Analysis of Influencing Factors in Planning Military UAV Missions using Machine Learning[*]

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Abstract

The article presents an approach to analyzing the factors that determine the success of military missions involving unmanned aerial vehicles (UAVs) based on the integration of simulation modeling and machine learning methods. A UAV mission planner has been developed that enables modeling of tactical scenarios, taking into account air defense and electronic warfare threats, weather conditions, and UAV flight characteristics. Based on the mission simulation data generated by the planner, a training dataset was formed for building machine learning models (logistic regression, decision trees, ensemble methods, neural networks) to predict mission success and assess the impact of individual factors. The results show that the key determinants of effectiveness are route and flight parameters as well as threat intensity, while external conditions and UAV characteristics play a secondary role. The findings enable the formulation of practical recommendations for optimizing mission planning and enhancing the safety of UAV deployment.

Keywords

UAV, simulation modeling, machine learning, mission planning, risk assessment, threats, factor analysis

1. Introduction

Modern military operations increasingly rely on the deployment of unmanned aerial vehicles (UAVs), which perform a wide range of tasks – from reconnaissance and fire control to strike missions deep in the enemy's rear. The success of such operations is largely determined by numerous factors: the technical characteristics of the UAVs themselves, environmental conditions, multi-objective target selection, the level and dynamics of threats, enemy actions, and chosen tactical scenarios. Consequently, there is a growing need for intelligent technologies capable of identifying the most significant parameters and predicting mission effectiveness.

One of the promising approaches is the integration of simulation modeling with machine learning methods. Simulation models enable the reproduction of various scenarios of UAV combat use and the generation of data for analysis, while machine learning algorithms can detect patterns, assess the influence of individual factors, and generate recommendations for improving planning effectiveness.

This research is particularly motivated by the rapid proliferation of UAVs in modern conflicts, particularly during the war in Ukraine, where drones play a key role in reconnaissance, precision strikes, and the targeting of critical infrastructure. Mission planning in such contexts occurs under uncertainty caused by enemy air defense and electronic warfare systems, variable operational and environmental conditions, as well as inherent limitations of the UAVs themselves.

Traditional mission planning methods often inadequately account for the complex interactions among multiple factors, which may lead to equipment loss or reduced operational efficiency. The application of machine learning in combination with simulation-generated data enables the development of tools for multifactor analysis and the identification of key variables that determine

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mission success or failure. This creates opportunities for developing intelligent decision support systems capable of adapting mission plans according to specific operational conditions and minimizing risks.

2. State of the Art and Problem Statement

The planning of combat and reconnaissance missions with the use of unmanned aerial vehicles (UAVs) is a multi-component task that requires the integration of optimization methods, artificial intelligence technologies, geographic information systems, and simulation modeling. Optimization methods enable the determination of efficient UAV routes and flight parameters under resource and threat constraints. Artificial intelligence technologies provide adaptability in planning, prediction of enemy behavior, and real-time decision-making. Geographic information systems deliver precise spatial information on terrain, infrastructure, and threat zones for safe and well-grounded UAV mission route planning. Simulation modeling makes it possible to test mission scenarios and evaluate the effectiveness of strategies before their actual execution.

The system we have developed is designed to support tactical and operational mission planning with UAVs, taking into account group tactics and wave attacks, different launch and maneuvering scenarios, as well as bypassing areas affected by enemy air defense (AD) and electronic warfare (EW) systems [1]. Mission execution simulation allows for the assessment of probable mission effectiveness prior to implementing them into a real flight control system. Machine learning methods demonstrate strong synergy when combined with simulation modeling approaches and can therefore enhance our UAV mission planner.

The development of simulation models inherently involves improving the accuracy of the virtual environment since it refers to a real system. Without direct access to the causal rules governing the actual system, it is necessary to approximate the outcomes of various scenarios using probabilistic and statistical models. In contrast, machine learning relies on algorithms that self-adjust based on data and are primarily applied to prediction tasks.

From this arises several scenarios for the joint use of simulation modeling and machine learning (ML) methods (Figure 1).

