Journal of Kryvyi Rih National University
Journal homepage: https://journal-knu.com.ua/en
Article's History: Received: 14.06.2025 Revised: 04.11.2025 Accepted: 24.12.2025 Published: 28.12.2025
Vol. 23, No. 2, 2025
ISSN 2306-5451
e-ISSN 2519-2736

UDC 629.5.018.2:656.615:519.86
DOI: 10.31721/2306-5451-2025-2-23-72-80

Mission planning and route optimisation for short-range maritime drones under operational constraints

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Abstract. The rapid advancement of autonomous maritime technologies underscores the growing relevance of optimising delivery operations in coastal and offshore zones, particularly when energy and navigational constraints are present. The aim of this study was to develop a route optimisation model tailored for short-range maritime drones operating under limited battery capacity and environmental instability. The methodology involved the formulation of a mathematical model that integrated both distance-dependent propulsion costs and time-dependent navigation overheads, allowing for the minimisation of total mission execution time. Using simulation-based validation, it was established that even short route segments required considerable energy input due to the need for continuous control, stabilisation, and real-time navigation support. The results confirmed the feasibility of applying the model to delivery scenarios with segmented routes and dynamic return-to-base strategies. It was demonstrated that exceeding critical energy thresholds on a given segment led to route interruption and reconfiguration, which the model accounts for through embedded constraints and conditional branching logic. Additionally, detailed energy consumption profiles were generated for each route segment, revealing the dominance of navigational overheads in short transitions. The developed model provided a reliable framework for evaluating mission viability before deployment. The practical value of the research lay in its

Suggested Citation:
Melnyk, O., Burlachenko, D., Nykytyuk, P., & Kochetkov, O. (2025). Mission planning and route optimisation for short-range maritime drones under operational constraints. *Journal of Kryvyi Rih National University*, 23(2), 72-80. doi: 10.31721/2306-5451-2025-2-23-72-80.

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applicability for maritime logistics planners, operators of autonomous surface vehicles, and engineers involved in the deployment of battery-powered maritime delivery systems in nearshore environments

Keywords: battery-constrained navigation; energy-aware logistics; unmanned vessel routing; simulation-based modelling; coastal delivery systems; propulsion energy analysis; autonomous transport planning

Introduction

The development of autonomous marine technologies has transformed the landscape of short-range maritime logistics. As the demand for flexible, low-emission, and crew-independent delivery solutions increases, traditional vessel-based systems often prove economically and operationally inefficient, especially in nearshore or "last-mile" segments. One of the pressing challenges lies in planning reliable routes for small autonomous craft under real-world conditions such as energy constraints, uncertain sea states, and the lack of intermediate infrastructure. Ensuring that these craft can complete delivery missions safely and efficiently, while maintaining energy reserves and navigational stability, remains a crucial but underexplored area.

Drone-based models have already shown a wide range of applications in logistics, as surveyed by M. Moshref-Javadi & M. Winkenbach (2021), confirming the strategic relevance of autonomous delivery platforms even in infrastructure-scarce environments. Research in this field has accelerated, with growing attention toward route planning and energy management. For instance, F. Kong *et al.* (2023) proposed a trajectory optimisation method for aerial delivery drones using attention-based neural networks. Although their work focuses on airborne systems, the underlying methodology of minimising delivery time while adapting to dynamic environments offers useful insights for maritime adaptation. W. Li *et al.* (2023) proposed a model predictive control method that incorporates state-space risk augmentation for unmanned surface vessel tracking, which is applicable to short-range drone navigation under uncertainty. A related study by X. Zhu (2023) applied heuristic techniques to optimise unmanned aerial vehicle delivery systems, providing insights transferable to marine routing under limited energy.

In a comprehensive review, A. Shuaibu *et al.* (2025) outlined key trends in last-mile delivery optimisation, identifying drone integration and energy-efficiency as dominant research trajectories. Their survey emphasised the growing need for hybrid models that support constrained delivery environments – a challenge also relevant to maritime settings. In addition, A. Kandel *et al.* (2020) investigated energy- and time-optimal routing for unmanned surface vehicles under flexible refuelling constraints, proposing a route selection logic that is directly applicable to drones operating under limited battery capacity and return-to-base (RTB) policies. H. Wang *et al.* (2025) extended this perspective by introducing a risk-aware path optimisation algorithm tailored to anchorage areas, emphasising the necessity to account for dynamic marine environments and route congestion – conditions commonly encountered in coastal logistics.

