.306	305.46
			ITAE	$\frac{5.48s + 78.20}{s^2 + 3.05s + 2.17}$	93.653	302.55
TF-3	p=3	z=0	ISE	$\frac{69.82}{s^3 + 1.76s^2 + 1.77s + 2.02}$	75.407	245.76
			IAE	$\frac{95.35}{s^3 + 2.81s^2 + 4.35s + 2.50}$	98.612	247.44
			ITSE	$\frac{97.26}{s^3 + 3.65s^2 + 5.20s + 2.42}$	93.969	253.66
			ITAE	$\frac{97.53}{s^3 + 3.30s^2 + 5.31s + 2.73}$	91.698	244.93
TF-4	p=3	z=1	ISE	$\frac{98.34s + 2.15}{s^3 + 79.05s^2 + 7.45s + 5.03}$	94.705	294.87
			IAE	$\frac{66.89s + 2.35}{s^3 + 92.97s^2 + 6.11s + 5.23}$	92.615	274.96
			ITSE	$\frac{10.98s + 2.43}{s^3 + 91.75s^2 + 3.30s + 3.81}$	97.239	262.90
			ITAE	$\frac{92.87s + 2.26}{s^3 + 82.56^2 + 5.39s + 5.20}$	98.082	255.51
TF-5	p=3	z=2	ISE	$\frac{5.98s^2 + 2.86s + 1.36}{s^3 + 46.03s^2 + 45.78s + 3.72}$	94.365	288.18
			IAE	$\frac{12.44s^2 + 3.02s + 1.16}{s^3 + 35.10s^2 + 44.26s + 3.18}$	94.998	277.96
			ITSE	$\frac{31.60s^2 + 3.77s + 1.51}{s^3 + 92.88s^2 + 49.06s + 12.76}$	86.225	271.08
			ITAE	$\frac{39.06s^2 + 2.41s + 1.48}{s^3 + 59.49s^2 + 41.78s + 7.12}$	89.650	287.07

At the same time unit step responses of the obtained transfer functions were compared with the real system response. A total of four graphs are presented for each fitness function, showing the compatibility of transfer functions with the real system response.

Figure 5 shows the comparison of the unit step responses of the transfer functions determined according to the ISE fitness function with the real system response. As can be seen from the Table 1, accuracy rates were between 75.407% (ISE, TF-1) and 97.41% (ISE, TF-3). Similar to the results in the Table 1, graphically, TF-3 transfer function gave the best result, and TF-1 transfer function gave the worst result.

