APPLICATION OF GENETIC ALGORITHM FOR MODELING AND IDENTIFICATION OF UNMANNED AERIAL VEHICLE MOTION

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This paper presents a comprehensive study of system identification of an unmanned aerial vehicle (UAV) of an airplane type based on experimental data collected during longitudinal flight. The study focuses on identifying and deriving mathematical models of the UAV in the pitch control channel without feedback or controllers. Using MATLAB System Identification Toolbox, linear mathematical models are developed as integral-differentiating relations of the second and third order. Another approach obtains a linear model using a genetic algorithm by optimizing the structural scheme of the UAV's longitudinal short-period motion. The paper provides a comparative analysis of these models, assessing their accuracy, computational complexity, and applicability in control design on stationary PCs and onboard computers in adaptive systems. The results highlight trade-offs between modelling approaches, offering valuable insights for researchers and engineers in UAV system identification and control.

KEYWORDS

Genetic algorithm, mathematical model identification, artificial intelligence, automatic control system, unmanned aerial vehicle, linear mathematical model, machine learning.

1 INTRODUCTION

Unmanned Aerial Vehicles (UAVs) have seen widespread adoption across various industries due to their flexibility, efficiency, and ability to operate in environments that may be hazardous or difficult for humans to access. As UAV technologies have advanced, mathematical modeling and control systems have become fundamental to improving their performance, stability, and autonomy [Liu 2025, Liang 2024]. This article aims to synthesize and analyze the different approaches used to construct mathematical models for UAVs, particularly focusing on the control systems that define their behavior in dynamic environments.

The control systems of UAVs are critical for their safe and reliable operation, whether for manual, semi-automatic, or fully autonomous flight. As UAV systems become more sophisticated, especially in terms of autonomy and decision-making, the role of control systems has evolved significantly. The focus has shifted towards methods that allow UAVs to adapt to changing environments, optimize their trajectories, and enhance their overall performance [Chudasama 2024].

In this context, mathematical modeling serves as a cornerstone for UAV design and optimization. Accurate models enable simulations that can predict how a UAV will behave in different scenarios, which is essential for system development, testing, and validation. Traditional modeling techniques have been widely used in UAV research, but newer approaches leveraging machine learning (ML), neural networks, and optimization algorithms are reshaping how models are constructed, with a growing emphasis on dynamic system identification and real-time adaptability [Drgona 2022].

This article explores the methods used to construct mathematical models of UAVs, with a particular focus on their control systems [Es-haghi 2024]. The study examines classical techniques alongside emerging methods that incorporate intelligent algorithms, such as machine learning-based control systems. The analysis of these approaches highlights their advantages and challenges, particularly when dealing with nonlinearities, uncertainties, and real-time adaptation. In addition, the article identifies key trends in current research and outlines potential future directions for developing more robust and adaptive UAV control systems [Pistone 2024, Yue 2023].

By synthesizing and comparing different mathematical modeling approaches, this article aims to provide a comprehensive understanding of the state-of-the-art methods in UAV system identification and control [Jose 2024, Kurdel 2022, Labun 2018 & 2020, Nekrasov 2017, Panda 2014 & 2021, Pandova 2020, Sukhodub 2018 & 2019, Harnicarova 2019, Nahornyi 2022]. It also seeks to contribute to the ongoing research efforts aimed at improving the efficiency, safety, and autonomy of UAVs in real-world applications.

2 EQUATION OF UAV DYNAMICS

Modern UAVs widely use automatic control systems (ACS) in all flight modes, which is a necessary condition for the effective use of these aircraft (UAV) [Khalid 2022]. UAVs can serve as a platform for conducting research, synthesis and analysis of control algorithms for unmanned systems of various types and purposes. The existence of ACS in the control circuits of aircraft or UAVs is due to the improvement of piloting characteristics, in particular stability and controllability, as well as the increasing integration of these systems with navigation, sighting and navigation complexes and landing support systems [Radi 2024, Rubi 2021, Zhao 2024]. Such integration increases the efficiency, safety and reliability of UAV use in various flight scenarios [Trad 2024, Zhong 2023]. For manned UAVs, flight control includes manual, semi-automatic and automatic modes. Manual control is carried out by the operator using instrument readings and visual cues, direct or via a video camera. The operator processes this information to control the UAV by changing the position of the controls using a remote-control panel. This system may also include a radio signal receiver-transmitter, algorithms for changing the parameters of the control laws, the control laws themselves, propeller speed and torque regulators, and servo drives [Hajiyev 2015, Sanchez-Rivera 2020].