Several Ukrainian researchers have made valuable contributions in this domain. O. Melnyk *et al.* (2024) analysed the prospects of unmanned systems in logistics and emphasised the lack of integrated route-energy models suited to dynamic port environments. Study of these authors provided a conceptual framework for applying drones in constrained maritime zones and suggested that energy thresholds should guide mission planning. While not focused on logistics, the methodology for assessing real-world limitations is transferable to delivery systems operating under uncertainty. In another paper, S. Kurdiuk *et al.* (2025) developed reliable data transmission systems for marine drones, addressing communication failures as a limiting factor in real-time route adjustment. These findings reinforce the notion that logistical performance depends on both hardware capabilities and adaptive control schemes. X. Li & H. Zhang (2025) extended this by proposing cooperative planning for ship-drone systems in maritime supply chains, reflecting the growing need for collaborative transport models. A. Tolooie *et al.* (2024) extended this with supply chain optimisation under energy uncertainty, which applies conceptually to marine use. J. Xu *et al.* (2025) demonstrated the potential of RL-based simulators such as UPEGSim for dynamic adaptation in underwater pursuit scenarios. Similar frameworks could be adapted to autonomous maritime drones for real-time strategy learning and adaptive energy route selection. There is an attractive research area.

This research proposed a formalised mathematical model for planning and optimising maritime delivery routes under operational energy constraints. The model considered segment-specific propulsion and navigational costs, introduced interruption conditions, and validated feasibility through simulation. The goal was to enable safe and efficient planning of autonomous missions in coastal delivery scenarios.

Materials and Methods

This study employed a structured mathematical modelling approach combined with simulation-based validation to develop and assess an energy-aware routing framework for battery-powered maritime delivery systems. The research was conducted in three main phases: model construction, parameter definition and calibration, and scenario-based simulation analysis. The core methodological basis of the study was the deterministic mathematical modelling method, which was used to derive an analytical representation of the energy consumption and route planning logic. The model includes variables for propulsion energy (proportional to distance), navigation overhead (proportional to time), and delivery node servicing (modelled via berthing time and delivery indicators). Equations (1) through (9) were formulated to represent key physical constraints, including total energy availability, travel time accumulation, and route interruption conditions. This method was chosen because it allows precise control over input parameters and ensures repeatability under various route configurations. The use of a bi-objective approach to balance delivery time and energy constraints follows the principles outlined in supply chain literature, such as the model proposed by Y. Cardona-Valdés *et al.* (2014), which accounts for uncertainty in logistics networks. The deterministic structure ensured that every simulated mission yields quantifiable outcomes under known initial conditions.

To model real-world navigation and delivery tasks, computational geometry techniques were employed to calculate distances between delivery points using the Euclidean metric. The geometric data, including positions of the base and intermediate delivery points, were generated as coordinate pairs (x_i, y_i), which form the spatial input to the route optimisation task. These coordinates were defined to simulate a realistic maritime delivery environment and were used as input into the model to determine route lengths and transitions. The simulation modelling method was applied to validate the feasibility and robustness of the developed route optimisation algorithm. Custom Python scripts were developed to simulate delivery sequences and calculate energy consumption for each leg of the route, using parameters such as average drone speed, propulsion coefficient (α), and navigation coefficient (β). These parameters reflect average performance values for medium-sized battery-powered maritime drones and ensure comparability with contemporary studies.

The factual material of the study consisted of simulated logistics missions involving six route segments, including a base station and five delivery nodes. The parameters of each segment (distance, time, propulsion energy, navigation energy) were recorded in tabular format and used to assess the effectiveness of the model under different energy constraints. No real-world sensor data or live mission telemetry were used; however, reference values for energy consumption were adapted from academic sources and industry reports, such as those from the International Energy Agency (2022) and Global Maritime Forum (2024). These documents provided context for setting boundary values and operational norms.

