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Integrated frequency-based method for flight planning of stratospheric gliders with anomaly filtering

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Abstract: *This paper presents, for the first time, an integrated method for flight planning of stratospheric gliders operating within swarm-based multilevel systems, which combines frequency analysis of time series of key flight performance indicators with an adapted Irwin criterion for filtering anomalous parameter deviations. The proposed approach enables the detection of long-period oscillations caused by stratospheric atmospheric processes and collective swarm dynamics, and allows for the timely identification of critical deviations that may disrupt swarm coordination, lead to additional energy losses, or cause degradation of the multilevel control system. The developed method is aimed at ensuring stability, adaptability, and energy efficiency of long-duration stratospheric soaring and can be applied to improve the effectiveness of flight planning for stratospheric gliders in multilevel autonomous systems. Existing approaches to flight planning for stratospheric vehicles are generally focused on local optimization of energy consumption or kinematic parameters and are based on the assumption of process stationarity. At the same time, most studies leave unresolved the issues of comprehensive analysis of the spectral structure of flight parameters, integration of frequency-domain methods into route evaluation procedures, and formalized detection of anomalies that may impair swarm coordination, accumulate energy losses, and degrade multilevel control systems. The objective of this study is to develop and substantiate an integrated algorithm for frequency analysis of flight planning indicators of stratospheric gliders in swarm-based multilevel systems using an adapted Irwin criterion for anomaly filtering. The proposed algorithm is intended to improve the accuracy of assessing long-period oscillations of flight parameters, enhance swarm interaction stability and energy efficiency of prolonged stratospheric soaring, and increase the reliability of multilevel autonomous control systems. The obtained results provide a scientific basis for the further development of adaptive control algorithms for swarm stratospheric gliders and may be used to improve the performance of autonomous multilevel systems in monitoring, communication, and surveillance applications.*

Keywords: *stratospheric gliders, swarm systems, multilevel control, flight planning, frequency analysis, Irwin criterion, anomaly filtering, energy efficiency*

1. INTRODUCTION

Flight planning of stratospheric gliders belonging to the class of high-altitude pseudo-satellite platforms (High-Altitude Platform Systems, HAPS) constitutes a complex multi-criteria process that requires the integration of traditional, intelligent, and statistical methods to ensure long-endurance and reliable operation under stratospheric conditions. The efficiency of HAPS flight planning is largely determined by the stability and coherence of a set of quantitative performance indicators, including the energy efficiency of prolonged loitering, maintenance of the operational altitude layer, spatio-temporal coverage of the observation area, trajectory stability, consistency of swarm interaction, and the reliability of the multi-level control system, as reported in several previous studies [1–3].

During the modeling and experimental validation of flight planning algorithms for stratospheric gliders, these indicators are typically represented as time series or discrete samples that describe the long-term dynamics of flight parameters in the stratosphere. Such data often contain anomalous values caused by measurement errors, onboard sensor instability, the influence of high-altitude atmospheric processes, or numerical peculiarities of optimization algorithms [4]. The presence of anomalies may significantly distort the results of frequency analysis, leading to spurious spectral components, overestimation of harmonic amplitudes, and incorrect assessment of long-period parameter oscillations. This, in turn, complicates the interpretation of amplitude–frequency characteristics and reduces the reliability of integrated flight planning performance indicators [5]. As a result, erroneous engineering and control decisions may be made in swarm-based multi-level HAPS systems [6].

To address these challenges, it is expedient to apply a comprehensive methodological approach that combines frequency analysis with anomaly detection and filtering procedures. The studies emphasize the necessity of preliminary data cleansing to remove gross errors before spectral transformations [7]. The use of an adapted Irwin criterion for detecting and excluding anomalous deviations in flight parameters enables the improvement of spectral estimates' accuracy and robustness, which is particularly important for analyzing long-duration processes inherent in stratospheric loitering. At the same time, the formalization of the impact of such filtering on frequency analysis results and aggregated HAPS flight planning performance metrics remains insufficiently explored, limiting the objective comparison of planning algorithms and reducing the reliability of multi-level autonomous control systems [8].