To describe dynamic processes in control loops, a mathematical model of the control object is required. The complexity and completeness of these models depend on the tasks set in the development and/or research [Jiang 2020, Krenicky 2018]. More complex mathematical models of UAVs consider the features of the UAV design (body flexibility, aerodynamic features, etc.), intermodular interaction, and cross-connections of control channels. However, simplified mathematical models of UAV motion dynamics are sufficient for the analysis and synthesis of control loops.

Linearization of the mathematical model of UAV spatial motion significantly simplifies the analysis of its dynamics and makes it possible to apply the transfer function apparatus [Mizouri 2020]. Also, mathematical models of spatial motion can be simplified due to the symmetry of the UAV and the use of only isolated types of motion [Mobarez 2016].

The spatial motion of the UAV includes three degrees of freedom of translational and three degrees of freedom of rotational motion. The equations of translational dynamics are often used written in a velocity coordinate system [Tahir 2019]:

$$\begin{aligned} & m\dot{V} = P\cos\alpha\cos\beta - X_a - G\sin\Theta; \\ & mV\dot{\Theta} = P(\sin\alpha\cos\gamma_a + \cos\alpha\sin\beta\sin\gamma_a) + Y_a\cos\gamma_a - Z_a\sin\gamma_a - G\cos\Theta; \\ & -mV\dot{\Psi}\cos\Theta = P(\sin\alpha\sin\gamma_a - \cos\alpha\sin\beta\cos\gamma_a) + Y_a\sin\gamma_a + Z_a\cos\gamma_a; \end{aligned} \quad (1)$$

The equations of translational kinematics in projections on the axis of the normal coordinate system have the form:

The equations of rotational dynamics look the simplest in a bound coordinate system:

$$\begin{aligned} & \dot{Y}_g = \dot{H} = V\sin\Theta; \\ & \dot{X}_g = V\cos\Theta\cos\Psi; \\ & \dot{Z}_g = -V\cos\Theta\sin\Psi; \end{aligned} \quad (2)$$

The equation of the kinematics of the rotational motion of the aircraft or the Euler equation:

$$\begin{aligned} & I_x\dot{\omega}_x + (I_z - I_y)\omega_z\omega_y = M_x; \\ & I_y\dot{\omega}_y + (I_x - I_z)\omega_x\omega_z = M_y; \\ & I_z\dot{\omega}_z + (I_y - I_x)\omega_y\omega_x = M_z; \end{aligned} \quad (3)$$

To simplify the synthesis of the ACS, the study considers the dynamics of the UAV during longitudinal short-period motion (SPM) [Aslanyan 1984]. A linear mathematical model of the UAV motion was developed in the form of a structural diagram and its s-model was obtained in the Simulink program of the MATLAB environment.

$$\begin{aligned} & \dot{\psi} = (\omega_y\cos\gamma - \omega_z\sin\gamma)\sec\vartheta; \\ & \dot{\gamma} = \omega_x + tg\vartheta(\omega_z\sin\gamma - \omega_y\cos\gamma); \\ & \dot{\vartheta} = \omega_y\sin\gamma + \omega_z\cos\gamma; \end{aligned} \quad (4)$$

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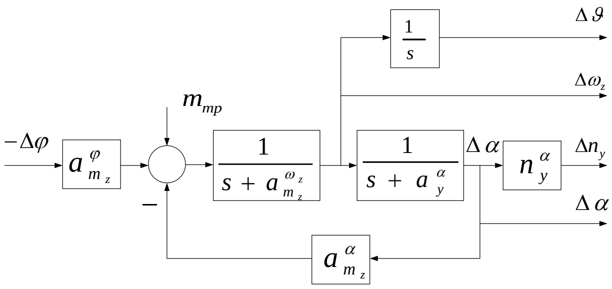

Figure 1. Structural scheme of a linear mathematical model of longitudinal short-period motion

The controlled parameters of the aircraft for the selected type of spatial movement are pitch and attack angle, pitch angular velocity and vertical overload.

