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Estimating of UAV Battery Status with BSA Based Sugeno Type Fuzzy System

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Abstract

A hybrid model based on Sugeno type fuzzy system and Back-Tracking Search Optimization Algorithm (BSA) was developed for the estimation of battery status, which is one of the most important parameters affecting the remaining endurance of a rotary wing Unmanned Aerial Vehicle (UAV), in this study. In the model, flight altitude, ground speed and current values obtained from the battery were determined as input variables; battery status was used as output variable. The data were normalized and the Sugeno type fuzzy system was modelled with different rule numbers and each model structure was optimized with BSA. The obtained simulation results show that the proposed model has high compatibility with true data and its prediction success is high. In addition, it is observed that the model performance is sensitive to the membership function type, number of rules and parameter settings. In this direction, optimizing Sugeno type fuzzy systems with BSA offers an effective and reliable approach in modelling complex and nonlinear systems such as UAV battery status.

1. Introduction

Unmanned Aerial Vehicles (UAVs) are aircraft that perform their flights without human intervention, usually controlled by remote control or autonomous systems. These vehicles are equipped with various sensors and cameras and are used in many different areas such as mapping, aerial observation, security services, environmental analysis, agriculture and military operations. First developed for military purposes, UAVs are now widely used in commercial and civil areas.

The existence of control stations is of great importance for the efficient and safe use of UAVs. Control stations serve as a platform that enables the mutual transmission of information such as basic aircraft system data, payload data and images, and location information between the aircraft and the ground station. This data exchange is critical for monitoring and managing the flight process of the aircraft. In addition, control stations transmit the necessary commands for flight control from the ground to the aircraft in real time, and data such as the aircraft's current location, battery status, and flight route are also continuously received. Thus, the safety and efficiency of the flight are ensured, and the ability to intervene in the event of any adverse situation is provided. Therefore, control stations play a vital role in the effective performance of flight management and data communication in order for UAVs to operate safely, efficiently, and correctly (Austin, 2011).

Since the data sets transferred between control stations and UAVs are not sufficiently available in the literature, significant difficulties may arise in the analysis processes aimed at improving UAV performance. Because UAV data sets are widely used in estimating important parameters such as fuel consumption, battery status and endurance that determine the performance of the aircraft. Various studies have been conducted in the literature on improving these parameters in many different areas such as aerodynamic design, propulsion system design, image analysis, high-efficiency battery use, route planning and autonomous systems (Konar, 2018; Bouhoubeiny et al., 2016).

In the literature, the use of heuristic methods in studies aimed at improving UAV flight performance is became increasingly common. One of the main reasons for this is that heuristic methods have the ability to model nonlinear and complex systems effectively. Such heuristic models offer important solutions to engineering problems thanks to their capacity to manage uncertainties and nonlinear relationships. By using advanced optimization methods and learning algorithms, the accuracy of fuzzy systems can be increased and processing times can be shortened. These approaches provide significant advantages in improving the performance of UAVs

(Arik, 2018; Konar, 2020; Konar et al., 2016; Karaburun et al., 2024; Konar et al., 2024).

Luo et al. designed a digital signal processor-based system to obtain UAV data in their studies. They obtained UAV data via the Ground Control Station via wireless data transmission (Luo et al., 2012).

Ozkat et al. proposed a data-driven predictive maintenance model for multi-rotor UAVs. This model aimed to estimate the remaining useful life (RUL) of the aircraft using flight data (Ozkat et al., 2023).

Ho et al. developed a method to optimize data collection processes over wireless sensor networks and UAVs. In their study, they aimed to increase the overall performance of the system by proposing various algorithms to make data transmission between sensor networks and UAVs more efficient (Ho et al., 2015).

Konar et al examined how the Back-Tracking Search Optimization Algorithm (BSA) can be applied to optimize various parameters during the flight of an unmanned helicopter and to increase flight efficiency in their study (Konar et al., 2024).

Allarie et al. performed optimizations based on data estimation in real-time decision making processes of UAVs and worked on Field-Programmable Gate Array (FPGA) implementation of genetic algorithm (Allaire et al., 2009).