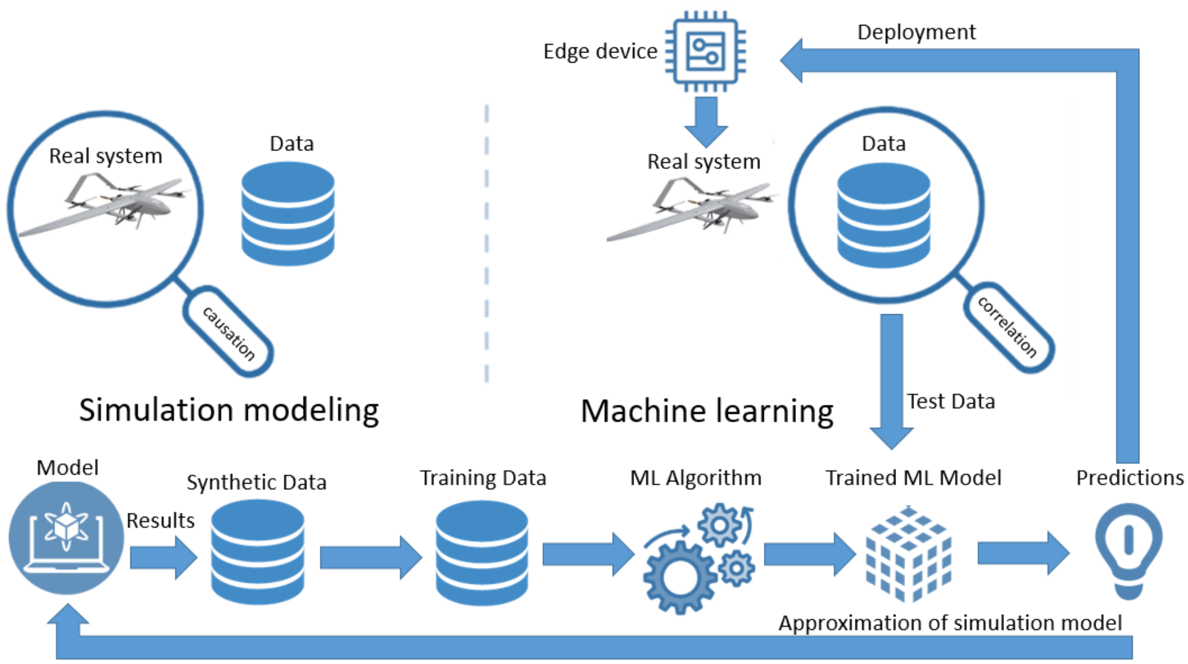

Figure 1: Synergistic Application of Simulation Modeling and Machine Learning.

ML researchers may use a simulation model as a mechanism for generating unlimited labeled data to evaluate the performance of new ML algorithms. Alternatively, properly verified and validated simulation models can generate relevant training datasets for ML models.

Moreover, synthetic data obtained from simulation can help data processing researchers validate their hypotheses using ML models with proof-of-concept before investing in data collection methods and technologies. In addition, ML models developed from a simulation model can serve as lightweight and portable versions that can be effectively deployed directly on edge devices – namely, UAV onboard systems.

We conducted an analysis of scientific publications that apply machine learning methods for analyzing, forecasting, and improving the effectiveness of UAV missions.

In [2], a review is provided of ML techniques applied across various aspects of UAV operation – from mission planning to communications, monitoring, and sensor data processing. Key directions and gaps are highlighted, in particular the absence of fully integrated solutions.

Study [3] describes the application of deep reinforcement learning for the development of cooperative strategies that maximize the survival of UAV swarms in hostile environments with radar systems.

In [4], a Bayesian network is constructed on the basis of incident and accident reports to analyze UAV risk factors (technical failures, human factors, technologies), model probability dependencies and risk levels, and assess their combined impact on UAV accident severity.

An ML model for predicting energy consumption (voltage, current, battery discharge) under varying weather conditions is considered in [5]. This represents an interesting integration of real UAV logs with meteorological data for forecasting UAV energy usage, with the best results obtained for ensemble gradient boosting models.

The advantages and challenges of large language models (LLMs) in achieving UAV security and protection are examined in [6]. It is determined that LLMs can function as high-level planners, translating natural language instructions into practical flight tasks, such as waypoint generation for trajectory planning or group UAV formation coordination [7].

Article [8] presents a review of UAV route planning methods, including deterministic models, stochastic approaches, evolutionary methods, and machine learning techniques. The authors emphasize that in real UAV applications, supervised learning can leverage historical flight records – such as chosen routes, speeds, and weather data – to develop regression or classification models that support flight trajectory prediction.

In [9], a method is proposed for large-scale UAV swarm mission planning using an ensemble predictive model of trajectory length. The authors tested the effectiveness of the proposed method across 15 simulated missions of different scales. The mission input data included the number and location of UAVs, the number and location of targets, and the number, location, and radius of threat sources. However, the software tool presented in the study has no integration with geographic information systems, meaning that all trajectories remain hypothetical and educational in nature.

Although modern literature devotes considerable attention to UAV swarm planning and the concept of swarm intelligence [10, 11] – which involves interaction and coordination among group members – military mission planning in enemy rear areas is fundamentally different in nature. In such missions, UAV groups are formed to strike a specific target, with each drone assigned an individual route that considers maneuvering, flanking approaches, varying attack angles, and defined ranges of action. In these conditions, interaction between drones is nearly absent, and the use of swarm intelligence is unnecessary, since the primary complexity lies in the strategic planning of individual routes and the synchronization of their effects, rather than in collective coordination.

3. Research aim and objectives

The aim of this study is to develop and validate an approach for analyzing factors influencing the success of military operations involving unmanned aerial vehicles (UAVs) by integrating simulation modeling into a mission planner and employing machine learning methods.

To achieve this aim, the following objectives were set:

- to formalize the space of factors determining UAV mission effectiveness, including UAV characteristics, mission route parameters, environmental conditions, and enemy threats.
- to develop an approach for generating data based on simulation modeling of UAV missions in the mission planner under various tactical conditions.
- to construct and test machine learning models (logistic regression, decision trees, ensemble methods, neural networks) for classifying mission outcomes and assessing the impact of factors.
- to identify the key variables that most significantly influence mission success and conduct a comparative analysis of their importance.
- to formulate recommendations for improving UAV mission planning, enabling the adaptation of mission tactics according to operational environment conditions and minimizing the risk of mission failure.

4. Research methodology

UAV military mission planning is a multi-level process that involves the interaction of command structures, forward units, analysis of enemy actions, and the identification of targets for reconnaissance and strike operations (Figure 2).

