Вестник РУДН. Серия: Инженерные исследования
RUDN Journal of Engineering Research

2024;25(4):348–356

ISSN 2312-8143 (Print); ISSN 2312-8151 (Online)
journals.rudn.ru/engineering-researches

DOI: 10.22363/2312-8143-2024-25-4-348-356
UDC 623.746
EDN: EWJUVW

Research article / Научная статья

Methods of a Priori Statistical Analysis of Disturbed Motion of Aircraft in Turbulent Environments

Alexander S. Ermilov, **Olga A. Saltykova**✉

RUDN University, *Moscow, Russia*
✉ saltykova-oa@rudn.ru

Article history

Received: October 30, 2024
Revised: November 21, 2024
Accepted: November 28, 2024

Conflicts of interest

The authors declare that there is no conflict of interest.

Authors' contribution

Undivided co-authorship.

Abstract. The article discusses the methods of a priori statistical analysis used for predicting perturbed motion of aircraft in turbulent environments. Theoretical approaches such as the comparative method and mathematical modeling method are used to analyze the a priori analysis methods. The paper also utilizes statistical methods to evaluate the effectiveness of stochastic models to account for random perturbations caused by turbulence. Special attention is paid to the use of Bayesian analysis, maximum likelihood method and Monte Carlo method applied for probabilistic prediction of the aircraft trajectory. The presented models are illustrated with formulas that describe the dynamics of vehicle motion in turbulent conditions, including equations of motion based on Newton's and Euler's laws. The parameters that determine the dynamics of the perturbed motion of the aircraft in a turbulent environment, such as linear and angular velocities, turbulence intensity, aerodynamic forces, moments of inertia and meteorological conditions, are studied to evaluate the correctness of the calculations. This allows the effects of turbulence on the control and flight trajectory of the aircraft to be taken into account. The results of the study demonstrate the high accuracy of the proposed methods in predicting aircraft motion deviations and emphasize the importance of further development of computational approaches to integrate these methods into real-time control systems, especially for application in conditions of uncertainty and complex external influences. Further research could focus on improving the adaptability of models for different types of aircrafts, taking into account the optimization of computational methods to reduce computational complexity. This will make it possible to improve the efficiency of forecasts in a shorter time and reduce resource costs.

Keywords: a priori analysis, aircraft, stochastic models, turbulent environments, Bayesian analysis, Monte Carlo method, trajectory prediction

For citation

Ermilov AS, Saltykova OA. Methods of a priori statistical analysis of disturbed motion of aircraft in turbulent environments. *RUDN Journal of Engineering Research.* 2024;25(4):348–356. http://doi.org/10.22363/2312-8143-2024-25-4-348-356

Методы априорного статистического анализа возмущенного движения летательных аппаратов в турбулентных средах

А.С. Ермилов, О.А. Салтыкова✉

Российский университет дружбы народов, *Москва, Россия*
✉ saltykova-oa@rudn.ru

История статьи
Поступила в редакцию: 30 октября 2024 г.
Доработана: 21 ноября 2024
Принята к публикации: 28 ноября 2024

Заявление о конфликте интересов
Авторы заявляют об отсутствии конфликта интересов.

Вклад авторов
Неразделенное соавторство.

Аннотация. Рассмотрены методы априорного статистического анализа, используемые для прогнозирования возмущенного движения летательных аппаратов (ЛА) в турбулентных средах. Для анализа методов априорного анализа применяются теоретические подходы, такие как сравнительный метод и метод математического моделирования. Использованы статистические методы, позволяющие оценить эффективность стохастических моделей для учета случайных возмущений, вызванных турбулентностью. Особое внимание уделено использованию байесовского анализа, метода максимального правдоподобия и метода Монте-Карло, применяемых для вероятностного прогнозирования траектории движения ЛА. Представленные модели иллюстрированы формулами, которые описывают динамику движения аппарата в турбулентных условиях, включая уравнения движения, основанные на законах Ньютона и Эйлера. Для оценки правильности расчетов изучены параметры, определяющие динамику возмущенного движения ЛА в турбулентной среде, такие как линейные и угловые скорости, интенсивность турбулентности, аэродинамические силы, моменты инерции и метеорологические условия. Это позволяет учитывать влияние турбулентности на управление и траекторию полета ЛА. Результаты исследования демонстрируют высокую точность предложенных методов в прогнозировании отклонений движения ЛА и подчеркивают важность дальнейшего развития вычислительных подходов для интеграции этих методов в системы управления в реальном времени, особенно для применения в условиях неопределенности и сложных внешних воздействий. Дальнейшие исследования могут быть направлены на повышение адаптивности моделей для различных типов ЛА с учетом оптимизации расчетных методов для уменьшения вычислительной сложности. Это позволит повысить эффективность прогнозов в более короткие сроки и снизить затраты ресурсов.