In this case, the control signal is the required pitch angle, which is equivalent to the angle of deflection of the UAV control stick in the pitch channel.

The parameters of the amplifying and aperiodic links of the structural diagram of the linear mathematical model of the longitudinal short-period motion of the aircraft (like $a_{m_z}^{\varphi}, a_{m_z}^{\omega_z}, a_{m_z}^{\alpha}, a_y^{\alpha}$) are the parameters that characterize the dynamics of the control object.

3 QUALIMETRIC METHOD FOR ASSESSING OCCUPATIONAL SAFETY RISKS

In this study, the flying wing UAV (Fig. 2) served as the control object. The UAV was flown in both "cruise flight" and other flight modes, where there was no negative feedback applied in either the thrust control channel or the aircraft's spatial angle control channel.

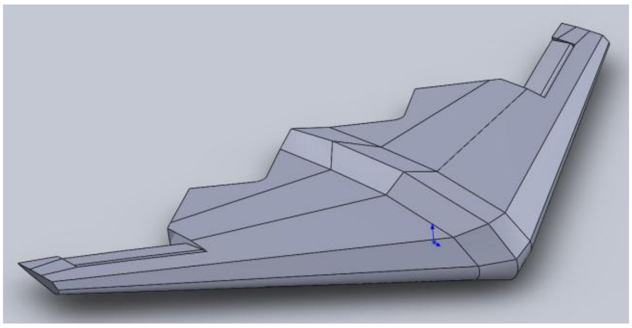

Figure 2. Structural scheme of a linear mathematical model of longitudinal short-period motion

During the experimental flights, various motion parameters of the model, including speed, altitude, angles, angular velocities, and accelerations, were recorded by the APM 2.6.0 controller and later used for system identification. Manual control was provided through the FS-I6 remote control. The flight data of input signal PWM and angular speed were visualized in graph form within the MATLAB environment, as shown in Fig. 3.

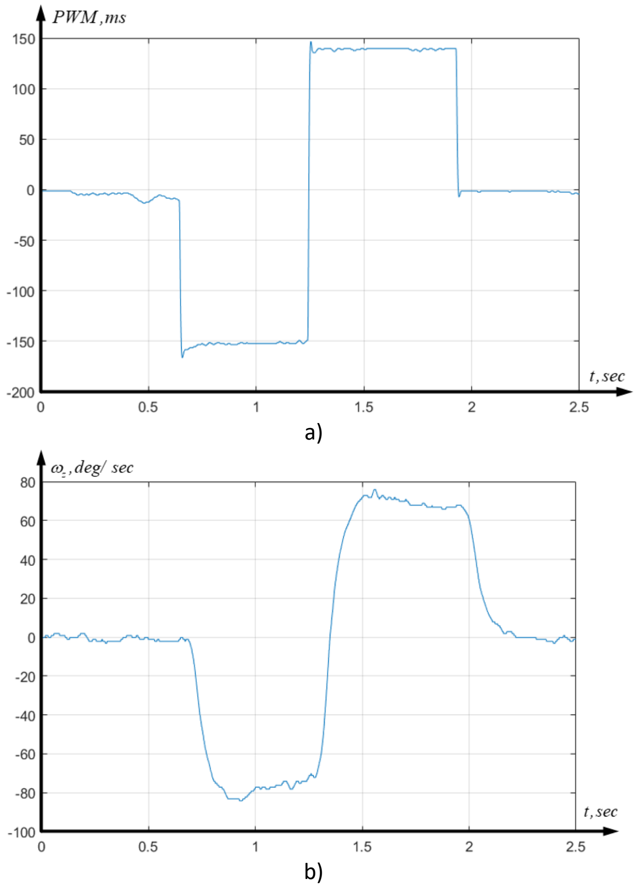

Figure 3. Input PWM signal in pitch canal (a) and output UAV pitch angular speed (b)

Since the identification process in MATLAB uses algorithms like the least squares method and its derivatives, the raw data was not pre-processed or filtered before being used.