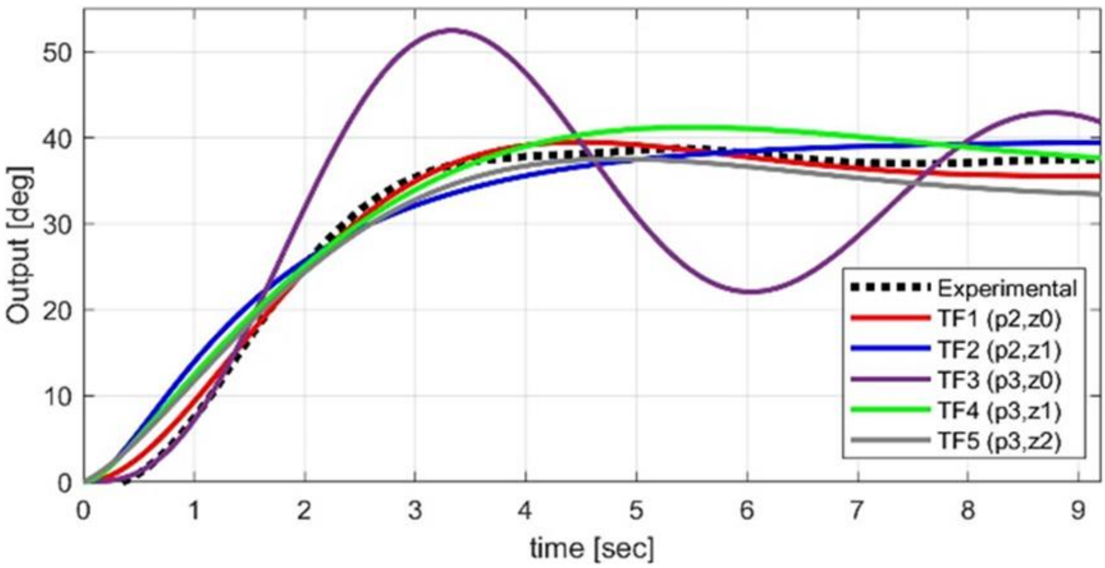

Fig 5: Comparison of the time response of five different transfer functions with the real system response for the ISE fitness function

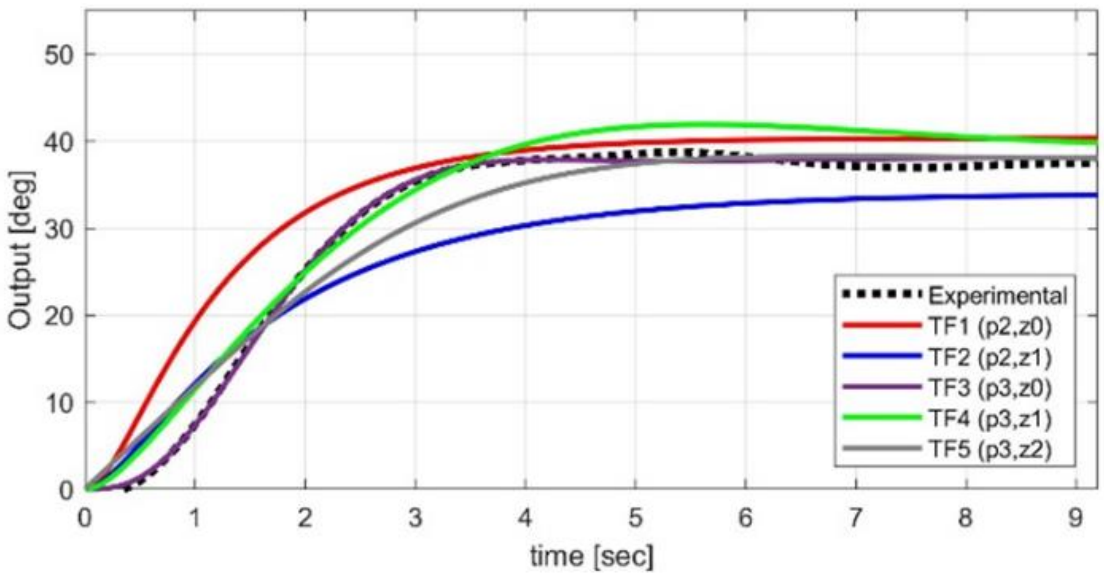

Fig 6: Comparison of the time response of five different transfer functions with the real system response for the IAE fitness function

Figure 6 shows the comparison of the unit step responses of the transfer functions determined according to the IAE fitness function with the real system response. As can be seen from the Table 1, accuracy rates were between 85.105% (IAE, TF-2) and 98.612% (IAE, TF-3). Similar to the results in the Table 1, graphically, TF-3 transfer function gave the best result, and TF-2 transfer function gave the worst result.Figure 7 shows the comparison of the unit step responses of the transfer functions determined according to the ITSE fitness function with the real system response. As can be seen from the Table 1, accuracy rates were between 86.225% (ITSE, TF-5) and 97.239% (ITSE, TF-4). Similar to the results in the Table 1, graphically, TF-4 transfer function gave the best result, and TF- transfer function gave the worst result.