Ключевые слова: априорный анализ, летательные аппараты, стохастические модели, турбулентные среды, байесовский анализ, метод Монте-Карло, прогнозирование траектории

Для цитирования
Ermilov A.S., Saltykova O.A. Methods of a priori statistical analysis of disturbed motion of aircraft in turbulent environments // Вестник Российского университета дружбы народов. Серия: Инженерные исследования. 2024. Т. 25. № 4. С. 348–356. http://doi.org/10.22363/2312-8143-2024-25-4-348-356

Introduction

Disturbed motion of aircraft in turbulent environments is one of the key problems of aerodynamics, flight dynamics and control. Turbulent flows arising in the atmosphere significantly complicate the prediction of the aircraft trajectory, causing random disturbances that can lead to a change in its motion and deterioration in controllability. The problem lies not only in modeling such motion, but also in developing analysis methods that allow one to estimate potential deviations of motion from a given trajectory and predict them with a high accuracy.

Understanding turbulent environments is important in the design and operation of aircraft, as it can have a significant impact on flight safety and the efficiency of control systems. To solve this problem, it is important to use methods of a priori statistical analysis, which allows one to make probabilistic forecasts about the behavior of the system before receiving the observed data.

The aim of this work is to study the methods of a priori statistical analysis of the disturbed motion of aircraft in turbulent environments and to assess their applicability for modeling and predicting the behavior of aircraft under uncertainty.

1. Mathematical models of disturbed motion

Technical devices designed to move in the atmosphere or outer space by creating lift or jet propulsion are called aircrafts. They include both manned and unmanned vehicles, such as airplanes, helicopters, airships, rockets, spacecraft, and drones. Depending on the flight environment and operating principle, aircraft can use aerodynamic forces (e.g. airplanes and helicopters) or jet propulsion (e.g. rockets) to maintain flight and maneuver.

Turbulence is a chaotic and unpredictable movement of air flows that occurs in the atmosphere, which has a significant impact on flight dynamics [1]. Turbulent flows are characterized by rapid changes in wind speed and direction at different points in space, which leads to disturbances in the trajectory, stability, and controllability of the aircraft (Figure 1).

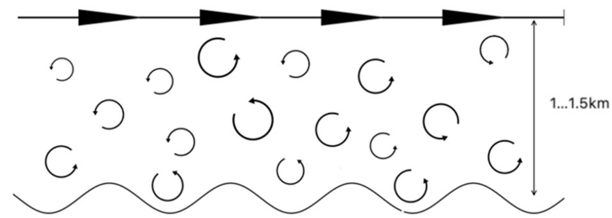

Figure 1. Schematic of dynamic turbulence
Source: made by A.S. Ermilov, O.A. Saltykova

Turbulence near the ground, especially in urban environments and rough terrain, occurs due to the interaction of air flows with various obstacles, such as buildings, trees, and other artificial or natural structures. These objects create zones of disturbed flow, where the air movement becomes chaotic, therefore vortices and sharp changes in wind speed and direction are formed (Figure 2).

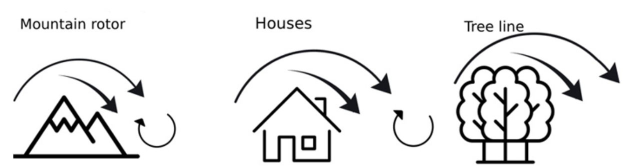

Figure 2. Formation of perturbed air flows near the ground
Source: made by A.S. Ermilov, O.A. Saltykova

Under conditions where an aircraft is subject to random disturbances, its trajectory deviates from the calculated one, which requires the development of special methods for describing and predicting such deviations. The dynamics of an aircraft under disturbed conditions is characterized by complex nonlinear processes that require taking into account not only traditional aerodynamic forces and moments, but also random changes in these parameters under the influence of the environment [2].