Additionally, algorithmic decision-making logic was used to implement conditional RTB strategies. This was done by embedding constraints in the model that trigger route interruption when cumulative energy consumption exceeds predefined thresholds. This methodological step simulates how real-world delivery drones would behave under limited battery scenarios and mimics onboard route control systems. No empirical field trials or hardware testing were conducted. Instead, the study relied entirely on secondary data and virtual testing, ensuring reproducibility and theoretical robustness. Supporting literature and data-driven parameter choices were sourced from peer-reviewed journals and recognised international publications. This integrated methodological design – combining deterministic modelling, geometric computation, simulation validation, and constraint-based optimisation – was selected to ensure that the research output could be used as a practical tool for energy-conscious mission planning in short-range maritime logistics.

Model input parameters: $P = \{p_0, p_1, \ldots, p_n\}$ – set of delivery points, where p_0 – the base; (x_i, y_i) – position (coordinates) of the point *pi*; *v* – average speed of the drone (nm/h); E_{max} – the maximum energy consumption (for example, in kWh); *eij* – energy consumption at the site $i \to j$; *t*stop – average berthing time at a point (cargo transfer); $\delta i \in \{0, 1\}$ – an indicator of whether delivery should be made at the point *pi*. Assume a set of delivery points was defined as: $P = \{p_0, p_1, \ldots, p_n\}$, where p_0 – the drone's base station. Each point had coordinates (x_i, y_i) and a delivery indicator:

$$\delta_i = \begin{cases} 1, & if\ at\ \text{point}\ p_i\ delivery\ performed \\ 0, & otherwise \end{cases}. \quad (1)$$

It was assumed that the drone's speed to be constant and equal to *v*, the energy reserve to be $E_{\max}$, and the average stopping time to be t_{stop}. The distance between any two points *i* and *j* was defined as:

$$d_{ij} = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2}. \quad (2)$$

The travel time was defined as:

$$t_{ij} = \frac{d_{ij}}{v}. \quad (3)$$

These values were the basis for building the route's energy and time map. Energy consumption along the route, where the energy consumed by the drone on the section $i \to j$ was modelled as a combination of propulsion system costs (proportional to distance) and navigation and stabilisation costs (proportional to time):

$$e_{ij} = \alpha \cdot d_{ij} + \beta \cdot t_{ij}, \quad (4)$$

where α and β – empirical energy consumption coefficients.

The condition for total energy consumption is that the total energy consumption along the entire route must not exceed the permissible value:

$$\sum_{n-1}^{k=0} e_{r_k\, r_{k+1}} \leqslant E_{max}. \tag{5}$$

The total route execution time consists of the total execution time, which includes the sum of the travel time between points and the parking time at the points where the delivery is made:

$$T = \sum_{n-1}^{k=0} (t_{r_k\, r_{k+1}} + \delta_{r_k} \cdot t_{\text{stop}}). \tag{6}$$

Returning to the base occurs if the energy reserve limit is reached and this does not allow one to move to the next point without returning, a condition must be met:

$$\sum_{j=0}^{k} e_{r_j\, r_{j+1}} > E_{r_{k+1}} 0_{max}. \tag{7}$$

That initiates the addition of a subroute:

$$r_k \rightarrow p_0 \rightarrow r_{k+1}. \tag{8}$$

The objective function will be to minimise the total time, taking into account stops, returns, and deliveries:

$$min_R \, [\sum_{k=0}^{n-1} t_{r_k r_{k+1}} + \sum_{i \in R} \delta_i \cdot t_{\text{stop}} + \sum_{return} t_{rj_0} + t_{0 r_{j+1}}]. \tag{9}$$

The model allows not only to build optimal routes but also to take into account the real limitations of the drone as a hardware device, which brings it closer to practical application in Dynamic Positioning logistics. Based on the constructed mathematical model for optimising the drone's route, taking into account distance, time, and energy constraints, a simulation analysis was performed to validate this model on a route with six segments connecting delivery points (P1-P5) and the base station (Base). In each segment, the impact of the travel distance and navigation duration on the total energy consumption was taken into account. The following parameters were used for modelling: average drone speed – $v = 12$ nm/h; power consumption per distance – $\alpha = 0.5$ kWh/nm; navigation consumption – $\beta = 0.1$ kWh. Based on these parameters, the energy consumption for each segment of the route was calculated using formula (10):

$$e_{ij} = \alpha \cdot d_{ij} + \beta \cdot \frac{d_{ij}}{v}, \tag{10}$$

where d_{ij} – length of the corresponding segment.