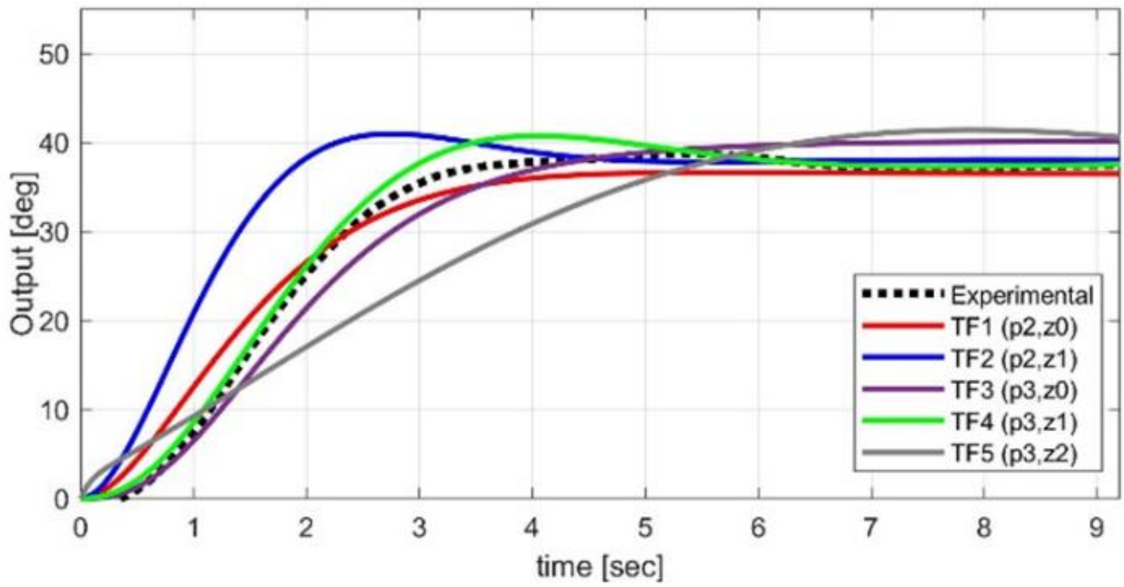

Fig 7: Comparison of the time response of five different transfer functions with the real system response for the ITSE fitness function

Figure 8 shows the comparison of the unit step responses of the transfer functions determined according to the ITAE fitness function with the real system response. As can be seen from the Table 1, accuracy rates were between 89.650% (ITAE, TF-5) and 98.082% (ITAE, TF-4). Similar to the results in the Table 1, graphically, TF-4 transfer function gave the best result, and TF-5 transfer function gave the worst result.