To describe the motion of an aircraft under turbulent flow conditions, mathematical models are used that include both deterministic and stochastic components. The main parameters that determine the motion are linear and angular velocities, the position of the center of mass, orientation angles (roll, pitch, yaw) and the forces acting on the apparatus.

The classical model of aircraft flight dynamics includes two types of equations: equations describing translational motion (based on Newton's law) and equations describing rotational motion (based on Euler's equations).

Translational motion is described by Newton's second law in vector form:

$$m\frac{d\vec{V}}{dt}=\vec{F}, \tag{1}$$

where m — mass of an aircraft; $\frac{d\vec{V}}{dt}$ — acceleration vector representing the derivative of the velocity vector $\vec{V}$ with respect to time; $\vec{F}$ — the resulting force acting on the aircraft (including aerodynamic force, gravity and thrust).

The rotational motion of the aircraft is described by Euler's equations, which relate the moment of force to angular accelerations:

$$\frac{d\vec{L}}{dt}=\vec{M}, \tag{2}$$

where $\vec{L}$ — angular momentum of the aircraft relative to the center of mass; $\frac{d\vec{L}}{dt}$ — the derivative of angular momentum with respect to time, describing the angular acceleration; $\vec{M}$ — resultant moment of forces acting on the aircraft.

Together, these equations define a complete dynamic model of aircraft motion that takes into account both its translational and rotational motion. However, in a turbulent environment, these algorithms must be modified by adding stochastic perturbations to parameters such as drag force, lift force, and moments of inertia [3].

Models of motion in a turbulent environment can be divided into two types: deterministic and stochastic.

Deterministic models describe motion based on known initial conditions and environ-mental parameters [4]. It is assumed that all external influences on the aircraft, including turbulent flows, are known and can be accurately described, which is unlikely in real conditions.

Stochastic models, such as random process or Gaussian disturbance models, allow the uncertainty associated with the effects of turbulent flows to be taken into account. For example, the von Kármán wind turbulence model and the Iver model are widely used to describe the structure of turbulent flows in the atmosphere [5]. They allow the statistical characteristics of turbulence, such as the intensity and spectrum of disturbances, to be calculated, which is the basis for predicting the effects of turbulence on aircraft motion.

When modeling the disturbed motion of an aircraft in turbulent environments, it is important to take into account many parameters that can affect the trajectory and dynamics of the flight. They characterize both external factors, such as atmospheric turbulence and meteorological conditions, and the internal properties of the aircraft itself, including its aerodynamic characteristics and mass. Correctly taking these parameters into account allows us to create more accurate mathematical models that predict the behavior of the apparatus in complex conditions (Table).

Parameters determining the dynamics of perturbed motion of an aircraft in a turbulent environment

Parameter	Description	Impact on Flight Dynamics
Linear velocities	Velocities along the X, Y, Z axes, affected by external forces.	Determine the flight trajectory and rate of position change.
Angular velocities	Rotational speeds around the X, Y, Z axes.	Influence the orientation and stability of the aircraft.
Turbulence intensity	Amplitude and frequency of air mass disturbances, determining the force acting on the aircraft.	Lead to deviations in trajectory and orientation.
Aerodynamic forces	Lift and drag, dependent on the angle of attack.	Affect lift and drag, influencing altitude and flight speed.
Moments of inertia	Resistance to changes in angular velocities.	Influence rotational stability.
Mass of the aircraft	Affects inertia and susceptibility to external disturbances.	Greater mass reduces trajectory deviation but increases inertia.
Thrust forces	Engine forces, varying under external influences.	Affect speed and trajectory.
Meteorological conditions	Pressure, temperature and air density.	Affect aerodynamics and controllability.

Source: made by A.S. Ermilov, O.A. Saltykova, data from [6; 7].