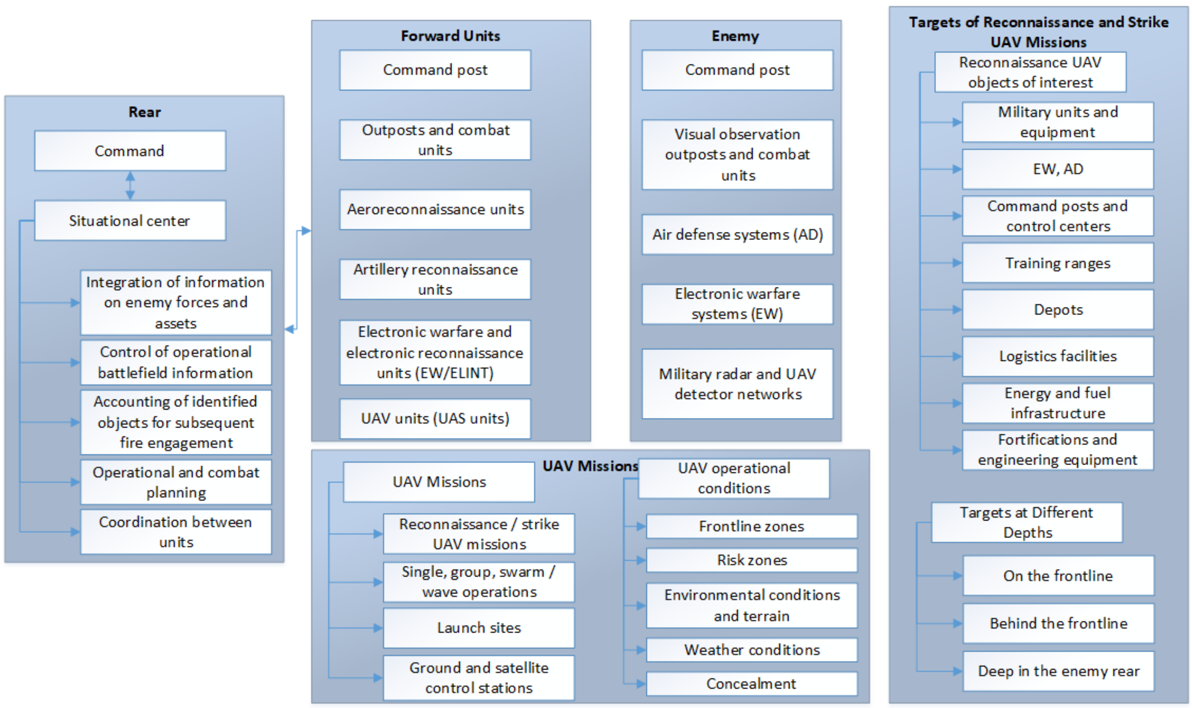

Figure 2: Conceptual Representation of UAV Mission Planning Task.

At the command level, the situational center plays a key role, ensuring the integration of information on the location of enemy forces and assets, control of operational battlefield data, and accounting of identified objects for subsequent fire engagement. Another critical task is coordination between units and operational planning, which involves aligning UAV missions with the actions of other forces. Notably, the DELTA system – a Ukrainian military product ecosystem –

is used for conducting combat operations. The system consists of a mobile application, a military messenger, secure battlefield streaming, a digital map, and planning tools and integration with other systems [12].

In forward units, key roles are fulfilled by outposts and combat units that provide direct support for UAV mission execution. These structures include:

- aerial reconnaissance units, which provide data on enemy positions.
- artillery reconnaissance units, which identify potential enemy artillery firing points.
- electronic warfare and electronic reconnaissance units (EW/ELINT), which provide situational awareness of the radio environment and enemy countermeasures.
- unmanned aerial system units (UAS units), responsible for UAV launch, control, and technical maintenance, including launch sites and ground control stations.

The enemy, in turn, possesses a wide range of counter-UAV measures. These include command posts, observation outposts, artillery units, air defense systems, electronic warfare systems, and radar detector networks. These assets serve as key targets for reconnaissance and strike missions.

In general, UAV mission targets vary in depth of engagement: directly at the frontline; within the tactical zone behind the front line; and in the strategic depth of the enemy's rear. Typical objects of interest for reconnaissance and strike UAV missions include military units and equipment, command posts and control centers, depots and logistics hubs, energy and fuel infrastructure, as well as fortifications and engineering equipment.

UAV missions are classified according to their purpose and operational format. They can be reconnaissance or strike missions, executed as single sorties, group operations, swarms, or wave attacks. Operational conditions are taken into account, including the nature of frontline zones, the presence of countermeasures and other threats, environmental features (terrain, urban areas), and concealment levels.

Thus, the UAV mission planning process represents a complex system of interaction between command structures, forward units, and technical assets, taking into account the characteristics of the combat environment and potential enemy actions.

In this study, an integrated approach is applied, combining simulation modeling within a specially developed UAV mission planner and machine learning methods to analyze key factors determining the effectiveness of combat tasks.

1. Simulation Modeling

We developed a UAV mission planner for strategic and tactical operation planning (Figure 3), which provides for:

- modeling complex combat scenarios.
- selection and prioritization of targets.
- forecasting potential UAV losses.
- consideration of countermeasures from electronic warfare (EW) and air defense (AD) systems.
- automatic generation of routes for UAV groups with the possibility of wave attacks.
- evaluation of probable mission effectiveness before uploading into the real flight control system.

During the modeling process, mission routes are generated with corresponding tactical and technical characteristics (route length, speed, flight altitude, number of maneuver points, number of UAVs in a group, launch modes, etc.). Subsequently, task execution simulation accounts for dynamic losses within the operational zones of AD and EW systems.