Stansbury et al. examined command, control and communication technologies for UAVs in detail (Stansbury et al., 2009).

When the studies in the literature are examined, there are studies in which UAV data are obtained and different heuristic methods are used to improve UAV flight performance. However, UAV data is generally not easily accessible due to reasons such as security, trade secrets, legal regulations and technological limitations. Therefore, UAV data is generally shared in a limited way, which causes restrictions on the development of UAV technologies and the use of heuristic methods.

In this study, a hybrid method consisting of Sugeno type fuzzy system and BSA, which are heuristic methods, was used to estimate the battery status affecting the UAV flight duration. For this purpose, firstly the flight data on a rotary wing UAV were recorded by transmitting it to the ground control station via telemetry. After testing the accuracy of the recorded data, the input and output parameters were determined using these data. The UAV's flight altitude, ground speed and current values drawn from the battery were selected as input parameters, while the battery status (in percent) was selected as the output parameter. The Sugeno type fuzzy system structure was trained using the selected input-output data. During the training, the parameters of the Sugeno type fuzzy model structure were optimized using BSA. Thus, the input-output parameters that do not have a direct relationship between them were correlated and BSA based Sugeno type fuzzy model structures were proposed to estimate the battery status affecting the UAV endurance. The obtained simulation results with using proposed models are presented through tables and figures.

2. Methods

In this study, hybrid models based on Sugeno type fuzzy system and BSA are proposed in order to estimate the battery status affecting UAV endurance. In this section, Sugeno type fuzzy model structure and BSA used in the study are explained.

2.1. Sugeno Type Fuzzy System

Fuzzy logic is a mathematical approach that enables people to think and make decisions in the most accurate way within uncertainties and imprecise information. This logic is a system that develops solutions for situations where binary logic systems do not produce definite results such as 1 or 0. Fuzzy logic tries to calculate the probability of occurrence of these situations by assigning membership degrees for situations that binary logic systems cannot express. Fuzzy logic structures are widely used especially in solving engineering problems and have different types such as Mamdani and Sugeno. In this study, Sugeno type fuzzy model structure, which is frequently preferred in the literature, is preferred. Sugeno type fuzzy logic system is a systematic approach that includes the phases of fuzzing the inputs, determining the rule weights, applying logical operations belonging to fuzzy sets and calculating the results with linear equations (Takagi and Sugeno, 1985; Sugeno and Kang, 1988; Jang et al., 1997). In this study, models consisting of three inputs and single output are proposed in order to estimate the battery status affecting the UAV endurance.

In parameter adjustment of Sugeno type fuzzy model structure, different functions such as triangular, trapezoidal or gaussian type membership functions are preferred. Since triangular membership functions are generally used in literature, triangular membership function is preferred in this study. In case the inputs are characterized by triangular membership functions, each membership function is defined with three parameters. Typical rule structure for 3 inputs of Sugeno type fuzzy system proposed by Takagi, Sugeno and Kang is given in Equation 1 (Takagi and Sugeno, 1985; Sugeno and Kang, 1988; Jang et al., 1997).

$$if\ x = A_1, y = B_1, t = C_1 \Rightarrow z = f(x,y,t) = px + qy + kt + r \quad (1)$$

Here, x, y and t are the input variables of the system. z is a polynomial that depends on the x, y and t variables representing the output. p, q, k and r represent the coefficients in the output polynomial.

In this study, the Sugeno type fuzzy rule base representation with two rules proposed for three inputs and one output is given in Fig. 1. In Fig. 1, μ represents the value of the membership degree, z_1 represents the polynomial of the first rule output, and z_2 represents the polynomial of the second rule output. To obtain the total result z, Equation 2 expresses the weight (w) average method, which is frequently used in the inference method.