Accordingly, the objective of this article is to develop and substantiate an integrated frequency analysis algorithm for flight planning indicators of stratospheric gliders operating in swarm-based multi-level systems, utilizing an adapted Irwin criterion for anomaly filtering. The proposed algorithm is intended to improve the accuracy of evaluating long-period oscillations of flight parameters, enhance the stability of swarm interaction and the energy efficiency of long-endurance stratospheric loitering, and increase the overall reliability of multi-level autonomous control systems.

Alongside anomaly-aware frequency-based approaches, the scientific literature presents a wide range of traditional and intelligent flight planning methods that can be adapted to the operation of stratospheric gliders. Approaches based on real-time trajectory modification using target priority ranking [9–11], cooperative search for dynamic objects in multi-swarm systems [12], and task allocation among aerial platforms to maximize spatial coverage [13] provide a methodological foundation for the development of swarm-based HAPS flight planning algorithms.

Considerable attention has also been devoted to accounting for external factors, particularly meteorological conditions, in flight planning. Atmospheric processes in the stratosphere and variations in air flow velocities significantly affect energy efficiency and trajectory stability, necessitating the incorporation of meteorological data into long-endurance loitering planning strategies [14].

Intelligent decision support systems that integrate classical planning methods with adaptive real-time algorithms play a key role in enhancing the autonomy and reliability of swarm-based multi-level HAPS systems [15, 16]. In this context, the integration of an adapted Irwin criterion into the analysis of flight planning performance indicators improves the reliability of spectral characteristics used for control decision-making and creates prerequisites for increasing energy efficiency, stability, and coherence of swarm interaction among stratospheric gliders.

Genetic and bio-inspired algorithms, including swarm intelligence methods, are widely employed for coordinating groups of aerial vehicles and can be effectively applied to the formation and adaptation of swarm configurations of stratospheric gliders under energy constraints and multi-level control requirements [18]. Stochastic heuristic algorithms are also used in cooperative trajectory optimization tasks; however, their effectiveness strongly depends on specific operational scenarios and environmental conditions [19, 20].

2. EXPERIMENTAL METHODS

To ensure the general applicability of the methodology for evaluating flight routes of stratospheric gliders (HAPS) in both civilian and military swarm-based multi-level systems, it is necessary to adapt the classical Irwin criterion. The original criterion, developed for homogeneous statistical samples, may not adequately handle data obtained from diverse aerial platforms or short-duration missions, where naturally occurring peaks in energy consumption or operational load could be misinterpreted as anomalies.

The adapted Irwin criterion, within the framework of optimal route assessment, allows:

- ✓ *Detection and exclusion of anomalous measurements*, preventing distortions in the integral evaluation of a route;
- ✓ *Preservation of natural parameter variations*, which are typical for short-duration missions or specific types of aerial vehicles;
- ✓ *Processing of multi-parameter datasets*, including flight duration, energy consumption, safety, and route regularity;
- ✓ *Methodological flexibility*, allowing integration of new parameters or mission-specific factors without altering the core evaluation framework.

Thus, the modified Irwin criterion constitutes a key component of the proposed methodology, increasing the reliability of route efficiency assessment and improving the accuracy of integral mission performance indicators.

Various combinations of factors are used to compute the optimal flight route for each performance indicator. For a comprehensive assessment of HAPS route planning efficiency, it is recommended to consider the following groups of indicators:

A. Route planning efficiency: route length (A1), mission duration (A2), mission cost (A3);

B. Regularity and reliability: mission execution frequency (B1), planning and execution disruptions (B2), average mission preparation time (B3);

C. Mission effectiveness: accuracy of acquired data (C1), responsiveness to emergencies (C2), delivery or distribution of required materials (C3);

D. Safety: risk of collision with other aerial vehicles (D1), risk of communication loss (D2), data confidentiality and security (D3), hazardous meteorological conditions (D4);

E. Energy efficiency: fuel or electrical energy consumption required to accomplish the mission (E1), flight range and endurance relative to energy consumption (E2).

The quantitative values of these indicators are presented in Table 1. After normalizing the initial indicators, aggregating them into groups A–E, and excluding gross errors using the modified Irwin criterion, the efficiency indicators of HAPS routes are computed. The corresponding algorithm is illustrated in Figure 1.