Results of simulation experiments:

- assigned target damage.
- UAV losses during task execution.
- mission routes in the format of start and finish coordinates, number of intermediate points, route length, number of UAVs involved, speed, duration, etc.

2. Training Dataset Formation

The simulation model in the mission planner includes the following agent populations:

- Drone – UAV agent.
- Mission – mission agent.
- WayPoint – route point agent.
- Target – target agent.
- Radar – AD/EW threat zone agent.

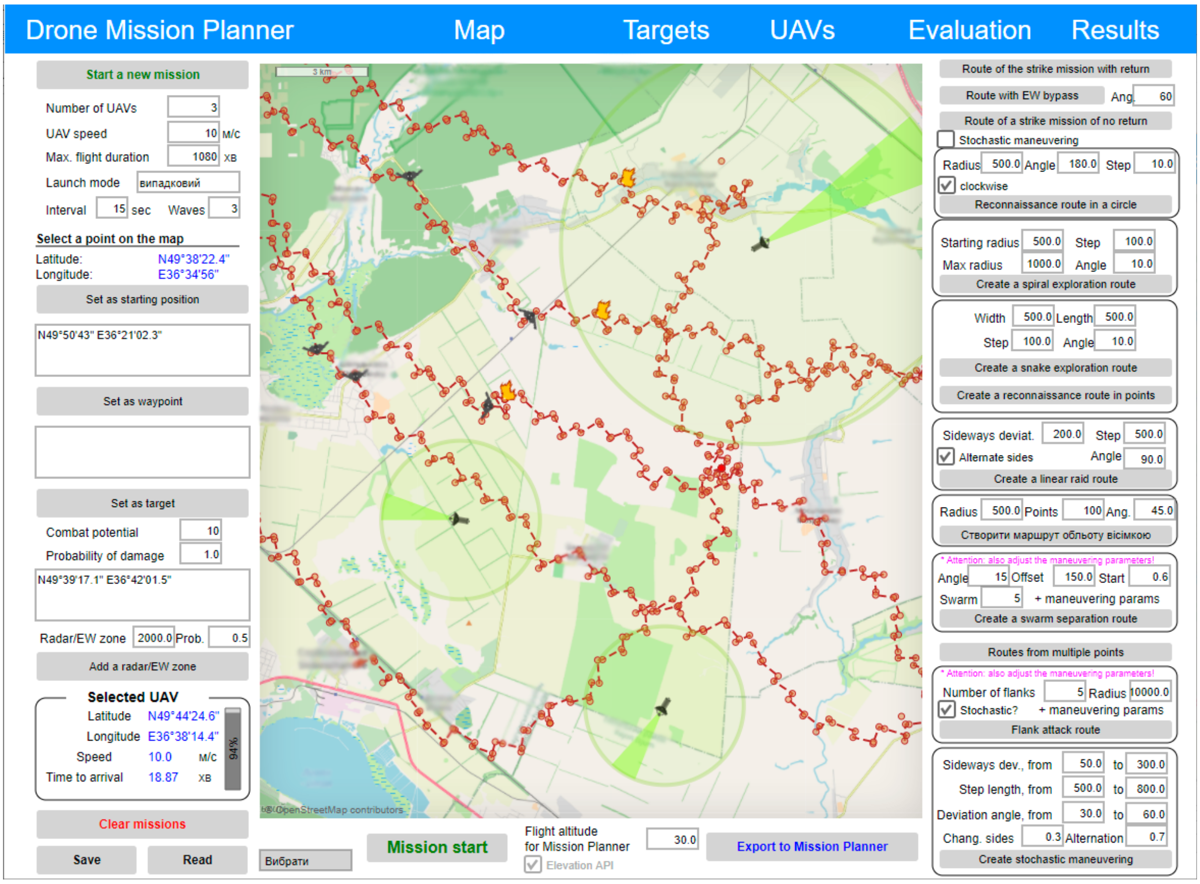

Figure 3: UAV Mission Planner Interface.

Additionally, we have formed a database that can be easily integrated and adapted for interaction with real combat management systems and the situational center.

This database includes:

- Flight logs – telemetry data generated in the mission planner during mission simulation, and in real operations, provided by the autopilot. The geographic information system used is OpenStreetMap, and terrain data is handled via the Google Maps Elevation API.
- Mission plan table – data on UAV mission routes generated in the planner.
- Threat intelligence table – deployed threat zones (AD, EW) in the planner, and in real operations, data from reconnaissance units or integrated monitoring systems.

- Weather table – obtained from external APIs; we use the OpenWeather API, which provides historical data, current weather conditions, and hourly forecasts for any location.
- Mission outcome table – aggregated data after mission simulations.

The integration of these diverse data sources enabled the creation of a unified dataset, where each row corresponds to a single UAV mission (Table 1). This dataset includes both technical route parameters and external factors that determine mission execution conditions. Features were selected based on their importance for assessing mission success and their suitability for use in machine learning algorithms for outcome prediction.