4 SYSTEM IDENTIFICATION TOOLBOX APPROACH

In this study, MATLAB's System Identification Toolbox was employed to develop a linear integral-differentiating model of the UAV's pitch control channel see Fig. 4. The coefficients of the numerator and denominator polynomials of the mathematical models are calculated using the least squares method. The experimental data, which were collected from a longitudinal flight where the UAV was controlled only in the pitch channel, served as input for the toolbox. This approach allowed for the extraction of the UAV's system dynamics in the form of a transfer function. The transfer function represents the relationship between the UAV's pitch control input and its pitch output, which is essential for understanding the aircraft's behaviour during flight.

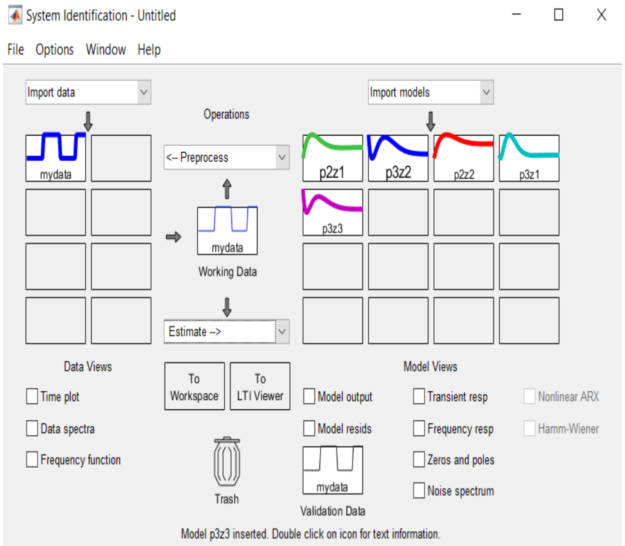

Figure 4. MATLAB System Identification Toolbox

Results of identification can be seen on Figs. 5-10.

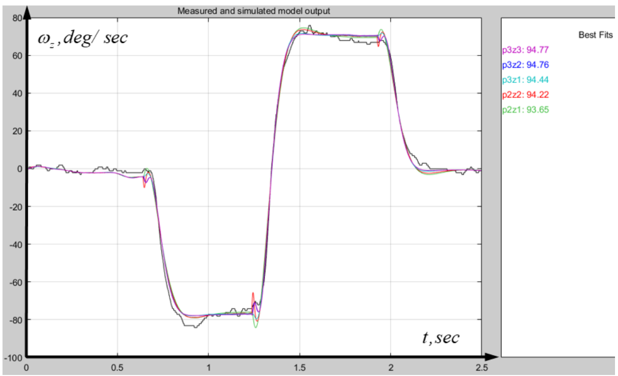

Figure 5. Results of UAV identification using MATLAB System Identification Toolbox