Table 1. Group performance indicators for the routes.

Indicators (K_i)	**Draft plan (n)**						
	1	**2**	**3**	**4**	**5**	**6**	**7**
A1 (min)	0.1	0.3	0.2	0.5	0.7	0.4	0.9
A2 (min)	0.2	0.4	0.1	0.6	0.8	0.3	0.5
A3 (min)	0.5	0.3	0.1	0.3	0.5	0.7	0.9
B1(max)	0.8	0.6	0.4	0.2	0.4	0.6	0.8
B2(min)	0.3	0.6	0.9	0.6	0.3	0.6	0.9
B3 (min)	0.2	0.3	0.4	0.5	0.6	0.7	0.8
C1(max)	0.7	0.8	0.3	0.5	0.2	0.6	0.7
C2(max)	0.5	0.6	0.3	0.7	0.3	0.3	0.5
C3 (max)	0.3	0.8	0.7	0.5	0.8	0.6	0.7
D1(min)	0.3	0.2	0.5	0.3	0.4	0.7	0.8
D2(min)	0.7	0.5	0.4	0.2	0.8	0.4	0.5
D3 (max)	0.3	0.2	0.5	0.7	0.4	0.8	0.3
D4(max)	0.7	0.6	0.5	0.4	0.8	0.3	0.5
E1(min)	0.7	0.6	0.5	0.4	0.7	0.3	0.5
E2 (max)	0.8	0.8	0.7	0.5	0.7	0.6	0.7

Temporal parameters include the total flight duration, the time required to reach control points, and constraints related to mission time windows. Optimization with respect to this criterion aims to ensure timely mission execution with minimal time expenditure while considering the specified constraints. Parameters that define the technical capabilities of the UAV system include energy or fuel reserves, flight range and endurance, payload capacity, propulsion system characteristics, as well as the capabilities of navigation, sensing, and control systems. These parameters impose constraints on feasible flight routes and determine the limits of their optimization. Based on the physical nature of the flight process and the main directions of optimization, the system of criteria for evaluating the efficiency of a UAV flight route plan can be represented as a set of quantitative and qualitative indicators that comprehensively reflect the degree of mission objective achievement, mission reliability, temporal efficiency, and compliance with the technical capabilities of the unmanned aerial system:

$$\begin{cases} A \to \min(A1 \to min, A2 \to min, A3 \to min) \\ B \to \max(B1 \to max, B2 \to min, B3 \to min) \\ C \to \max(C1 \to max, C2 \to max, C3 \to max) \\ D \to \max(\mathrm{D1} \to min, \mathrm{D2} \to min, \mathrm{D3} \to max, \mathrm{D4} \to max) \\ E \to \min(\mathrm{E1} \to min, \mathrm{E2} \to max) \end{cases} \quad (1)$$