Table 1
Description of the Dataset for Machine Learning

Feature	Data Type	Description
MissionID	Integer (ID)	Unique Mission ID in Planner
DroneType	Categorical	UAV Type (reconnaissance, strike, FPV, loitering munition)
RouteLength	Numeric (km)	Total Mission Route Length
AltitudeMean	Numeric (m)	Average Flight Altitude Above Ground Level
Formation	Categorical	Operational Format (Single, Group, Swarm, Wave)
WaypointsCount	Numeric	Number of Waypoints (Maneuver Points) per Mission
Weather_Wind	Numeric (m/s)	Average Wind Speed During Mission
Weather_Cloud	Numeric (%)	Cloudiness During Mission
Threat_EW	Binary (0/1)	Presence of EW Systems in Route Area
Threat_AD	Binary (0/1)	Presence of AD Systems in Route Area
Duration	Numeric (min)	Mission Duration
Loss	Binary (0/1)	UAV Loss During Mission (Yes/No)
Success	Binary (0/1)	Mission Outcome (Success/Failure)

This set of features encompasses both technical route parameters and UAV characteristics, as well as external environmental factors and enemy threats, enabling the construction of predictive and analytical models for risk assessment and mission planning optimization.

3. Application of Machine Learning Methods

To analyze the factors influencing UAV mission success, several machine learning approaches were applied:

- Logistic Regression – as a baseline interpretable model to establish initial relationships between features and mission outcomes.
- Decision Trees – to identify important features and generate explainable decision rules.

- Ensemble Methods (including Random Forest and XGBoost) – to improve classification accuracy and provide more reliable feature importance estimation.
- Neural Networks – to explore complex nonlinear relationships that may not be captured by simpler models.

4. Interpretation of Results

The above models allowed us to determine the relative importance of various factors and identify the variables that most significantly affect the probability of mission success. This, in turn, forms the basis for integrating ML analysis results directly into the mission planner, providing users with recommendations for optimal UAV operation planning.

5. Data analysis and modeling results

To better understand the dataset structure and identify potential relationships between variables, an initial exploratory data analysis (EDA) was conducted.

Figure 4 presents a heatmap of correlations among numerical and ordinal variables. A strong positive correlation is observed between RouteLength and the number of waypoints (WaypointsCount, r≈0.98), which is expected as longer routes typically contain more waypoints. A high correlation is also found between RouteLength and flight duration (Duration, r≈0.87), confirming that mission time depends on distance. Features related to mission success (Success) show negative correlations with threat factors (Threat_EW and Threat_AD_num, r≈-0.20), indicating their influence on the probability of mission completion. As expected, the Loss variable is strongly inversely correlated with Success (r≈-0.81). This analysis confirms the relevance of route and threat factors for building predictive models of mission outcomes.

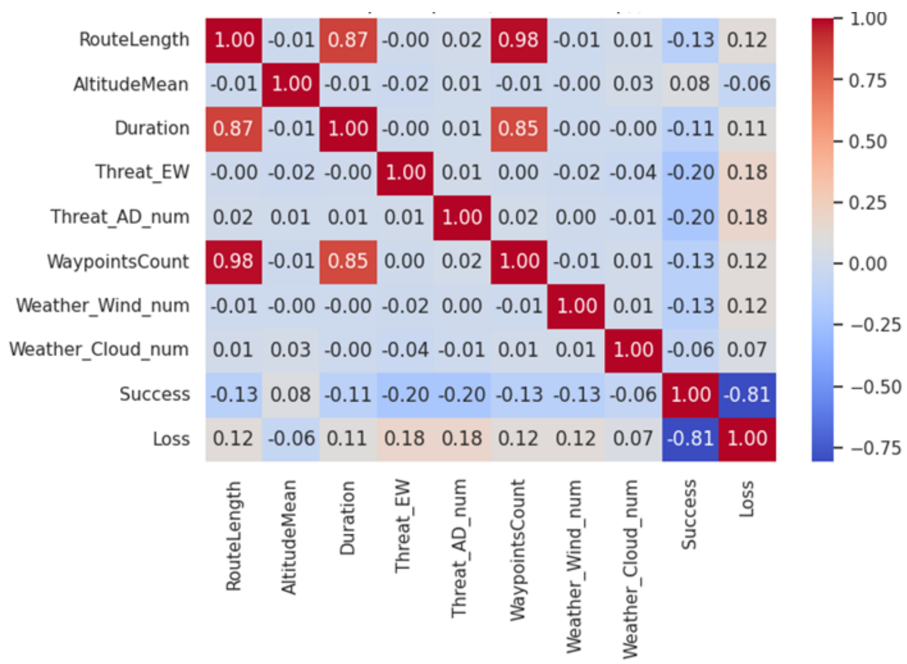

Figure 4: Feature Correlation Heatmap.

Figure 5 illustrates the distribution of mission route length (RouteLength) considering mission formation (Formation) and the presence of electronic warfare threats (Threat_EW).

Across all formation types (e.g., swarm, single), route lengths are fairly uniformly distributed between 20–200 km. The impact of EW threats is reflected in shifts in distributions: for swarms, missions with longer routes occur more frequently even in the presence of EW threats. For single UAVs, EW threats are more often associated with medium and longer routes, potentially increasing the risk of UAV loss. These and other visualizations allow preliminary insights into the dataset structure and highlight the necessity of machine learning models for uncovering complex patterns.

The performance metrics of the evaluated models are presented in Table 2. The baseline logistic regression model demonstrated the highest classification accuracy (Accuracy = 0.685) and AUC (0.727), indicating its capability to reliably distinguish between successful and failed missions even with a relatively simple linear structure. Its recall (0.454) was moderate, meaning the model did not always detect all failure cases.