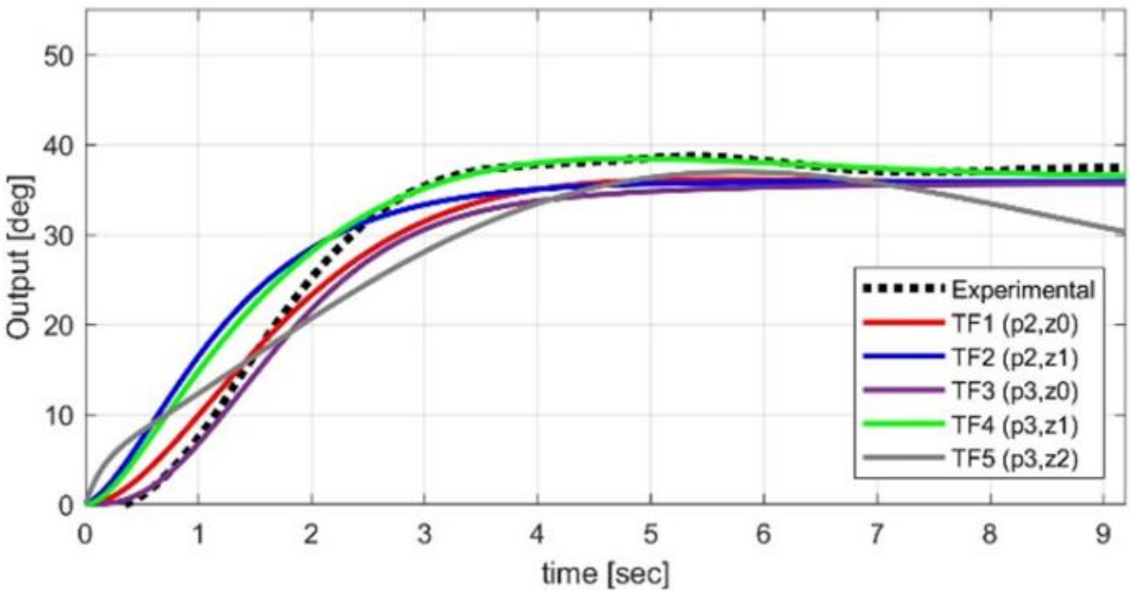

Fig 8: Comparison of the time response of five different transfer functions with the real system response for the ITAE fitness function

When the comparative results obtained were examined, it was seen that the TF-3 transfer function determined according to the IAE fitness function with an accuracy value of 98.612% could provide the most compatible answer with the real system behaviour. The lowest accuracy value was observed to be 75.407% in the TF-3 response determined according to the ISE fitness function.

4. Conclusion

The system identification process using experimental data can provide modelling that can meet the real system dynamics with high accuracy in cases where mathematical modelling cannot be done or the model cannot be verified. The success criterion of the system identification process is accepted as the accuracy ratio of the proposed model with the real model response.

In this study, an experimental set of a Single-DoF Copter system was created and transfer functions that could model the system dynamics with the highest accuracy were investigated using a metaheuristic method. Five different transfer functions have been proposed, in which the zero and pole values are optimized and adjusted by the Vibrating Particle System algorithm. A total of four different fitness functions, namely ISE, IAE, ITSE and ITAE, were used to adjust a total of five different transfer functions with different zero and pole values. The unit step response applied to the system was used to verify the transfer functions. The accuracy values of the transfer function models obtained as a result of the optimization processes were evaluated using the MAPE performance criterion.

Unit step responses of transfer functions and real system responses are presented comparatively in tables and graphs. When the numerical results were examined, it was seen that the TF-3 transfer function with an accuracy value of 98.612%, determined according to the IAE fitness function, provided the real system dynamics at the highest rate. It has been observed that the proposed method can successfully obtain a transfer function model that can represent the system dynamics of an experimental Single-DoF Copter with high accuracy. It is anticipated that this approach can be used to predict transfer functions and nonlinear models in different systems and is a method open to development.

Nomenclature

ARX	: Auto Regressive with Exogeneous Inputs
ARMAX	: Auto Regressive Moving Average with Exogenous Variable Models
BP	: Bad Particle
CIO	: Combined Input-Output
DC	: Direct Current
DOF	: Degree of Freedom
ESC	: Electronic Speed Controller
GP	: Good Particle
BP	: Best Position
ISE	: Integral Square Error
IAE	: Integral Absolute Error
ITSE	: Integral Time Squared Error
ITAE	: Integral Time Absolute Error
MAPE	: Mean Absolute Percentage Error
MIMO	: Multiple Input Multiple Output
NARX	: Non-Linear Autoregressive Exogenous
OE	: Output Error
PI	: Proportional Integral
PRBS	: Pseudo Random Binary Sequence
PWM	: Pulse Width Modulation
SAS	: Stability Augmentation System
SISO	: Single Input Single Output
UAV	: Unmanned Aerial Vehicle
VPSA	: Vibrating Particle System Algorithm

CRediT Author Statement

Kübra Çiftçi: Conceptualization, Methodology, Software, Writing – Original Draft, Writing – Review & Editing, Resources. **Muhammet Arif Şen:** Conceptualization, Methodology, Software, Writing – Original Draft, Writing – Review & Editing. **Hasan Huseyin Bilgic:** Conceptualization, Methodology, Software, Writing – Original Draft, Writing – Review & Editing, Supervision

References

Almufti, S., (2022). Vibrating Particles System Algorithm: Overview, Modifications and Applications. Icontech International Journal [online], 6 (3), 1–11. Available from: https://icontechjournal.com/index.php/iij/article/view/226.