Mathematical models of disturbed aircraft motion are a combination of deterministic equations of motion and stochastic models of turbulent effects. This allows one to describe both short-term changes in the aircraft trajectory under the influence of random disturbances and long-term changes in the stability and controllability of the device. To improve the accuracy of mathematical models, it is necessary to use a priori statistical analysis.

2. Basic approaches to a priori analysis

A priori analysis is a statistical method that is based on the use of previously known data or assumptions to construct mathematical models and forecasts. In the context of aircraft dynamics in a turbulent environment, a priori analysis allows for uncertainties in motion parameters and external influences, such as turbulent flows, to be taken into account long before direct measurements or experiments are carried out. This approach makes it possible to predict the behavior of a system in conditions where precise data have not yet been obtained, but there is enough information to form reasonable hypotheses.

There are several main approaches to a priori analysis that are used to estimate the disturbed motion of an aircraft. One of the most well-known methods is the Bayesian approach (application of Bayes' theorem) to update a priori assumptions based on the data obtained:

$$P(\theta|D)=\frac{P(D|\theta)P(\theta)}{P(D)}, \tag{3}$$

where $P(\theta|D)$ — posterior probability of a parameter θ after receiving the data D; $P(D|\theta)$ — likelihood function describing the probability of observing data D at a given parameter value θ; $P(\theta)$ — prior probability of the parameter θ before receiving data; $P(D)$ — normalizing constant called the total probability of the data.

In the context of turbulence and disturbance modeling, θ may represent parameters describing turbulent flows, such as intensity, frequency of disturbances, or other physical characteristics of the medium [8]. Prior distribution $P(\theta)$ can be given on the basis of previous experiments, numerical simulations or theoretical estimates. The likelihood function $P(D|\theta)$ reflects the probability of observing real data D (e.g. wind speed measurements or aircraft trajectories) given known values of the turbulence parameters. After updating the prior distribution with data, a posterior distribution $P(\theta|D)$ is obtained, which provides a more accurate estimate of the turbulence and disturbance parameters. This process can be repeated as more data becomes available, gradually refining the model and making the forecasts more accurate.

The Bayesian approach allows one to take into account the initial uncertainty regarding the parameters of the disturbed motion and to correct them based on incoming information, which is especially important in conditions of complex and uncertain external influences, such as turbulent flows.

Maximum Likelihood Estimation (MLE) is used to estimate model parameters based on known data and prior assumptions [9]. In this method, the task is to find parameters θ that maximize the likelihood of the data D, that is, maximize the probability that the observation data could have been obtained with the given parameter values. This is expressed through the ***likelihood function***:

$$L(\theta)=P(D|\theta). \tag{4}$$

In turbulent conditions, the maximum likelihood method is used to estimate the parameters of the disturbance model, such as the intensity and frequency of turbulent flows. For example, if the observational data D describe the deviations of the aircraft trajectory in turbulent conditions, then θ can represent the parameters of the turbulent effects, such as the mean velocity and variance of the disturbances.

Another effective tool for a priori analysis is the *Monte Carlo method*, especially in the case of complex stochastic systems [10]. In modeling the disturbed motion of an aircraft, it allows for statistical analysis of various flight trajectories in a turbulent environment, assessing the probability of various deviations from the calculated trajectories (Figure 3).

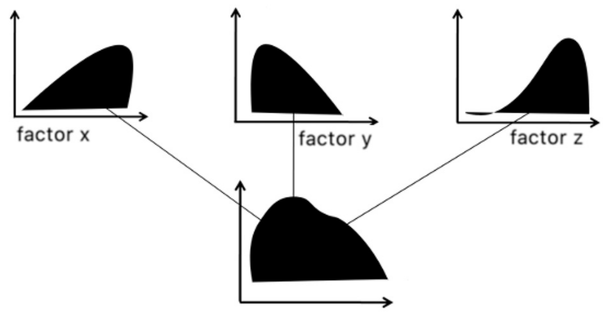

Figure 3. Scheme of the Monte Carlo method
S o u r c e: made by A.S. Ermilov, O.A. Saltykova

The factors *x, y* and *z* represent various external parameters such as wind speed, direction of turbulent flows and other disturbing forces. Probability distributions are modeled for each of these factors, which are then used to estimate the deviation of the aircraft from the calculated trajectory. The points on the graphs represent a set of possible outcomes obtained using the Monte Carlo method, which allows us to estimate the influence of each factor on the resulting motion of the apparatus.