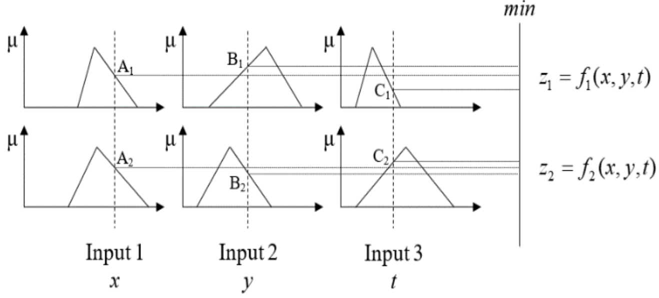

Figure 1. Three input-single output Sugeno type fuzzy model structure for two rules.

$$z=\frac{w_1z_1+w_2z_2}{w_1+w_2}=\frac{\sum_{i=1}^{Rule\,number} w_i z_i}{\sum_{i=1}^{Rule\,number} w_i} \tag{2}$$

As given in Equation 2, the output polynomial for each rule includes the coefficients of the input variables *p, q* and *k* and the constant coefficient *r*. Therefore, four parameters are used for the output. According to this structure given in Fig. 1, since the triangular membership function is preferred for each input in the Sugeno type fuzzy model, a total of nine parameters are used, three for the first input, three for the second input and three for the third input. In the Sugeno model with three inputs and single output, the total number of parameters to be calculated for each rule is 13. The parameter definition of the Sugeno model with three inputs and single output is given in Table 1.

Table 1. Parameter matrix of three input-single output Sugeno type fuzzy model structure for two rules.

Rule Order	Inputs and Output			
	Input 1	Input 2	Input 3	Output
Rule 1	$a_{11}a_{12}a_{13}$	$b_{11}b_{12}b_{13}$	$c_{11}c_{12}c_{13}$	$p_{11}q_{12}k_{13}r_{14}$
Rule 2	$a_{21}a_{22}a_{23}$	$b_{21}b_{22}b_{23}$	$c_{21}c_{22}c_{23}$	$p_{21}q_{22}k_{23}r_{24}$

Correct determination of Sugeno type fuzzy model parameters is an important factor that directly affects the success of the model. Correct adjustment of parameters allows the model to better represent real world data and thus increase the prediction accuracy. In particular, when different model structures, membership functions and parameter adjustments are used, significant improvements in the performance of the model can be observed.

2.2. Back-Tracking Search Optimization Algorithm

Back-Tracking Search Optimization Algorithm (BSA) is an evolutionary algorithm introduced to the literature by Civicioglu in 2013 (Civicioglu, 2013). BSA, which stands out with its features such as its uncomplicated structure, low number of operators and ease of application, is frequently preferred in various optimization problems (Civicioglu, 2013; Duan and Luo, 2014; Wang et al., 2014; Zhang et al., 2015; El-Fergany, 2015; Chen et al., 2017). However, similar to other evolutionary algorithms, BSA has some limitations. These limitations are; the change of the trace population due to the gradual decrease in population diversity during the evolution phase and the difficulty of producing new solutions. The loss of population diversity can negatively affect the discovery ability and general success of the algorithm. In order to overcome this problem, the use of impulse operator to increase the population diversity in BSA has been developed. The impulse operator allows the population to explore a wider search area and contributes to the algorithm finding a solution more effectively. In this way, the population diversity of BSA is increased and outputs that are more successful are produced.

BSA consists of five main steps: initialization, first selection stage, mutation, crossover and second selection stage (Civicioglu, 2013).

In the initialization phase, since BSA is not sensitive to the initial values of the population, a random number is usually chosen. These random initial values, expressed by Equation 3, define the initial individuals randomly distributed between the boundaries determined for each dimension in the solution space. Here, *P* is the population, *U* is the uniform random distribution function. $P_{i,j}$ is a target individual in the population. low_j is the lower bound in the solution space and up_j is the upper bound in the solution space.

$$P_{i,j} \sim U\left(low_j, up_j\right) \tag{3}$$

In the first selection phase, a new historical population *oldP* is used to calculate the search direction for each selection. BSA stores this historical population in its memory for use in subsequent decision-making mechanisms. After *oldP* is created, the population members are randomly sorted and are ready to be used in the next step.