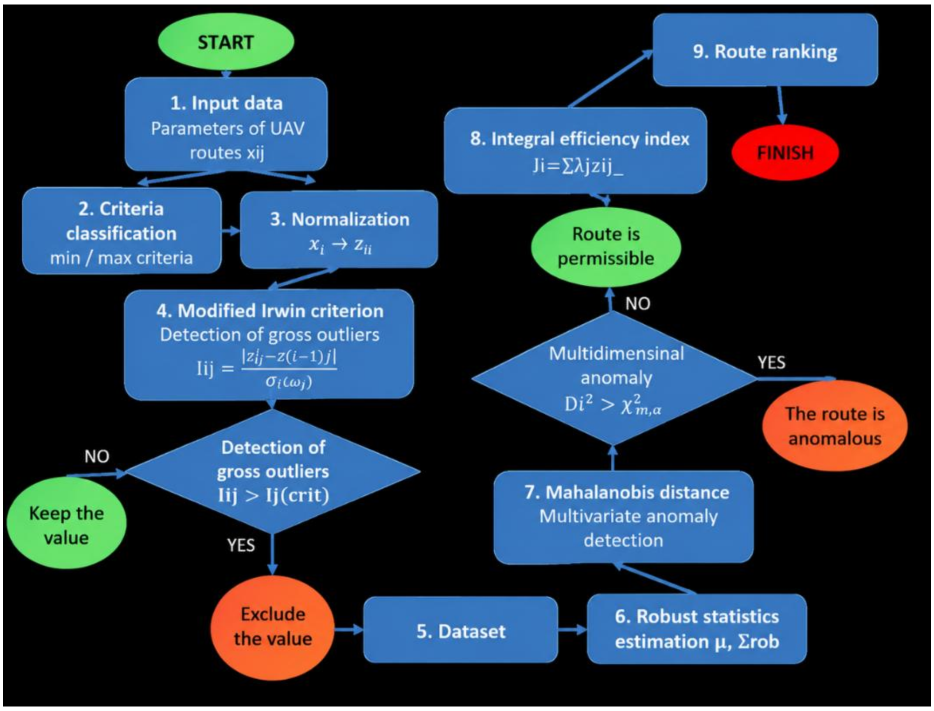

Figure 1. Multi-criteria UAV flight route assessment using the adapted Irwin criterion and robust Mahalanobis distance. Source: Authors' own development.

The computations are performed for each route planning alternative n=1, … , 7. At the first stage, a set of primary normalized indicators {A1, A2, … , E2} is formed for each route, reflecting various aspects of mission planning efficiency and execution performance. Subsequently, all indicators are transformed to a common optimization direction to ensure the correctness of further aggregation procedures:

$$x_{ij} = \begin{cases} 1 - x_{ij}, \text{for the criterion type } min \\ x_{ij}, \text{for the criterion type } max \end{cases} \tag{2}$$

where x_{ij} – is the normalized value of the j – th indicator for the i – th oute.

Since all indicators in group A are minimization criteria, the following transformation is applied after normalization:

$$\text{A} = \frac{1}{3}(A1 + A2 + A3) \tag{3}$$

The resulting value A(n) ∈ [0,1] represents the efficiency level of route planning, where higher values correspond to more optimal route options.

For the calculation of the indicator, A:

Indicator	Value	Type	Normalized
A1	0,1	min	0,9
A2	0,2	min	0,8
A3	0,3	min	0,7

The proposed approach enables:

✓ standardized processing of heterogeneous indicators to compare different aspects of efficiency;

✓ reduction of the influence of anomalous values, thereby enhancing the robustness of aggregated metrics;

✓ transparent interpretation of results at the level of grouped criteria;

✓ scalability of the indicator system, allowing the inclusion of additional parameters without altering the overall algorithm structure.

During the calculation of the optimal HAPS route, the dynamics of key flight parameters – energy consumption, speed, altitude, and control characteristics – are analyzed, as presented in Table 2. The primary method for studying the structure of flight parameter time series and their periodic components is spectral analysis, theoretically based on Fourier methods.

Table 2. Group performance indicators for the routes.

Plan (n)	**A (Route)**	**B (Energy)**	**C (Mission Success)**	**D (Controllability)**	**E (Reliability)**
1	0,73	0,57	0,50	0,55	0,55
2	0,70	0,53	0,57	0,53	0,60
3	0,57	0,47	0,44	0,55	0,60
4	0,47	0,50	0,57	0,53	0,55
5	0,43	0,57	0,43	0,58	0,50
6	0,50	0,53	0,50	0,50	0,65
7	0,37	0,57	0,63	0,45	0,50

For a rigorous analysis of parameter variability, it is advisable to employ smoothed time series of flight parameters in which deterministic trends are eliminated and stochastic noise is reduced. Simulation methods become especially effective when observed data demonstrate pronounced periodic behavior. Under such conditions, the evolution of dynamic series can be approximated by a set of sinusoidal components derived through Fourier decomposition. The fidelity of cyclic behavior representation depends on the number of harmonics considered; in practice, limiting the model to no more than four harmonics is sufficient to capture seasonal effects while avoiding excessive model complexity.

The application of spectral analysis to flight parameter dynamics enables the detection of stable cyclic patterns, which is critical for precise optimal route determination, enhanced reliability of energy consumption and flight time predictions, and improved route robustness. During optimal route computation, multiple factor combinations are evaluated for each parameter to reflect their interdependencies.