Regularization is used to solve ill-conditioned problems when there is an excessive amount of a priori data or there is high uncertainty in the initial parameters (Figure 4).

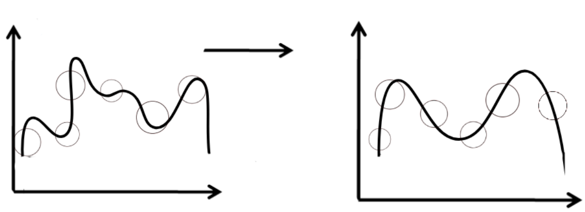

Figure 4. Regularization scheme
S o u r c e: made by A.S. Ermilov, O.A. Saltykova

In aircraft control, regularization methods play an important role when working with data obtained in real time from sensors, for example, about the position and speed of the aircraft. In conditions of turbulence or other external influences, the readings may contain significant noise, which complicates the calculation of correct control actions [11]. Regularization helps to smooth out such fluctuations, making the data more reliable for decision-making [12].

In some cases, a priori analysis can be based on *deterministic* ***approaches***, when the a priori values of the parameters are assumed to be known and unchanged [13]. These methods make it possible to significantly simplify calculations, but their use is justified only under conditions of a low degree of uncertainty. For example, deterministic a priori methods can be useful for analyzing aircraft motion in weak turbulence or in conditions when the nature of the disturbances is well understood [14].

3. Application of a priori models and approaches to the analysis of aircraft dynamics

One example of the application of a priori models is the analysis of the motion of unmanned aerial vehicles (UAVs) in turbulent flows at low altitudes [15]. Turbulence near the earth's surface can be intense and unpredictable, which complicates control and trajectory prediction. In such situations, a priori probability models are used to describe the parameters of turbulent flows (for example, the average value of wind speed and its dispersion). These models allow calculating deviations from the calculated trajectory and assessing the probability of significant disturbances. The main equations describing the dynamics of aircraft motion include Newton's equations for translational motion:

$$m\frac{d\vec{V}}{dt}=\overrightarrow{F_{\text{аэр}}}+\overrightarrow{F_{\text{турб}}}+\overrightarrow{F_{\text{грав}}}\ , \tag{5}$$

where m — mass of the device; $\vec{V}$ — velocity vector; $\overrightarrow{F_{\text{аэр}}}$ — aerodynamic forces; $\overrightarrow{F_{\text{турб}}}$ — disturbances caused by turbulent flows; $\overrightarrow{F_{\text{грав}}}$ — gravity.

After applying Newton's equations to analyze the aircraft dynamics in turbulent conditions, the influence of turbulent disturbances on the trajectory of motion can be assessed. Value $\overrightarrow{F_{\text{турб}}}$, which is a random force caused by turbulence, can fluctuate depending on the characteristics of the atmosphere and the flight altitude. This leads to the aircraft trajectory deviating from the calculated ones, causing additional maneuvers to stabilize the flight. Using a priori models, it is possible to predict the most probable deviations and adjust the control systems in advance to minimize the effects of turbulence. This approach improves the stability of the aircraft and prevents abrupt changes in trajectory, which is especially important for unmanned systems or when flying at low altitudes, where turbulence is more pronounced.

One of the effective methods of a priori analysis in aircraft control is the *Bayesian approach*, which allows dynamically updating turbulence forecasts as new data arrives. This method is actively used in high-altitude flight conditions, where turbulence can suddenly occur and have a significant impact on the trajectory.

At cruising altitude (usually above 10 km), where aircrafts often encounter turbulence, control is performed using a priori data on the probability of occurrence of turbulent zones [16]. Initially, the control system has a priori information on turbulence obtained from meteorological models, and it is specified as a priori probability of the parameter θ — the turbulence intensity.