Route interruption condition: strategy for returning to base in case of energy shortage. In autonomous logistics systems, one of the most critical scenarios is an unforeseen excess of energy consumption, when the drone cannot complete the current route and must return to the base to recharge. In the maritime environment, where recharging is only possible at certain checkpoints, this situation must be anticipated at the routing stage. Formalisation of the interruption condition. Let E_{max} be the maximum available energy reserve of the drone. After passing through k segments of the current route, the accumulated energy consumption is:

$$E_k = \sum_{j=0}^{k-1} e_{r_j r_{j+1}}, \tag{11}$$

where e_{ij} – energy consumption in the section $i \rightarrow j$.

The drone must return to the base if:

$$Ek + e_{r_k 0} > E_{max}. \tag{12}$$

For the implementation of the mathematical model and simulation-based validation, a custom-built Python script was developed. This script first obtains distances between delivery points, then calculates travel time on those segments, and energy consumption through propulsion and navigation overhead. The routes can thus be analysed, and an assessment of mission feasibility is conducted under operational constraints. Below on Figure 1 given a snippet of the code representing a core fragment of the computation flow applied in the study.

```python
import numpy as np

# Route points: [x, y] coordinates for Base, P1, P2, P4, P5, P3
points = np.array([
    [0, 0],    # Base
    [1, 2],    # P1
    [3, 3],    # P2
    [5, 2],    # P4
    [6, 5],    # P5
    [4, 6],    # P3
])

alpha = 0.5   # propulsion energy per nautical mile, kWh/nm
beta = 0.1    # navigation overhead per hour, kWh/h
v = 12        # average drone speed, nautical miles per hour

def calc_distance(p1, p2):
    return np.linalg.norm(p2 - p1)

def energy_consumption(d, t):
    return alpha * d + beta * t

# Example calculation of energy consumption for each segment
for i in range(len(points)-1):
    d = calc_distance(points[i], points[i+1])
    t = d / v
    e = energy_consumption(d, t)
    print(f'Segment {i+1}: distance={d:.2f} nm, time={t:.2f} h, energy={e:.2f} kWh')
```

Figure 1. Algorithm implementation code
Source: developed by the authors

As shown in the example, the algorithm iterates through the delivery route, measures the distance segment-wise by the Euclidean metric, and estimates both travel time and energy required for each leg of the way. Critical legs, where energy consumption could nearly exceed the available level of the battery, get thus identified, so that the mission plan can be adjusted dynamically. The script output gives quantitative insight into the energy profile of the proposed route to help with route optimisation and risk mitigation in short-range maritime drone operations.

Results and Discussion

Mathematical model of the optimal delivery route by sea drone. In autonomous maritime logistics, one main challenge is optimising the drone's route for deliveries between multiple points, such as between ports, mooring stations, or platforms. Unlike airborne drones, offshore platforms have significantly slower travel speeds, longer inertial turnaround times, and limited battery life. Therefore, the route should not just be the shortest, it should be time-efficient, taking into account speed restrictions and the distribution of points. In real-world applications of maritime drones, delivery routes should be built not only on the basis of minimum distance but also taking into account energy constraints, time spent at parking lots, and possible returns to the base for recharging. This brings the model closer to practical implementation in logistics scenarios.

Below is a mathematical model of a maritime drone's delivery route, which includes time optimisation, energy constraints, parking time at delivery points, and options for partial return to the base for recharging. The Figure 2 shows the planned route of an autonomous maritime drone making a delivery between five logistics points (P1-P5), returning to the base station (Base). Each edge of the route contains a distance in kilometres calculated on the basis of the Euclidean metric between the corresponding coordinates. The directions of movement are indicated by arrows and the movement takes place along the route: Base → P1 → P2 → P4 → P5 → P3 → Base. This route takes into account the optimisation of the range, number of stops, and total delivery time constraints.