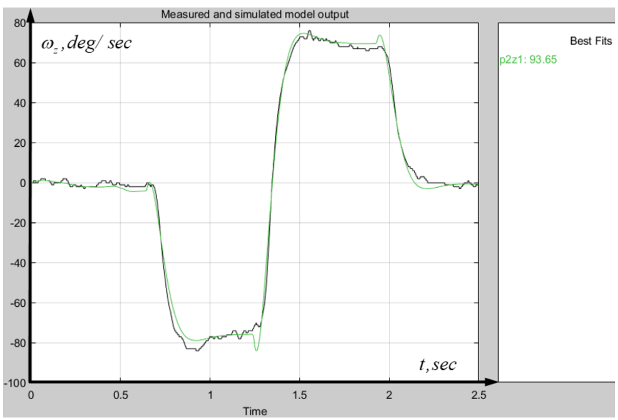

Figure 6. Results of UAV identification of model with 2 poles and 1 zero

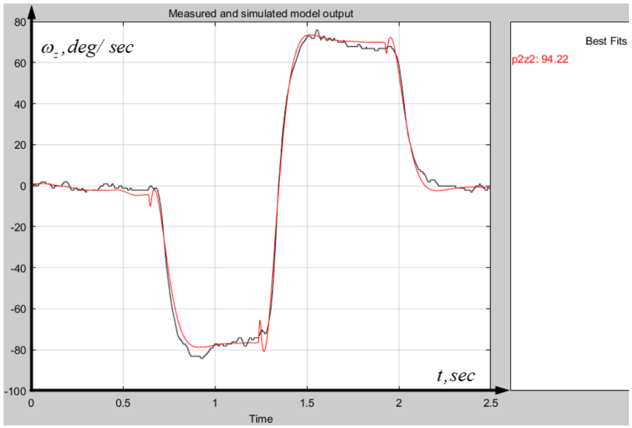

Figure 7. Results of UAV identification of model with 2 poles and 2 zeros

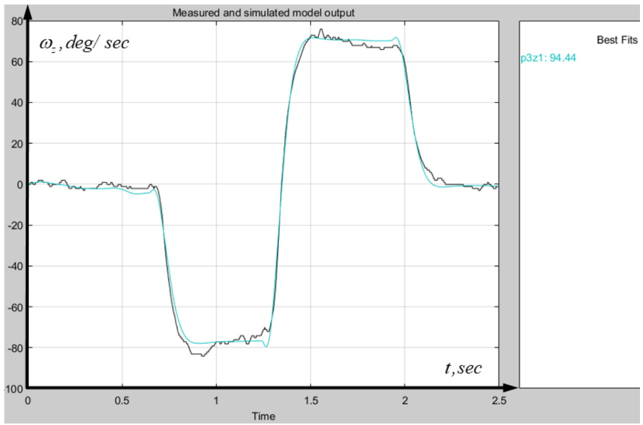

Figure 8. Results of UAV identification of model with 3 poles and 1 zero

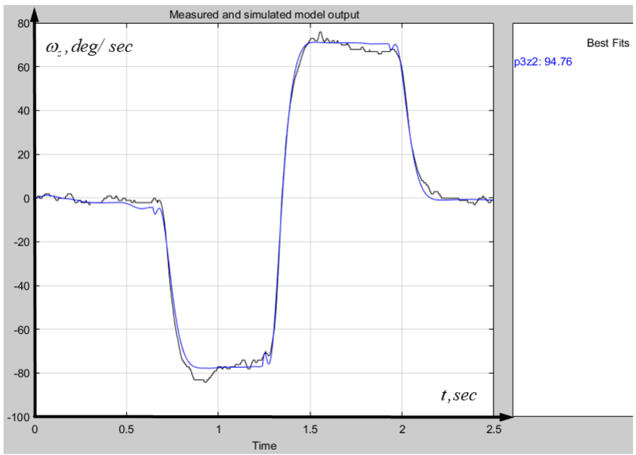

Figure 9. Results of UAV identification of model with 3 poles and 2 zeros

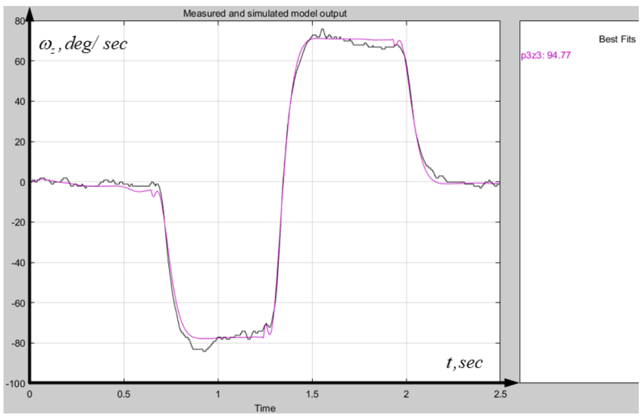

Figure 10. Results of UAV identification of model with 3 poles and 3 zeros

Figures 6-10 present that increasing number of poles and zeros of Laplace model equation gives better fit. In Table 1 shows parameters of all identification equations with marks in each one category. The solution with two poles and one zero demonstrates an accuracy comparable to results from 2 to 5 in terms of error magnitude. However, achieving a marginal accuracy improvement of 1% is not justified given the necessity of increasing the system's order. Consequently, the first solution was selected as the most optimal.