Altan, A. and Hacioglu, R., (2017). İnsansız Hava Aracı Üzerinde Bulunan 3 Eksenli Yalpa Sisteminin Dış Bozucu Altında Modellenmesi. In: 2017 25th Signal Processing and Communications Applications Conference, SIU 2017. Institute of Electrical and Electronics Engineers Inc.

Bogdanski, K. and Best, M. C., (2017). A new structure for non-linear black-box system identification using the extended Kalman filter. Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering, 231 (14), 2005–2015.

Doğa Okcu, I. and Leblebicioğlu, K., (2022). Kapalı Döngü Test Verisi Kullanarak Helikopter Dinamik Sistem Tanımlaması. Fırat Üniversitesi Uzay ve Savunma Dergisi, 1 (1), 422–429.

Ebrahimi, B. and Barzamini, F., (2021). Aircraft System Identification Using Parametric Approaches and Intelligent Modeling. In: 2021 IEEE Aerospace Conference (50100). 1–12.

Fahmi Pairan, M., Syafiq Shamsudin, S. and Fadhli Zulkafli, M., (2020). Neural Network-Based System Identification for Quadcopter Dynamic Modeling: A Review. Journal Of Advanced Mechanical Engineering Applications [online], 1 (2), 20–33. Available from: http://penerbit.uthm.edu.my/ojs/index.php/jamea.

Fidan, Ş. and Erkan, E., (2023). Boost Konvertörün Black-Box Sistem Tanımlama Yöntemi ile Transfer Fonksiyonunun Elde Edilmesi ve Parçacık Sürü Algoritması Tabanlı PI Kontrolör Tasarımı [online]. Available from: http://as-proceeding.com/.

Fidan, S., Sevim, D. and Erkan, E., (2022). System Identification and Control of High Voltage Boost Converter. In: IEEE Global Energy Conference, GEC 2022. Institute of Electrical and Electronics Engineers Inc., 25–31.

Geluardi, S., Nieuwenhuizen, F. M., Venrooij, J., Pollini, L. and Bülthoff, H. H., (2018). Frequency Domain System Identification of a Robinson R44 in Hover. Journal of the American Helicopter Society [online], 63 (1), 1–18. Available from: https://search.ebscohost.com/login.aspx?direct=true&db=asn&AN=128077292&site=eds-live.

Gyongyosi, L., (2020). Objective function estimation for solving optimization problems in gate-model quantum computers. Scientific Reports [online], 10 (1), 14220. Available from: https://doi.org/10.1038/s41598-020-71007-9.

Hoffer, N. V., Coopmans, C., Jensen, A. M. and Chen, Y., (2014). A survey and categorization of small low-cost unmanned aerial vehicle system identification. Journal of Intelligent and Robotic Systems: Theory and Applications, 74 (1–2), 129–145.

Ivler, C. M., Rowe, E. S., Martin, J., Lopez, M. J. S. and Tischler, M. B., (2021). System identification guidance for multirotor aircraft: Dynamic scaling and test techniques. Journal of the American Helicopter Society, 66 (2), 1–16.

Kaveh, A. and Ilchi Ghazaan, M., (2017). Vibrating particles system algorithm for truss optimization with multiple natural frequency constraints. Acta Mechanica, 228 (1), 307–322.

Kaveh, A., Kaveh, A. and Ilchi Ghazaan, M., (2017). A new meta-heuristic algorithm: vibrating particles system. Scientia Iranica [online], 24 (2), 551–566. Available from: https://scientiairanica.sharif.edu/article_2417.html.