When sensors on board detect changes in air flows, the system updates the prior based on these observations using Bayes' theorem:

$$P(\theta|D) = \frac{P(D|\theta)P(\theta)}{P(D)}, \tag{6}$$

where $P(\theta|D)$ — updated posterior probability of turbulence after data acquisition D; $P(D|\theta)$ — likelihood of observed data.

The aircraft's control system, based on updated a posteriori data, can predict increased turbulence and adjust flight parameters in advance [17].

For example, if the data indicates an increased probability of severe turbulence ahead, the system can reduce speed or adjust altitude to mitigate the impact. This process ensures safe and stable flight, even under unexpectedly changing external conditions.

Conclusion

Methods of a priori statistical analysis of disturbed aircraft motion in turbulent environments demonstrate high efficiency in predicting trajectory deviations and flight dynamics. Stochastic models, such as the Bayesian approach, maximum likelihood method, and Monte Carlo method, allow for uncertainty and random disturbances characteristic of turbulent flows. These approaches make it possible to estimate the probability of motion deviations and improve the accuracy of forecasts under conditions of limited information. The use of a priori data and probabilistic models contributes to improving the stability and controllability of aircraft, especially when they operate in complex external conditions. However, despite significant progress, there remain challenges associated with the integration of such models into real aircraft control systems in real time. In the future, it will be necessary to improve computational methods for prompt processing of large volumes of data and adaptation of models to changing flight conditions. In addition, the development of universal approaches remains to be an important task, that will take into account the specifics of different types of aircraft and the ranges of turbulence they encounter.

References

1. Rassadin AA, Ryakhovsky AV. Modeling turbulent flow: a case study of wing profile streamlining. *Advances in Cybernetics*. 2024;5(2):64–74. (In Russ). https://doi.org/10.12345/jcyb.ru/issue5/64-74

2. Kurnyshev DA, Mitin TA, Nyrkov DD. The problem of the stability of the disturbed and undisturbed motion of the aircraft. *Modern Scientific Research: Current Issues, Achievements, and Innovations. Collection of articles of the XXXIV International Scientific and Practical Conference. Penza, August 15, 2023*. 2023:22–27. (In Russ.) EDN: XRTCHK

3. Raol JR, Singh J. *Flight mechanics modeling and analysis*. CRC Press; 2023.

4. Kozhevnikov YuV, Shibanov GP. Optimum average of high-speed to describe of aircraft by the flying-tests. *Mechatronics, Automation, Control*. 2023;24(9):489–495. (In Russ). https://doi.org/10.31857/S0234-202310050

5. Sirois J, Desjardins S, Peter G. Vortex-breakdown efficiency of planar regular grid structures — towards the development of design guidelines. *Fluids*. 2024;9(2):43. https://doi.org/10.3390/fluids9020043

6. Kreerenko SS, Kreerenko OD. Parametric identification of aerodynamic characteristics of a transport category aircraft using recurrent semi-empirical neural networks in the tensorflow environment. *Mathematical modeling and computational methods*. 2024;43(3):81–99. (In Russ.) https://doi.org/10.18698/2309-3684-2024-3-8199

7. Astakhov SA, Ivanov VP, Sergeev IA. Aerodynamic interaction simulation during track testing of aircraft products. *PNRPU Aerospace Engineering Bulletin*. 2023;(72):5–20. (In Russ.) https://doi.org/10.15593/2224-9982/2023.72.01

8. Kong Y, Mahadevan S. Identifying Anomalous Behavior in Aircraft Landing Trajectory Using a Bayesian Autoencoder. *J Aerosp Inf Syst*. 2024;21(1):19–27. https://doi.org/10.2514/1.J062834

9. Bayat S, Amiri R. Advances in UAV-Assisted Localization: Joint Source and UAV Parameter Estimation. *IEEE Trans Veh Technol*. 2023;72(11):14268–78. https://doi.org/10.1109/TVT.2023.3190744

10. Fedulov VA, Bykov NV, Baskakov VD. Estimating of the effectiveness of the weapon system against of small unmanned aerial vehicles by computer simulation. *Systems of Control, Communication and Security*. 2023;(4):63–104. (In Russ.) https://doi.org/10.24412/2410-9916-2023-4-63-104