The resulting aggregated efficiency metrics facilitate a shift from isolated parameter level analysis to a concise multidimensional characterization of the overall effectiveness of each route planning alternative. This aggregation mitigates the impact of random disturbances in the source data and provides a foundation for constructing an integral performance indicator and subsequent route prioritization.

To further increase the descriptive power of route efficiency evaluation and to incorporate the dynamic behavior of navigation, energy, and control-related parameters, the proposed approach additionally incorporates the Discrete Fourier Transform (DFT). In contrast to conventional methods that apply spectral analysis to individual time series, the DFT is directly embedded in the process of forming aggregated efficiency indicators for SG flight route assessment.

3. RESULTS AND DISCUSSION

In the process of optimizing flight routes for SGs, it is necessary to analyze the dynamics of key flight parameters such as energy consumption, velocity, altitude, and controllability. One of the effective approaches for studying such time series is the Fourier method, which allows representing periodic fluctuations of the parameters as a sum of harmonics. In this case, the Fourier decomposition for a flight parameter $\tilde{yt}$ can be expressed as:

$$\tilde{y}_t = a_0 + a_1 \cos t + b_1 \sin t \tag{4}$$

where a_0, a_1, b_1 are coefficients that determine the amplitude and phase of the fundamental harmonic.

The values of these coefficients are determined using the least squares method, which minimizes the sum of squared deviations of the theoretical series levels from the experimental data:

$$a_0 = \frac{\sum y_t}{n}; \quad a_k = \frac{2\sum y_t \cos kt}{n}; \quad b_k = \frac{2\sum y_t \sin kt}{n} \tag{5}$$

which allows taking into account local fluctuations and trends that occur during flight. For route analysis in this study, discrete observation points are used: t=0,2,4,…,68, corresponding to 35 flight measurements evenly distributed in time or space:

$$0;\ \frac{2\pi}{35};\ \frac{4\pi}{35};\ \frac{6\pi}{35};\ \ldots;\ \frac{64\pi}{35};\ \frac{66\pi}{35};\ \frac{68\pi}{35}.$$

After determining the coefficients, trend removal is performed, which allows isolating fluctuations associated with the characteristics of a specific route from the overall trend of flight parameter changes. The calculated values of the coefficients a_0, a_1, b_1 are presented in Table 3 and are used in the subsequent HAPS route optimization model.

Table 3. First harmonic component of the planned route performance indicator.

Route indicator	y	$y\cos t$	$y\sin t$
A1	0,73	0,733	0
B1	0,57	0,557888	0,101242
C1	0,50	0,468117	0,175687
D1	0,55	0,472147	0,282095
E1	0,55	0,414189	0,361866
A2	0,70	0,436443	0,547282
…	…	…	…
D7	0,45	0,421306	-0,15812
E7	0,50	0,491965	-0,08928

Using the calculated values of the first-harmonic coefficients a_1 and b_1, the Fourier equation for the HAPS flight parameter is formulated as:

$$\overline{y}_t = 0{,}5366 + 0{,}025771 \cos t + 0{,}018696 \sin t \tag{6}$$

This equation represents the fundamental periodic component of the dynamic series and explicitly describes the oscillations of the parameter around the mean value $a0$. The use of the first harmonic provides sufficient accuracy in reproducing the main trends of parameter variations while simplifying the model, which is particularly important for SG route optimization. To verify the presence of more complex periodic fluctuations in the flight parameter series, the coefficients of the second harmonic are calculated using the same least-squares method:

$$\underline{y}_t = 228{,}22 + 0{,}025771 \cos t - 0{,}018696 \sin t + 0{,}006365 \cos 2t + 0{,}011625 \sin 2t \tag{7}$$

A comparison of the theoretically smoothed values of the dynamic series with experimental data showed that including the second harmonic does not significantly improve the approximation. The main trends in flight parameter variations are well captured by the first harmonic. This indicates that, for SG route optimization, considering only the first harmonic is sufficient, simplifying the model and reducing computational complexity without compromising the accuracy of the primary periodic components of flight parameters. The results of the corresponding calculations are presented in Figure 2.