Nugroho, L. and Akmeliawati, R., (2018). Comparison of black-grey-white box approach in system identification of a flight vehicle. Journal of Physics: Conference Series [online], 1130 (1), 012024. Available from: https://dx.doi.org/10.1088/1742-6596/1130/1/012024.

De Oliveira, E. C. L., de Araujo, J. P. L., da Silva Silveira, A., Silva, O. F., Vidal, J. F. and de França Silva, A., (2019). Quadrotor Black-Box System Identification Using Metaheuristics.

Özcan, A. B. and Caferov, E., (2022). Frequency Domain Analysis of F-16 Aircraft in a Variety of Flight Conditions. Journal, 03 (01), 21–34.

Pehlivan, K. and Akuner, C., (2020). Quadrotor Test Düzeneği Tasarımı ve Uygulaması. International Periodical of Recent Technologies in Applied Engineering, 2 (1), 15–24.

Saengphet, W., Tantrairatn, S., Thumtae, C. and Srisertpol, J., (2017). Implementation of system identification and flight control system for UAV. In: 3rd International Conference on Control, Automation and Robotics (ICCAR). 678–683.

Salameh, I. M., Ammar, E. M. and Tutunji, T. A., (2015). Identification of quadcopter hovering using experimental data. In: 2015 IEEE Jordan Conference on Applied Electrical Engineering and Computing Technologies (AEECT). 1–6.

Sanatel, Ç., (2020). Uzun Kısa Süreli Bellek Tabanlı Sistem Tanıma ve Uyarlamalı Kontrol. İstanbul Teknik Üniversitesi, İstanbul .

Sayll, A., Erden, F., Tüzün, A., Baykara, B. and Aydemir, M., (2023). A folding wing system for guided ammunitions: mechanism design, manufacturing and real-time results with LQR, LQI, SMC and SOSMC. Aeronautical Journal.

Simmons, B. M., (2021). System Identification for eVTOL Aircraft Using Simulated Flight Data. In: AIAA SCITECH 2022 Forum [online]. American Institute of Aeronautics and Astronautics. Available from: https://doi.org/10.2514/6.2022-2409.

Somov, Y., Somova, T. and Rodnishchev, N., (2021). Identification and Stochastic Optimizing the UAV Motion Control in Turbulent Atmosphere. Journal, 02 (02), 57–63.

Ťapák, P. and Huba, M., (2018). One Degree of Freedom Copter. In: Moreno-Díaz, R., Pichler, F., and Quesada-Arencibia, A., eds. Computer Aided Systems Theory – EUROCAST 2017. Cham: Springer International Publishing, 91–98.

Tugal, H., Okumuş, H. I. and Tugal, H., (2010). Bir Hava Isıtma Sisteminin Optimum Modellenmesi. In: Electrical, Electronics and Computer Engineering [online]. Available from: https://www.researchgate.net/publication/251987598.

Wei, W., Tischler, M. B. and Cohen, K., (2017). System identification and controller optimization of a quadrotor unmanned aerial vehicle in hover. Journal of the American Helicopter Society, 62 (4).

Yu, Y., Tang, P., Song, T. and Lin, D., (2020). A two-step method for system identification of low-cost quadrotor. Aerospace Science and Technology [online], 96, 105551. Available from: https://www.sciencedirect.com/science/article/pii/S1270963819309368.

Yuan, W. and Katupitiya, J., (2011). A time-domain grey-box system identification procedure for scale model helicopters. In: Proceedings of the 2011 Australasian Conference on Robotics and Automation.

Zaloğlu, M., Fİdan, Ş. and Erkan, E., (2023). Meta-Heuristik Optimizasyon Algoritmalarının Sistem Tanımlama Problemine Uygulanması ve Performans Karşılaştırması. In: 2nd International Conference on Engineering, Natural and Social Sciences [online]. Konya. Available from: http://as-proceeding.com/://www.icensos.com/.