Table 1. Parameters of all identification equations with marks

Name	Fit % (more is better)	Fit mark	Poles (less is better)	Poles mark	Zeros (less is better)	Zeros mark	Total mark
p2z1	93.65	0.9881	2	1.0000	1	1.0000	2.9881
p2z2	94.22	0.9941	2	1.0000	2	0.5000	2.4941
p3z1	94.44	0.9965	3	0.6667	1	1.0000	2.6632
p3z2	94.76	0.9998	3	0.6667	2	0.5000	2.1665
p3z3	94.77	1	3	0.6667	3	0.3333	2
Best value	94.77		2		1		2.9881

Best model is that include 2 poles and 1 zero see Fig. 11.

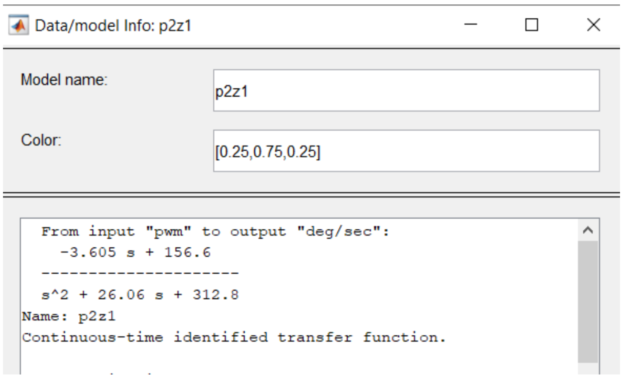

Figure 11. Identification UAV equation with 2 poles and 1 zero

The construction of the mathematical model obtained as a result of identification in Simulink Matlab has the following form (Fig.12).

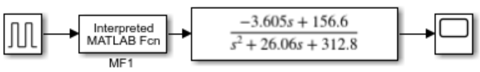

Figure 12. Identification UAV equation with 2 poles and 1 zero

Modelling of the obtained mathematical model of the aircraft's LSPM gives the following transient process see Fig. 13.

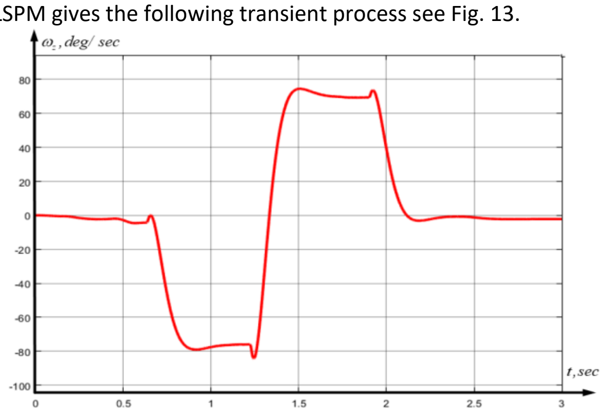

Figure 13. Pitch angle transient process identification UAV equation with 2 poles and 1 zero in Simulink MATLAB

It is evident from Figure 13 that the transient process is oscillatory in nature when the PWM action is applied. To use this model for research purposes, it is necessary to supplement the structural diagram with additional elements and feedback, which, on the one hand, will complicate the system, and on the other hand, will require additional adjustment. It is also worth noting that the resulting mathematical model contains coefficients for the numerator and denominator polynomials, which do not carry any information about the object under study and serve exclusively as coefficients that ensure the convergence of the identification results. To identify the mathematical model of the aircraft-type LSPM, which has parameters that clearly characterize the object of study, it is worth considering the use of a genetic algorithm in the identification problem.

5 GENETIC ALGORITHM APPROACH

The application of genetic algorithms (GAs) in the design and identification of mathematical models of unmanned aerial vehicles (UAVs) has gained significant attention due to their ability to optimize complex, multi-parametric systems. Genetic algorithms, inspired by the principles of natural selection, are particularly effective in solving non-linear optimization problems where traditional gradient-based methods struggle due to local minima or high computational complexity [Bazzocchi 2025].