In the mutation phase, a new population is formed by the mutation process defined by Equation 4. Here, the F value represents the coefficient of the variation scale. Mutation determines the search direction using the solution information obtained in the previous steps. In this way, the algorithm makes the solution search process more efficient by taking advantage of the previously obtained experiences.

$$M = P + F(oldP - P) \tag{4}$$

The crossover phase determines the final state of the population with the parameters obtained from the proportional mixture of individuals in the population. Depending on the type of optimization problem, the individuals with the best values in the population are used to create the target population. These individuals represent the best potential solutions in the solution space and allow the algorithm to produce better results.

In the second selection phase, an update process is performed. In this phase, the better individuals in the current population are selected and a new population is created. The best solution found is checked by comparing it with the entire population in each iteration cycle. The algorithm continues its cycle until the maximum number of iterations is reached or until the fitness value meets the predetermined target conditions. In this way, the algorithm constantly evolves and improves until it finds the optimum solution.

These steps are critical for the successful operation of BSA. Each phase of the algorithm performs a specific operation to help the population find better solutions, increasing the overall efficiency of the algorithm.

3. Definition of the Problem and Modeling Process

In this study, a hybrid approach consisting of Sugeno type fuzzy model system and BSA was used to estimate the battery status affecting the remaining endurance of a rotary wing UAV. For this purpose, firstly flight data were obtained as a result of flights made with a rotary wing UAV. From the obtained flight data, flight altitude, ground speed and current values drawn from the battery were selected as input parameters. Depending on the input parameters, the calculation of the battery status affecting the remaining endurance of the UAV as a percentage was determined as the output parameter. The block structure of these models, consisting of 3 inputs and 1 output, is given in Fig. 2.

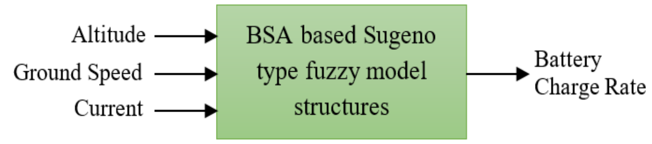

Figure 2. Block diagram of the proposed model structure using the BSA based Sugeno type fuzzy system.

After determining the input and output parameters, the training phase of the Sugeno type fuzzy system was started. In the training phase, BSA was preferred to adjust the parameters of the Sugeno type fuzzy model structure. In order to demonstrate the success of the proposed models, the mean squared error (MSE) defined by Equation 5 was selected as the performance criterion (Chicco et al., 2021). In Equation 5, O_k^d represents the true values. O_k represents the output values of the model. N is the number of samples and its value in this study is 3000.

$$MSE = \frac{1}{N}\sum_{k=1}^{N}(O_k^d - O_k)^2 \tag{5}$$

Fig. 3 shows the block diagram of the training phase of BSA-based Sugeno type fuzzy models. As seen in Fig. 3, in the first step, the training phase starts with the input data using the initial parameter values for the Sugeno type fuzzy model structure. The output values of the proposed model structure are compared with the true output values and the BSA updates the parameters of the Sugeno type model structure depending on the error value between output values. This cycle continues until an acceptable error value is obtained or until the BSA meets the stopping criterion. The number of parameters to be optimized during the training of Sugeno type fuzzy model structures using the BSA varies depending on the number of inputs, the type of membership function and the number of rules.

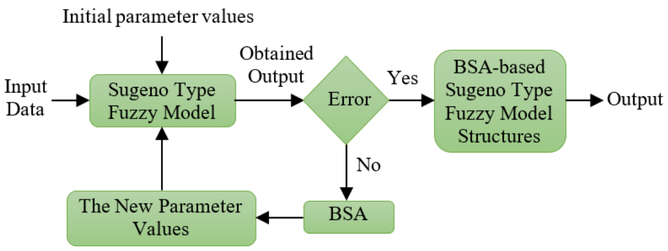

Figure 3. The block diagram of the training phase of BSA-based Sugeno type fuzzy models.