11. An Z, Wang Y, Zhang Q. Learning spatial regularization correlation filters with the Hilbert-Schmidt independence criterion in RKHS for UAV tracking. *IEEE Trans Instrum Meas*. 2023;72:1–12. https://doi.org/10.1109/TIM.2023.3256114

12. Israfilov A. Contemporary challenges in cybersecurity of unmanned aerial systems. *Universum: Technical Sciences*. 2024;119(2):19–21. (In Russ.) EDN: SOIKHN

13. Soldatov AS, Soldatov ES, Bogomolov AV. Technological platform for digital twin synthesis of an aircraft based on cyber-physical systems technology. *Large-Scale Systems Management (MLSD'2023)*: *Proceedings of the Sixteenth Conference.* Moscow, September 26-28, 2023, 2023:1092–1099. (In Russ.) https://doi.org/10.25728/mlsd.2023.1092

14. Qiao W, Wu S. The Modeling and Simulation of Turbulence for Civil Aircraft Compliance Verification Test. *J Phys Conf Ser. IOP Publishing*. 2023;2658(1):012056. https://doi.org/10.1088/1742-6596/2658/1/012056

15. Mohamed A, Cai W, Zhang R. Gusts encountered by flying vehicles in proximity to buildings. *Drones*. 2023;7(1):22. https://doi.org/10.3390/drones7010022

16. Yoshimura R, Ishikawa S, Tanaka T, Nakamura Y. Clear air turbulence resolved by numerical weather prediction model validated by onboard and virtual flight data. *Geophys Res Lett*. 2023; 50(12):e2022GL101286. https://doi.org/10.1029/2022GL101286

17. Jiang W, Gao L, Zhang X. An Investigation of Sudden Plunging Motion Mechanisms for Transport Aircraft during Severe Clear-Air Turbulence Encounter. *J Aerosp Eng*. 2023;36(3):04023011. https://doi.org/10.1061/(ASCE)AS.1943-5525.0001533

Список литературы

1. *Рассадин А.А., Ряховский А.В.* Моделирование турбулентного течения на примере задачи об обтекании профиля крыла // Успехи кибернетики. 2024. Т. 5. № 2. С. 64–74. https://doi.org/10.12345/jcyb.ru/issue5/64-74

2. *Курнышев Д.А., Митин Т.А., Нырков Д.Д.* Задача об устойчивости возмущенного и невозмущенного движения ЛА // Современные научные исследования: актуальные вопросы, достижения и инновации : сборник статей XXXIV Международной научно-практической конференции. Пенза, 15 августа 2023 года. 2023. С. 22–27. EDN: XRTCHK

3. *Raol J.R., Singh J.* Flight mechanics modeling and analysis. CRC Press, 2023.

4. *Кожевников Ю.В., Шибанов Г.П.* Оптимальное осреднение высотно-скоростных характеристик летательных аппаратов при их летных испытаниях // Мехатроника, автоматизация, управление. 2023. Т. 24. № 9. С. 489–495. https://doi.org/10.31857/S0234-202310050

5. *Sirois J., Desjardins S., Peter G.* Vortex-breakdown efficiency of planar regular grid structures — towards the development of design guidelines // Fluids. 2024. Vol. 9. No. 2. P. 43. https://doi.org/10.3390/fluids9020043

6. *Креоренко С.С., Креоренко О.Д.* Моделирование и параметрическая идентификация аэродинамических характеристик самолета транспортной категории с использованием нейросетей в среде Tensorflow // Математическое моделирование и численные методы. 2024. № 3 (43). С. 81–99. https://doi.org/10.18698/2309-3684-2024-3-8199

7. *Астахов С.А., Иванов В.П., Сергеев И.А.* Моделирование аэродинамического взаимодействия при трековых испытаниях изделий авиационной техники // Вестник Пермского национального исследовательского политехнического университета. Аэрокосмическая техника. 2023. № 72. С. 5–20. https://doi.org/10.15593/2224-9982/2023.72.01