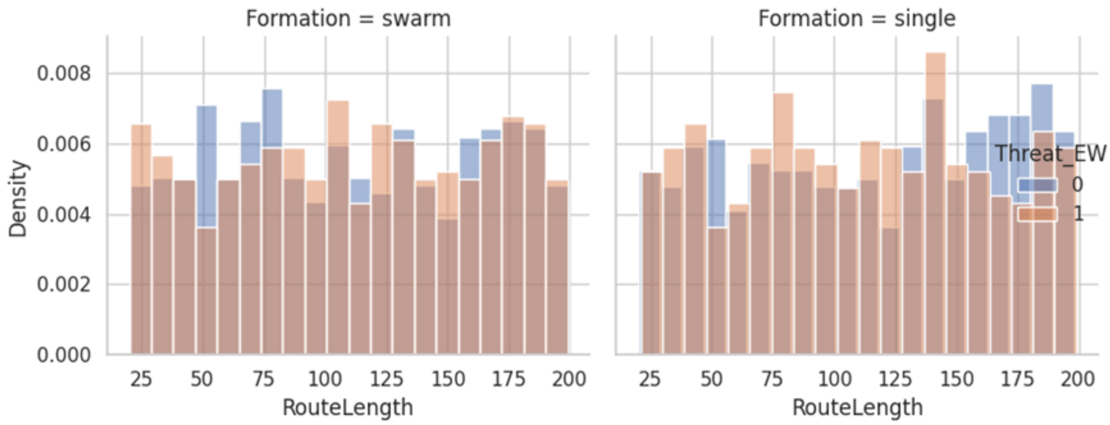

Figure 5: Distribution of Route Length by Mission Formation and Presence of EW Threats.

Decision tree-based models showed slightly lower accuracy (Decision Tree: 0.651, Random Forest: 0.651) but provided better interpretability and transparency of decision rules. Among ensemble methods, Random Forest was the most stable in terms of Precision and F1-score, while XGBoost showed a balance between Precision (0.509) and Recall (0.436) but lagged behind logistic regression in AUC. The neural network (MLP) achieved results comparable to ensemble methods (Accuracy = 0.637) but did not surpass classical algorithms in any key metric.

Since the baseline MLP demonstrated somewhat lower accuracy compared to other methods, an additional experiment was conducted to optimize its hyperparameters. A grid search with cross-validation was applied, varying the hidden layer architecture, activation functions, weight update methods, and regularization coefficient.

Table 2
Consolidated Model Performance Metrics

Model	Accuracy	Precision	Recall	F1-score	ROC_AUC
Logistic regression	0.685	0.588	0.454	0.512	0.727
MLP (tuned)	0.673	0.575	0.392	0.466	0.713
Random Forest	0.651	0.529	0.374	0.438	0.698
XGBoost	0.641	0.509	0.436	0.470	0.674
Baseline MLP	0.637	0.502	0.469	0.485	0.655
Decision Tree	0.651	0.527	0.396	0.452	0.654

The best-performing configuration included three hidden layers with sizes 128–64–32, the tanh activation function, the adam optimizer with an adaptive learning rate, and regularization with alpha ≈ 0.0061. The obtained results showed an improvement in classification accuracy to 0.673 (compared to 0.637 in the baseline model).

The confusion matrix analysis indicated that the network performed much better in classifying missions ending in failure (class 0), whereas for successful missions (class 1), Precision and Recall remained lower (0.58 and 0.39, respectively). However, compared to the baseline MLP, the improved version achieved better balance between the classes. This suggests that applying sampling strategies or class weight adjustments could further increase the sensitivity of the model to successful mission cases.

In conclusion, logistic regression provided the best balance between interpretability and performance, achieving the highest ROC_AUC metrics. Ensemble methods can be useful for scaling the problem and handling larger datasets, while neural networks are suitable for exploring complex interdependencies among factors.

6. Discussion

The obtained results indicate that assessing UAV mission success is a multifactorial task, containing both linear and nonlinear relationships among features. The highest contribution to predictive performance comes from factors such as route length, number of waypoints, threat intensity (AD and EW), and environmental conditions. The impact of individual variables can vary significantly depending on the specific operational scenario.

Logistic regression demonstrated the best performance among the evaluated models, suggesting a relatively linear nature of part of the dependencies in the data generated by the mission planner through simulation of multiple UAV missions. Ensemble methods, while less stable in results, allow identification of more complex combinations of factors. This confirms the appropriateness of a combined approach: interpretable models can be used to establish baseline decision rules, while more sophisticated algorithms can support in-depth analysis and discovery of nontrivial patterns.

To evaluate the contribution of individual features to UAV mission outcome prediction, three methods were applied – Logistic Regression, Random Forest, and XGBoost – allowing the assessment of feature importance based on their influence on model predictions and uncertainty reduction (Figure 6).