4. Simulation Results

In this study, in order to estimate the battery status affecting the remaining endurance of rotary wing UAV, BSA based Sugeno type fuzzy model structures are proposed as given in Fig. 3. For this purpose, 2220 flight data were obtained as a result of flights made with a rotary wing UAV. By the using these dataset, UAV's flight altitude, ground speed and current values drawn from the battery are selected as input parameters. Battery percentage charge rate is selected as the output parameter. In the proposed models, by considering the minimum and maximum values of the selected input and output data, the normalization ranges of the data are determined as [0, 2000], [0, 500], [180, 900] and [0, 100] for UAV's flight altitude, ground speed, current values drawn from the battery and battery percentage charge rate, respectively. The input and output parameters are normalized to the range of [0, 1] using these value ranges and it is aimed to obtain more successful results in the modeling. Each rule in the Sugeno type fuzzy model structure trained using the value ranges of the input-output parameters is defined with 13 parameters separately. The 13 parameters were obtained by summing 9 parameters for 3 inputs and 4 parameters for output, since the triangular membership function was preferred for each input. After determining the parameters, separate models were created using 2, 3, 4 and 5 rule numbers for Sugeno type fuzzy model structures. In the models created with different rule numbers, it was aimed to optimize 13 parameters with the BSA in a way that would obtain the minimum MSE. The control parameters of the BSA were selected as runtime 5, colony size 30, and iteration numbers 2500 and 5000. Each model proposed with different rule numbers was simulated separately using these control parameter values and the MSE values obtained as a result of the simulation are given in Table 2.

Table 2. Comparison of MSE values obtained from simulations performed with the proposed BSA based Sugeno type fuzzy model structures.

Rule Number	**Iterations**	
	2500	**5000**
2	2.31	2.00
3	2.86	1.70
4	1.78	***1.56***
5	2.23	1.70

When Table 2 is examined, the best MSE value obtained as a result of simulations with the proposed models is 1.56 in the Sugeno type model structure with 4 rules, at 30 colony numbers and 5000 iteration numbers. In the BSA-based proposed models, since no significant improvement in solution quality is observed at iterations greater than 5000 iteration numbers, larger iterations are not studied.

In the problem of estimating the battery status affecting the remaining endurance of the UAV, the comparison of the output values of the model determined to be better and the true output values is given in Fig. 4.

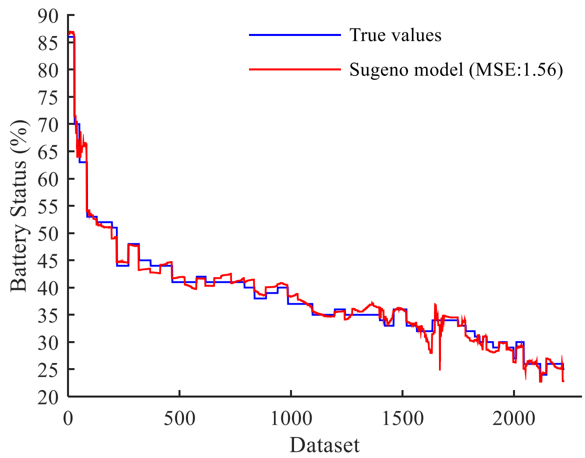

Figure 4. Comparison of the obtained values with the true values for the model with the smallest MSE value.

When Fig. 4 is examined, the compatibility between the values obtained with the proposed BSA-based Sugeno type fuzzy model and the true values is satisfactory. The iteration-

MSE change graph of the model determined to be better is given in Fig. 5.