8. *Kong Y., Mahadevan S.* Identifying Anomalous Behavior in Aircraft Landing Trajectory Using a Bayesian Autoencoder // Journal of Aerospace Information Systems. 2024. Vol. 21. No. 1. P. 19–27. https://doi.org/10.2514/1.J062834

9. *Bayat S., Amiri R.* Advances in UAV-Assisted Localization: Joint Source and UAV Parameter Estimation // IEEE Transactions on Vehicular Technology. 2023. Vol. 72. No. 11. P. 14268–14278. https://doi.org/10.1109/TVT.2023.3190744

10. *Федулов В.А., Быков Н.В., Баскаков В.Д.* Оценка эффективности системы поражения малоразмерных беспилотных летательных аппаратов методом имита-

ционного моделирования // Системы управления, связи и безопасности. 2023. № 4. С. 63–104. https://doi.org/10.24412/2410-9916-2023-4-63-104

11. *An Z., Wang Y., Zhang Q.* Learning spatial regularization correlation filters with the hilbert-schmidt independence criterion in RKHS for UAV tracking // IEEE Transactions on Instrumentation and Measurement. 2023. Vol. 72. P. 1–12. https://doi.org/10.1109/TIM.2023.3256114

12. *Исрафилов А.* Современные вызовы в области кибербезопасности беспилотных авиационных систем // Universum: технические науки. 2024. № 2–1 (119). С. 19–21. EDN: SOIKHN

13. *Солдатов А.С., Солдатов Е.С., Богомолов А.В.* Технологическая платформа синтеза цифрового двойника летательного аппарата на основе технологий киберфизических систем // Управление развитием крупномасштабных систем (MLSD'2023) : труды Шестнадцатой международной конференции. Москва, 26–28 сентября 2023 года. 2023. С. 1092–1099. https://doi.org/10.25728/mlsd.2023.1092

14. *Qiao W., Wu S.* The Modeling and Simulation of Turbulence for Civil Aircraft Compliance Verification Test // Journal of Physics: Conference Series. IOP Publishing, 2023. Vol. 2658. No. 1. P. 012056. https://doi.org/10.1088/1742-6596/2658/1/012056

15. *Mohamed A., Cai W., Zhang R.* Gusts encountered by flying vehicles in proximity to buildings // Drones. 2023. Vol. 7. No. 1. P. 22. https://doi.org/10.3390/drones7010022

16. *Yoshimura R., Ishikawa S., Tanaka T., Nakamura Y.* Clear air turbulence resolved by numerical weather prediction model validated by onboard and virtual flight data // Geophysical Research Letters. 2023. Vol. 50. No. 12. Article no. e2022GL101286. https://doi.org/10.1029/2022GL101286

17. *Jiang W., Gao L., Zhang X.* An Investigation of Sudden Plunging Motion Mechanisms for Transport Aircraft during Severe Clear-Air Turbulence Encounter // Journal of Aerospace Engineering. 2023. Vol. 36. No. 3. Article no. 04023011. https://doi.org/10.1061/(ASCE)AS.1943-5525.0001533

Сведения об авторах

Ермилов Александр Сергеевич*,* аспирант кафедры механики и процессов управления, инженерная академия, Российский университет дружбы народов, Москва, Россия; ORCID: 0009-0007-4549-172X; e-mail: eemilov-sasha@yandex.ru

Салтыкова Ольга Александровна*,* кандидат физико-математических наук, доцент кафедры механики и процессов управления, инженерная академия, Российский университет дружбы народов, Москва, Россия; ORCID: 0000-0002-3880-6662, eLIBRARY SPIN-код: 3969-6707; e-mail: saltykova-oa@rudn.ru

About the authors

Alexander S. Ermilov*,* Postgraduate student of the Department of Mechanics and Control Processes, Academy of Engineering, RUDN University, Moscow, Russia; ORCID: 0009-0007-4549-172X; e-mail: eemilov-sasha@yandex.ru

Olga A. Saltykova, Cand. Sc. (Physics and Mathematics), Associate Professor of the Department of Mechanics and Control Processes, Academy of Engineering, RUDN University, Moscow, Russia; ORCID: 0000-0002-3880-6662, eLIBRARI SPIN-code: 3969-6707; e-mail:saltykova-oa@rudn.ru