In UAV system identification, obtaining an accurate mathematical model is crucial for control system development, performance evaluation, and fault diagnosis. Traditional methods, such as parameter estimation through least squares or maximum likelihood techniques, require high-quality experimental data and can be sensitive to noise. GAs provides an alternative by exploring a broad solution space and iteratively refining model parameters based on a fitness function that minimizes the error between simulated and experimental responses [Yang 2014]. In other words, we can say that the accuracy of identification is closely correlated with the quality of UAV control. In turn, the quality of control correlates with the quality of the task being performed with the UAV. The quality methodology is based on the mathematical apparatus of the theory of qualimetry. Scientists in various fields and areas develop such methods that are used for different purposes [Kupriyanov 2023, Dyadyura 2024, Khomiak 2024a]. For example, the authors of [Cherniak 2024, Trishch 2024] propose approaches to the qualimetric assessment of the safety of production processes. The research of the authors of [Kukharchuk 2024, Vasilevskyi 2021a, Vasilevskyi 2021b, Vasilevskyi 2024, Vasilevskyi 2022, Vasilevskyi 2023] in the field of quality aims to improve the accuracy and consistency of measurements, which ultimately contributes to better results in scientific, industrial and environmental fields. Ensuring efficiency, accuracy, and reliability are key aspects for achieving high-quality results [Fedorovich 2024, Riabchykov 2022, Hrinchenko 2019]. All articles [Hovorov 2024a, Hovorov 2024b, Hovorov 2024c, Khomiak 2024b, Hovorov 2021, Hovorov 2025] are united by the study of the quality, reliability and efficiency of critical technical systems - energy infrastructure.

For instance, in the identification of UAV dynamic models, a genetic algorithm can be employed to optimize the parameters of transfer functions, state-space representations, or even integral-differential models [Pena-Garcia 2014]. By encoding these parameters as chromosomes and applying selection, crossover, and mutation operators, GAs iteratively converges to an optimal or near-optimal solution. This approach has been particularly effective in modelling short-period longitudinal dynamics, where aerodynamic coefficients and moment of inertia values need precise tuning [Nonut 2022].

Beyond system identification, genetic algorithms are widely used in UAV design optimization, particularly in aerodynamic shape optimization, structural weight reduction, and propulsion system efficiency improvements [Boutemedjet 2019].

To identify the parameters of the mathematical model of the longitudinal motion of the UAV of the aircraft type, a block for generating the input signal of the system and a block for logging the current transient process are added to the structural diagram of the LSPM. The genetic algorithm is a script that specifies the coefficients of the LSPM structure in Simulink from a random set. In total, one set stores 30 variants of seven parameters of the mathematical model of the LSPM of the UAV. When the algorithm is running, the old coefficients of the set are replaced by new ones, which in the last simulation gave the smallest discrepancy with the experimental data. The structural diagram with the blocks for implementing the genetic algorithm and the first random set of parameters is see in Fig. 14.

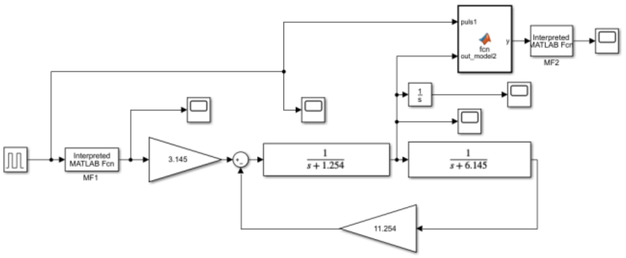

Figure 14. The mathematical model of the LSPM of the UAV with blocks for genetic algorithms in Simulink MATLAB

The identification of the parameters of the UAV mathematical model was carried out in two stages. At the first stage, a set with a random set of parameters was generated, which were alternately substituted into the mathematical model in Simulink MATLAB, after which the model was launched with further collection of data of the transient process and operation of the genetic algorithm. In total, 4200 simulations were carried out at the first stage. At the second stage, the initial random set was replaced with the best set from the first stage. The simulation results are seen in Fig. 15.