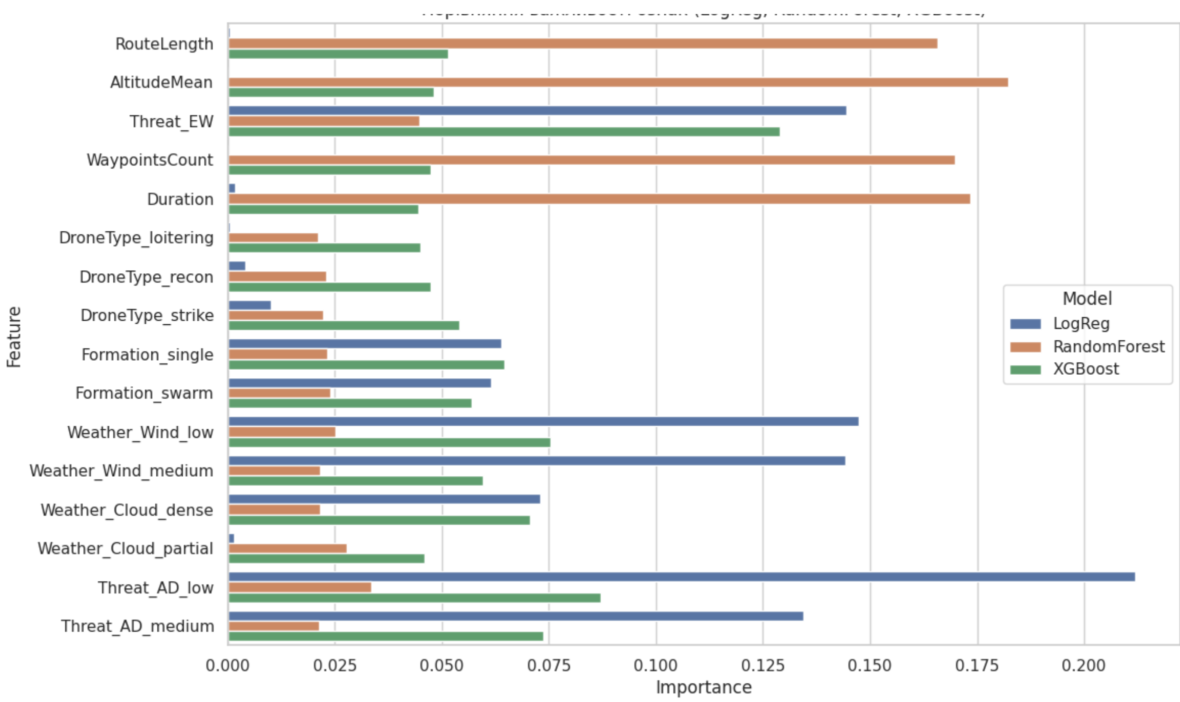

Figure 6: Feature Importance by Logistic Regression, Random Forest, and XGBoost.

The analysis showed that flight and route characteristics play a key role in route planning. The greatest influence is observed for mean flight altitude (AltitudeMean), highlighting its critical importance for mission effectiveness, avoidance of AD and EW threats, and consideration of weather conditions. Flight duration (Duration) is also significant as it directly affects battery/fuel resources, detection risks, and the necessity for precise path planning. The number of waypoints (WaypointsCount) reflects flight complexity and the UAV's maneuvering capability to avoid potential threats. Route length (RouteLength) similarly influences mission outcomes, indicating the relationship between flight duration and resource constraints.

Figure 7 presents diagrams showing how the probability of success varies depending on the length of the route, average altitude, and duration using the Random Forest method. Partial Dependence Plots indicate that increasing RouteLength beyond ~120 km reduces the likelihood of success, while higher AltitudeMean increases it. The effect of Duration is less pronounced and fluctuates around a stable level.

External factors, such as threats and weather, have a smaller but still important effect. Specifically, electronic warfare threats (Threat_EW) and low-altitude air defense systems (Threat_AD_low) contribute noticeably to the model, whereas weather conditions, such as clear skies or strong wind, have relatively lower importance. Drone formation characteristics (Formation_swarm, Formation_single) and UAV types (strike, recon, FPV, loitering munition) have a minor influence, indicating a secondary role in overall prediction.

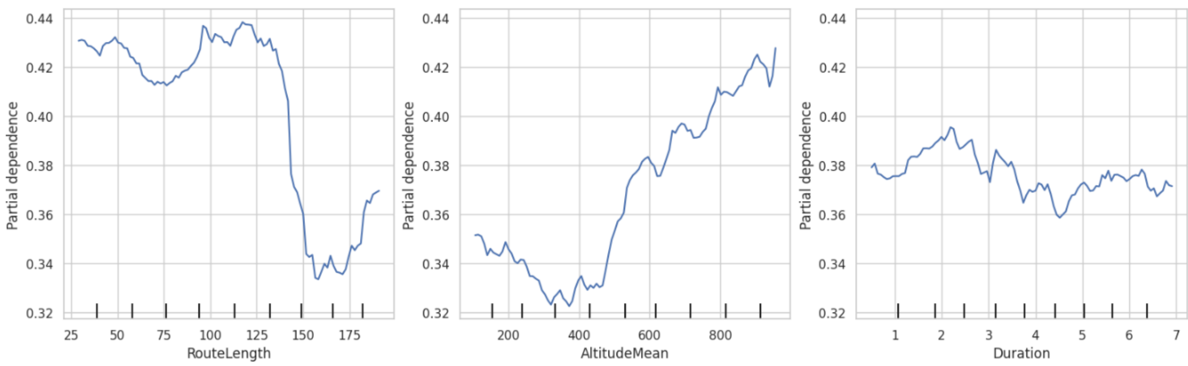

Figure 7: Partial Dependence Plot to the Random Forest Method.

Overall, the Random Forest analysis suggests that physical route parameters and flight characteristics are primary determinants of UAV mission effectiveness, while external threats, environmental conditions, and UAV specifics play a secondary role. These findings emphasize the need to focus planning algorithms on route and flight parameter optimization to enhance mission efficiency and safety.