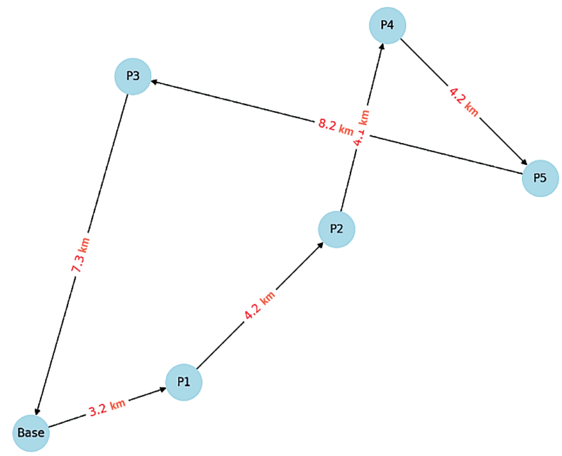

Figure 2. Schematic of a maritime drone delivery route with six segments

Source: developed by the authors based on studies by International Energy Agency (2022), Global Maritime Forum (2024)

Analysis of energy consumption of a maritime drone on the delivery route. The diagram in Figure 3 shows the quantitative distribution of energy consumption on individual route segments (from S_1 to S_6) during a continuous delivery mission performed by an autonomous maritime drone. The total energy consumed in each section is calculated as a complex function of the distance travelled and the navigation time according to (10).

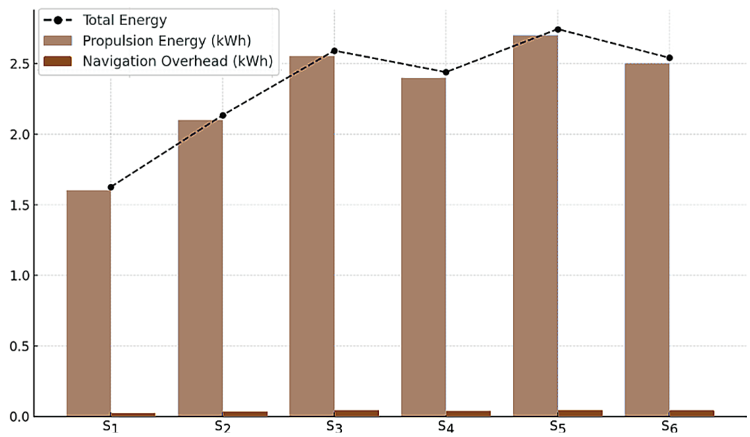

Figure 3. Segment-wise energy consumption profile of the autonomous maritime drone

Source: developed by the authors

Here, α is the coefficient of propulsive energy (kWh/nm), and β accounts for overhead consumption due to guidance, stabilisation and real-time telemetry. Although segments of longer physical length (e.g., S_5 and S_3) prevail for absolute consumption, the graph makes the point that even short jumps (e.g., S_1) carry a non-trivial baseline burden due to continual navigational support. This graph highlights the importance of considering various factors in drone maritime logistics: energy consumption isn't solely dependent on distance. As a result, optimisation algorithms need to take into account both spatial and temporal elements, especially when route energy budgets are nearing operational limits. Table 1 provides a detailed split of all physical and energetic parameters for every segment of the drone delivery path. The propulsion energy is proportional to the linear distance travelled, while the navigation energy is fixed overheads in terms of guidance, stabilisation, and system feedback for each transition.

Table 1. Detailed route parameters of maritime drone per segment

Segment	Distance (nm)	Travel time (hr)	Propulsion energy (kWh)	Navigation energy (kWh)	Total energy (kWh)
S_1	3.2	0.267	1.600	0.027	1.627
S_2	4.2	0.350	2.100	0.035	2.135
S_3	5.1	0.425	2.550	0.043	2.592
S_4	4.8	0.400	2.400	0.040	2.440
S_5	5.4	0.450	2.700	0.045	2.745
S_6	5.0	0.417	2.500	0.042	2.521

Source: developed by the authors based on studies N. Andrei *et al.* (2024), Y. Lu *et al.* (2025)

The column of total energy indicates that certain segments, specifically, S_3, S_4, and S_5, travel or consume more than 2.5 kWh per leg. In an energy-constrained system with a restricted battery budget (e.g., $E_{max} = 10$ kWh), the drone can simply not travel the entire path within a single cycle. This calls for conditional route planning, for instance, returning to base station for recharging or offloading payload delivery across multiple missions. Joint consideration of energy factors emphasises the importance of overall modelling: optimisation in terms of distance only in logistic algorithms may cause operation failure without consideration of navigational loads. That is, if further progress to the next point of the route and return to the base exceeds the available energy, the drone is obliged to stop delivery and change the route.