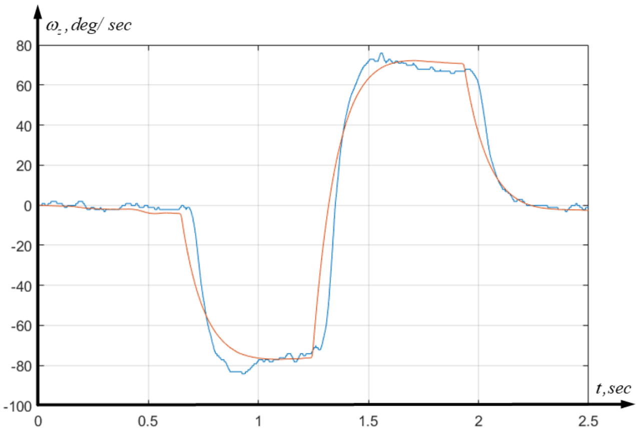

Figure 15. The results of the genetic algorithm (blue - experimental data, orange - the result of the second stage of identification)

From Fig. 15 it is evident that at the second stage of identification using the genetic algorithm the accuracy is 88.93%. The parameters of the mathematical model are as follows:

$$a_{m_z}^{\varphi} = 4.853583474121474;\ a_{m_z}^{\omega_z} = 8.736498853519922;$$

$$a_{m_z}^{\alpha} = 4.923536775097976;\ a_{y}^{\alpha} = 4.477069278176063.$$

This mathematical model corresponds to the mathematical structure of the LSPM and also contains coefficients that display the dynamics of the aircraft under study in the roll channel.

The $a_{m_z}^{\alpha}$ parameter characterizes the aircraft's stability margin at the angle of attack; the parameter $a_{m_z}^{\omega_z}$ characterizes the natural damping of the aircraft around the transverse axis; $a_{m_z}^{\varphi}$ - stabilizer efficiency, i.e. longitudinal controllability of the aircraft; a_{y}^{α} - maneuverability (turning radius) of an aircraft in the vertical plane.

The structural scheme of LSPM identification obtained using the genetic algorithm with an accuracy of 88.93% replicates the real control object, does not require additional adjustment, and also provides for obtaining the coefficients characterizing the UAV in the longitudinal control channel. When using the standard identification method System Identification Toolbox, obtaining mathematical models with their subsequent assessment took about two hours. The total operating time of two stages of the genetic algorithm was about six hours and 8400 simulations. The cost of three times more time to obtain a mathematical model of the UAV, if it is necessary to obtain it in an expanded form, is appropriate for analysis and further research. Moreover, due to the ability of the genetic algorithm to work with many unknowns and give a positive result, it can also be used in problems of identifying complete linear and nonlinear mathematical models of UAVs, which will significantly simplify the design process and reduce production costs.

6 CONCLUSIONS

This study demonstrated a comparative analysis of system identification methods for the pitch control channel of a fixed-wing UAV, focusing on two main methods: the System Identification Toolbox using the least-squares method and a genetic algorithm-based approach. The results highlight the trade-offs between accuracy, computational complexity, and practical applicability for UAV modelling and control.

The System Identification Toolbox with least-squares effectively provided mathematical models in the form of integral-differentiative relations, offering fast identification and high accuracy. However, these models relied on polynomial coefficients without a clear physical interpretation of the UAV dynamics, limiting their direct applicability to control system synthesis problems.

On the other hand, the genetic algorithm-based approach provided a more structured and interpretable model by optimizing the parameters of a predefined UAV dynamic system. Even though this method requires significantly more computational time, it achieved high accuracy (88.93%) and produced coefficients that directly characterize the UAV behaviour in the pitch channel. The angular velocity transient process does not have any oscillatory emissions, as does the real UAV, unlike the System Identification Toolbox models. In general, this suggests that genetic algorithms are especially useful when detailed dynamic parameters are required for further development of the control system.

The results show that both methods have their place in UAV system identification. The System Identification Toolbox with least-squares is well suited for rapid prototyping and initial modelling, while the genetic algorithm method provides deeper insights at the cost of increased computational effort. Future research could explore hybrid approaches using fast evaluation methods of traditional system identification as well as parallel computing algorithms to increase the accuracy of models and reduce the time cost. These advances will be critical to improving UAV control systems, especially for adaptive and real-time applications. Ultimately, this study provides a basis for selecting appropriate identification and modelling methods based on design constraints, whether prioritizing speed, interpretability, or accuracy. The results contribute to the broader field of UAV dynamics and control by assisting researchers and engineers in optimizing UAV performance for real-world applications.

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