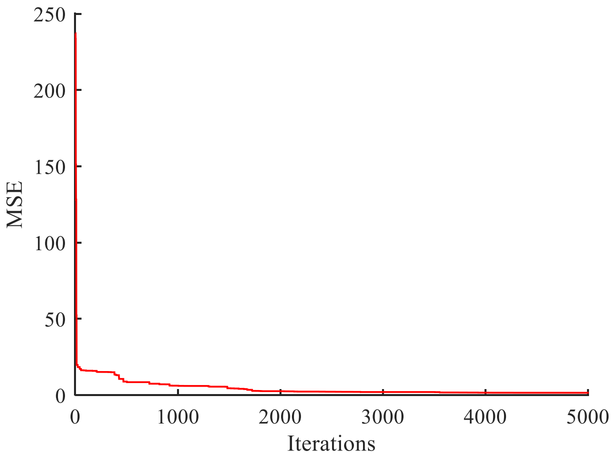

Figure 5. Iteration-MSE change graph for the model with the smallest MSE value.

When Fig. 5 is examined, it is seen that the MSE value decreases rapidly in the first 1000 iterations and becomes stable after 4000 iterations. The parameters of the BSA-based Sugeno type fuzzy model structure, which provides a better MSE value in the problem of estimating the battery status affecting the remaining endurance of the UAV, are given in Table 3.

Table 3. Normalized parameter values for the BSA based Sugeno type fuzzy model with the smallest MSE value

Rule Number	Input 1	Input 2	Input 3	Output
1.	0.3458 0.4167 0.9464	-0.4441 -0.0425 0.5499	-0.6590 -0.3510 -0.0912	-0.9891 -0.6074 -0.2817 0.8754
2.	-0.9452 -0.4481 1.0000	-1.0000 -0.6168 0.8946	-0.8266 -0.1993 0.9670	-0.9599 0.4984 0.5434 0.7876
3.	-0.9068 0.7220 0.9902	-0.6126 0.4140 1.0000	-0.1559 0.6890 0.6984	-0.6105 -0.1928 0.7569 0.8527
4.	-0.6561 -0.6543 0.8234	-0.3218 0.9182 1.0000	-1.0000 -0.7816 0.7695	-0.4288 -0.2732 -0.2614 -0.0128

When Table 3 is examined, it is seen that the values obtained for the BSA-based Sugeno type fuzzy model structure, which is determined to be better, are in the normalization range of [0, 1]. Therefore, the compatibility of the BSA-based proposed Sugeno type fuzzy model results with the true results is satisfactory in the problem of estimating the battery status affecting the remaining endurance of the UAV. This also emphasizes the success of the proposed model.

5. Conclusion

In this study, a hybrid model based on Sugeno type fuzzy logic system and BSA is proposed for the estimation of battery status, which is one of the main factors affecting the remaining endurance of a rotary wing UAV. In the model, UAV flight altitude, ground speed and current drawn from the battery were determined as input parameters; battery status was determined as output parameter. Data were normalized in the pre-processing phase, modeled with different rule numbers and each structure is optimized with BSA method.

Simulation results show that lower MSE value is obtained as 1.56 in the model containing 4 rules, with 5000 iterations and a colony size of 30 individuals. The high level of compatibility of the obtained estimation results with the true data reveals the accuracy and validity of the proposed model. These findings prove that the BSA-based Sugeno type fuzzy model is an effective and reliable method in estimating the UAV battery status.

In Sugeno type fuzzy models, determining the parameters correctly is a fundamental element that directly affects the model success. Parameter optimization enables the model to represent real world data more effectively and thus increase the prediction accuracy. Especially when different model structures, membership function types and parameter adjustments are applied, significant improvements in model performance can be observed.

By testing models with different numbers of rules within the scope of the study, it was determined that the learning capacity and analysis competence of each model varied. Using a larger number of rules and membership functions provides better modeling of complex and nonlinear relationships in the system. However, since using more parameters and rules than necessary in the model may increase the risk of overfitting, an appropriate balance must be established between model complexity and generalization performance.

As a result, in Sugeno type fuzzy models, carefully determining the parameters, selecting the appropriate rule number of model and choosing the membership functions that best suit the nature of the system significantly increase the overall accuracy, reliability and application success of the model. This approach contributes to the development of more robust decision support systems in real-time and vital applications such as monitoring the battery status of UAVs and estimating the remaining endurance.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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