To ensure safe delivery under conditions of limited energy availability, the routing strategy involved the creation of predefined return points. The route is partitioned into successive segments; each grouped according to a fixed energy budget. Upon completion of each group of segments, the system evaluates the feasibility of either continuing the mission or returning to the base station, with the possibility of redirecting to an intermediate recharging point if one is accessible. The entire route structure follows a flexible, tree-like configuration, where each branch reflects a specific residual energy threshold and incorporates a guaranteed fallback option. This structure enables dynamic adjustment of the mission path in response to the risk of exceeding critical energy limits. The general route is as follows:

$$R = R_1 + \text{Base} + R_2 + \text{Base} + \ldots + R_n + \text{Base}. \qquad (13)$$

This approach avoids critical situations of unforeseen delays, navigation difficulties, or increased energy consumption, ensuring a balance between route flexibility and autonomous delivery safety. In the example case of having an energy budget of up to 10 kWh, the energy consumption of the first three segments of the route totals approximately 6.35 kWh, thereby allowing them to be covered within the budget. But including the additional leg S_4 (2.44 kWh), plus the energy required to return to base (another ≈2.4 kWh), the total consumption would be 11.2 kWh, which is over the limit. Thus, the optimal solution would be to return to base immediately after completing S_3. This underscores the critical significance of energy-aware routing in autonomous offshore systems: even one additional segment without recuperation can cause the drone to be lost. Such scenarios must be included in route planning systems and risk model packages such as Dynamic Positioning Risk Assessment.

The simulation confirmed that even relatively short route segments impose significant energy demands, primarily due to background navigational overheads. In this regard, propulsion energy accounted for over 88% of the total energy budget in longer segments, but in shorter ones (e.g., S_1), navigation overhead constituted more than 5% of the total cost. This indicates the necessity of incorporating both time- and distance-based energy models into maritime routing algorithms. The findings of this study confirmed the significance of integrating both propulsion and navigational overheads into the route planning process for short-range maritime drones. This approach aligns with and expands upon several previous works reviewed.

For instance, F. Kong *et al.* (2023) proposed an attention-based optimisation for aerial drones; while their system is airborne, current model confirms their claim that dynamic adaptation is essential, especially when energy constraints are present. O. Melnyk *et al.* (2024) noted the absence of integrated energy-routing models in port-constrained environments. This work directly addresses this gap by formalising such a model and validating it through simulation. Furthermore, S. Kurdiuk *et al.* (2024) discussed communication reliability as a limiting factor for real-time correction. While current model assumes ideal connectivity, its structure can incorporate adaptive elements in future revisions, as suggested in their study.

In line with M. Nguyen *et al.* (2025), who explored hybrid energy management, this research underlined the importance of preplanned recharge or return routes. The article by L. Hulianytskyi & O. Rybalchenko (2023) investigated route planning for hybrid "drone + vehicle" systems with the aim of optimising joint missions. The authors proposed a mathematical model and implemented several algorithms, among which the ant colony method proved to be the most effective. The model allows for forming a route taking into account changes during the mission. The study demonstrated the potential of metaheuristic approaches in this area. At the same time, the work does not sufficiently consider the impact of drone limitations (resource, cargo), the dynamic nature of the environment, and adaptation to real conditions.

Lastly, A. Tolooie *et al*. (2024) extended last-mile logistics planning under uncertainty, a methodological stance current deterministic model complements by enabling future stochastic generalisations. Future iterations of the model could benefit from stochastic extensions, similar to how D. Alem *et al*. (2016) modelled logistics under uncertainty for disaster relief planning, enabling better resilience in volatile sea conditions. A related perspective was found in the work of Q. Shao *et al*. (2023), where a large neighbourhood search algorithm was applied to optimise dynamic delivery routing. While their study focused on urban takeaway logistics, the underlying heuristic principles align with the iterative route refinement logic adopted in this model, especially under energy and timing constraints. In summary, the majority of reviewed works confirm the necessity of adaptive, energy-aware planning strategies. This research synthesised their core insights into a cohesive model that not only supported those claims but also provided a formal decision-making framework for mission segmentation, feasibility evaluation, and delivery safety in constrained maritime environments.

Despite this growing body of work, there remains a notable gap in formal route modelling tailored to short-range delivery by autonomous surface vessels under strict energy constraints. Most existing models either neglect the navigation overhead or oversimplify battery limitations, leading to suboptimal or infeasible route recommendations. Additionally, only a limited number of works address the RTB logic required for operational safety in constrained missions. While real-time adaptive models exist, few integrate them with static planning stages in a simulation-validated mathematical framework.