To evaluate the operational usability of the models, we analyzed precision-recall trade-offs and calibration. Figure 8 presents the PR curve for the positive class (mission success) with an average precision of 0.561.

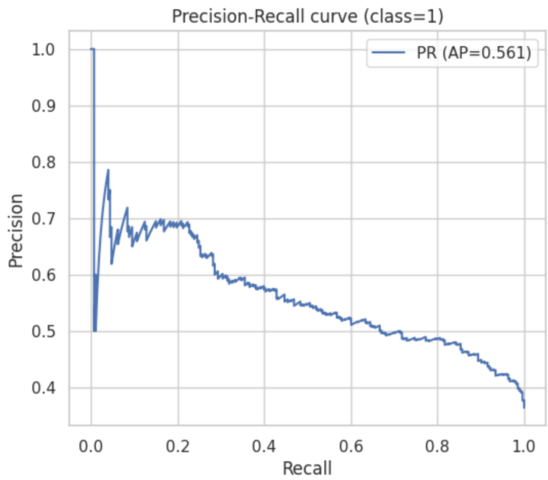

Figure 8: PR curve for the positive class (mission success).

Threshold analysis (Table 3) shows that the best F1 score (0.598) is achieved at a decision threshold of 0.30, where precision is 0.487 and recall is 0.773. This configuration provides a balanced trade-off, ensuring that most successful missions are correctly identified while maintaining moderate precision.

The corresponding confusion matrix illustrates this balance. Additionally, calibration analysis (Figure 9) indicates that predicted probabilities are reasonably well aligned with observed frequencies, which supports their use for decision-making and threshold adjustment in operational settings.

Table 3
Threshold analysis

Threshold	Precision	Recall	F1-score	Confusion Matrix (TP/FP/FN/TN)
0.20	0.443	0.912	0.596	164 / 313 / 24 / 249
0.30 (best F1-score)	0.487	0.773	0.598	255 / 222 / 62 / 211
0.40	0.521	0.590	0.533	329 / 148 / 112 / 161
0.50	0.575	0.392	0.466	398 / 79 / 166 / 107
0.60	0.651	0.253	0.364	440 / 37 / 204 / 69

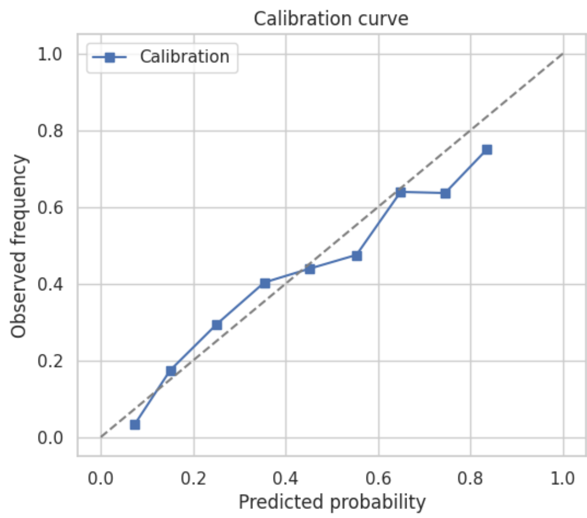

Figure 9: Results of calibration analysis.

To assess robustness and mitigate potential data leakage across operational groups, we performed grouped cross-validation using GroupKFold. The results show consistent performance across folds (Fold 1: AUC=0.725, Fold 2: AUC=0.734, Fold 3: AUC=0.707, Fold 4: AUC=0.713). The mean AUC across folds was 0.720 (std=0.011), indicating that the model generalizes well across different operational partitions.

These results are particularly important in a military context, as model interpretability is crucial: decisions must be understandable to commanders and integrable into real-world mission planning processes. Future work could incorporate target selection criteria, dynamic battlefield factors, and uncertainty in intelligence data.

7. Conclusions

In this study, a methodology for analyzing factors affecting UAV mission success was developed and validated, integrating simulation-based mission planning with machine learning methods. The feature space affecting UAV mission performance was formalized, including UAV characteristics, route parameters, environmental conditions, and enemy threats. A data generation mechanism based on simulation of tactical scenarios in the mission planner was implemented, enabling systematic study under various operational conditions.

Machine learning models (logistic regression, decision trees, ensemble methods, and neural networks) were constructed and evaluated for mission outcome classification. Logistic regression demonstrated the highest balanced performance (Accuracy = 0.685, ROC_AUC = 0.727). Key variables significantly influencing mission success probability were identified, including route length, number of waypoints, intensity of AD and EW threats, and environmental factors.

The grouped cross-validation analysis confirmed that the model maintains stable performance across different operational partitions (mean AUC=0.720 ± 0.011), suggesting that the observed factor importance and predictive accuracy are not artifacts of a specific subset of the synthetic data but can be generalized across distinct mission scenarios.

Practical recommendations have been formulated for UAV mission planning specialists, enabling adaptation of operational tactics according to environmental parameters and minimizing the risk of mission failure. Overall, the results demonstrate the effectiveness of integrating simulation-based mission planning with machine learning for analyzing and predicting UAV mission performance in complex tactical scenarios.

A key limitation of this study is the reliance on synthetic data generated by the simulation framework, which may not fully capture real-world operational complexity. Future research should incorporate external validation on real or shadow mission data to quantify the simulator-to-reality gap and improve model calibration for operational deployment.

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Declaration on Generative AI

During the preparation of this work, the authors used GPT-4 in order to: Grammar and spelling checks. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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