To assess the optimality of a flight route, a geometric approach based on the analysis of flight parameter graphs is employed. The core idea of this approach lies in quantitatively evaluating the influence of each individual parameter on route efficiency by determining the areas enclosed by the corresponding curves on the graph.

In this context, the area serves as an integral measure, reflecting the cumulative contribution of each parameter to the overall route characteristics. In this study, the area of each figure is calculated by dividing it into a finite number of elementary geometric elements, which are triangles with equal central angles. This method standardizes the calculation procedure and ensures comparability of results across different routes and sets of parameters.

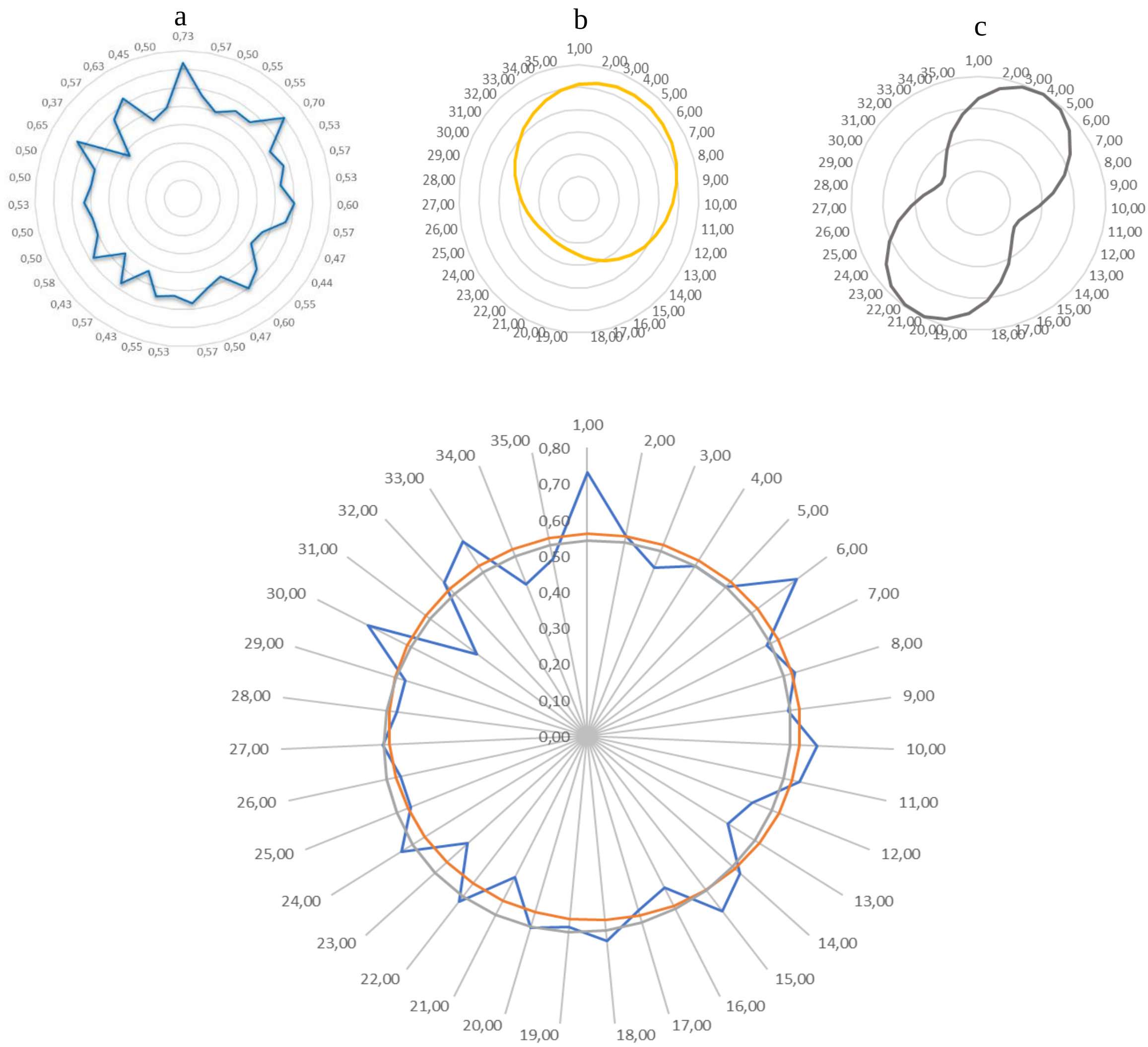

Figure 2. Radial comparison of UAV flight parameters: dynamics of the parameters influencing the selection of the flight route – a; route parameters calculated using the first Fourier harmonic – b. route parameters calculated using the second Fourier harmonic – c. Source: Authors' own development.

Each triangle is considered as an elementary unit, with its area determined using classical geometric formulas that account for the side lengths and the central angle. Summing the areas of all triangles provides an integral indicator of route efficiency, forming a reliable basis for comparing alternative trajectories and selecting the optimal route.

This approach reduces the influence of random fluctuations in individual parameters and enables a comprehensive assessment of route efficiency, combining information about flight dynamics with the geometric characteristics of the parameter graphs.

In the present case, the area of each figure is divided into n triangles, where n = 35. The area of each triangle is determined using the standard geometric formula that accounts for the lengths of the sides and the magnitude of the central angle. The total area of the figure is obtained as the sum of the areas of all triangles, providing an integral indicator of flight route efficiency:

$$S = \frac{1}{2} absin\left(\frac{2\pi}{35}\right) \tag{8}$$

According to the established constraints, Table 4 presents the parameters of the optimal SG route, calculated both with and without considering the Fourier series harmonics. Comparing the two approaches allows for evaluating the impact of periodic oscillations on key flight parameters and demonstrates that, for most parameters, using only the first harmonic provides sufficient accuracy in their assessment.

The Fourier method effectively characterizes the periodic oscillations of flight parameters for stratospheric gliders. Using only the first harmonic provides a sufficiently accurate representation of the dynamics of the analyzed parameters, simplifying the analysis without losing essential information about their fluctuations.