Conclusions

The conducted research resulted in the development of a deterministic mathematical model for optimising short-range maritime delivery routes under energy constraints. The model enables the evaluation of mission feasibility based on propulsion and navigation energy costs per segment, delivery stop duration, and the drone's total battery capacity. During simulation-based validation of a multi-point delivery scenario, several key quantitative outcomes were obtained. Specifically, the route analysed consisted of six segments connecting five delivery points and a RTB cycle. Using the defined parameters – average drone speed of 12 nm/h, propulsion energy coefficient $\alpha = 0.5$ kWh/nm, and navigation energy coefficient $\beta = 0.1$ kWh/h – the total energy consumption for each leg was calculated. The highest energy-consuming segment (S_5) required 2.745 kWh, while the lowest (S_1) required 1.627 kWh. The cumulative energy consumption for the complete route was approximately 13.06 kWh, which exceeded the predefined energy limit of 10 kWh. As a result, the model identified a RTB threshold occurring after the completion of segment S_3. By that point, the cumulative energy consumption reached 6.35 kWh, and continuing to segment S_4 (requiring 2.44 kWh) would have led to an energy shortfall for returning to the base. This finding confirms the effectiveness of the model's embedded interruption condition, which accurately predicts infeasible segments and enforces mission reconfiguration.

The model's ability to segment missions and identify risk thresholds supports practical applications in energy-aware logistics. It enables planners to define route groupings, configure recharge points, and simulate fallback strategies such as mid-mission returns or payload redistribution. While the model assumes stable sea conditions and constant speed, its modular design allows future extension through stochastic elements, such as environmental variability or real-time telemetry. The proposed model was found to be effective when applied for imitation of short-range delivery flights of naval drones in the context of limited energy supplies. By dividing energy consumption into propulsion and navigation, the model allowed for more dependable route feasibility tests. At the same time, the model used the assumption of stable sea conditions and doesn't take into account external disturbances, i.e., waves, wind drift, or currents. Future research could focus on extending the model by incorporating a stochastic representation of the environment or integrating real-time telemetry data from on-board sensors. Additionally, implementing adaptive route reconfiguration algorithms based on the vehicle's charge level presents a promising direction to enhance the reliability and flexibility of autonomous delivery systems.

Acknowledgements

None.

Funding

None.

Conflict of Interest

None.

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Планування місії та оптимізація маршрутів для морських безпілотників короткого радіуса дії в умовах експлуатаційних обмежень

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Анотація. Швидкий розвиток автономних морських технологій підкреслює зростаючу актуальність оптимізації операцій доставки в прибережних та морських зонах, особливо за наявності енергетичних та навігаційних обмежень. Метою цього дослідження була розробка моделі оптимізації маршруту, адаптованої для морських дронів малої дальності, що працюють в умовах обмеженої ємності акумулятора та нестабільності навколишнього середовища. Методологія включала формулювання математичної моделі, яка інтегрувала як залежні від відстані витрати на двигун, так і залежні від часу навігаційні накладні витрати, що дозволяло мінімізувати загальний час виконання місії. За допомогою валідації на основі моделювання було встановлено, що навіть короткі сегменти маршруту потребують значних витрат енергії через необхідність постійного контролю, стабілізації та підтримки навігації в режимі реального часу. Результати підтвердили можливість застосування моделі до сценаріїв доставки з сегментованими маршрутами та динамічними стратегіями повернення на базу. Було продемонстровано, що перевищення критичних порогів енергії на заданому сегменті призводить до переривання та реконфігурації маршруту, які модель враховує за допомогою вбудованих обмежень та логіки умовного розгалуження. Крім того, для кожного сегмента маршруту були створені детальні профілі споживання енергії, що виявляють домінування навігаційних накладних витрат у коротких переходах. Розроблена модель забезпечила надійну основу для оцінки життєздатності місії перед розгортанням. Практична цінність дослідження полягає в його застосовності для планувальників морської логістики, операторів автономних надводних транспортних засобів та інженерів, що займаються розгортанням систем морської доставки на акумуляторних батареях у прибережних середовищах

Ключові слова: навігація з обмеженим зарядом акумулятора; енергоефективна логістика; маршрутизація безпілотних суден; моделювання на основі симуляції; системи доставки по узбережжю; аналіз енергії рушійної сили; автономне планування транспорту