Table 4. UAV route parameter comparison: with vs. without Fourier harmonics.

Optimal parameter	Parameter value for each planned scenario	First harmonic contribution	Second harmonic contribution
A	0,018578	0,02277	0,024589
B	0,031891	0,028631	0,026887
C	0,026971	0,028783	0,026953
D	0,029462	0,028835	0,026949
E	0,021262	0,022861	0,024478
Result	0,897145	0,923157	0,908992

A comparison of optimal routes calculated with and without considering harmonics showed that harmonic analysis improves the accuracy of parameter evaluation, although it does not significantly affect the route selection itself.

Geometric analysis of the areas under the parameter curves allows for a quantitative assessment of the contribution of individual parameters to route efficiency and supports the selection of optimal flight trajectories. This approach combines harmonic analysis with integral parameter evaluation, providing a more reliable and well-grounded method for route optimization.

4. CONCLUSIONS

This study presents a comprehensive analysis of SG flight parameters using harmonic and geometric analysis methods to assess route optimality. The Fourier method effectively characterizes the periodic oscillations of SG flight parameters, with the use of the first harmonic providing a sufficiently accurate representation of parameter dynamics, simplifying the evaluation without loss of essential information. A comparison of optimal routes calculated with and without consideration of harmonics showed that harmonic analysis improves the accuracy of parameter assessment, although it does not significantly influence route selection. Geometric analysis of the areas under parameter curves allows for a quantitative evaluation of the contribution of individual parameters to overall route efficiency, supporting a more substantiated selection of optimal trajectories. The application of integral efficiency indicators, calculated using triangular area approximation, enables the transition from analyzing individual parameters to a compact multidimensional representation of route efficiency while reducing the impact of random fluctuations.

Future research may focus on extending the application of harmonic analysis by considering additional harmonics to evaluate high-frequency parameter variations and their impact on route safety and stability, integrating machine learning methods for predicting flight parameter dynamics and automated optimal route selection, developing adaptive models of route efficiency that account for external risk factors, and exploring multi-criteria optimization of UAV routes, including energy conservation, flight time reduction, and enhanced mission reliability.

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