A LightGBM Framework for Rapid Flight Time Prediction with High-Dynamic Validation

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Abstract：To meet the urgent need for real-time and accurate flight time prediction in intelligent aeronautical systems, this paper proposes a rapid prediction framework for aerial vehicle flight time based on the Light Gradient Boosting Machine (LightGBM). To validate the method's effectiveness, a high-dynamic autonomous flight scenario with a well-defined dynamic model was selected. Experimental results demonstrate that, compared to traditional physics-based numerical integration, the trained LightGBM model maintains prediction accuracy while reducing the time per prediction by approximately two orders of magnitude to the millisecond level. Furthermore, the model's lightweight nature helps reduce the energy consumption of computational tasks, aligning with sustainable computing principles. The proposed framework is generalizable, with its technical pathway also applicable to other aeronautical fields requiring rapid time prediction, such as estimating time of arrival in civil aviation.

Keywords: Machine learning, LightGBM, Bayesian optimization, Flight time, Prediction method.

1. INTRODUCTION

With the advancement of artificial intelligence and aerospace technologies, intelligent autonomous aerial vehicles (including unmanned aerial vehicles, advanced air mobility vehicles, and high-dynamic specialty aerial vehicles) are gradually becoming the core units for future air traffic and mission execution [1]. In the coordinated operations and real-time aerospace mission planning of these complex systems, the rapid and accurate prediction of aerial vehicle flight time is a critical prerequisite for achieving efficient decision-making and ensuring spatiotemporal coordination [2-3]. Whether for a swarm of UAVs conducting area surveillance or a high-speed aerial vehicle completing time-sensitive missions, accurately estimating the time to reach the target point is directly related to mission success and safety.

Traditional flight time prediction methods primarily rely on physics-based numerical integration or look-up tables [4]. While the former offers high accuracy, it suffers from long computation times, making it difficult to meet the demands of online real-time planning. The latter, although fast, has weak generalization capabilities and cannot adapt to dynamically changing initial conditions and environmental parameters. Therefore, developing a prediction model that combines both high accuracy and high real-time performance has become an urgent technical challenge in the domain of intelligent aeronautical systems.

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In recent years, machine learning algorithms represented by the Gradient Boosting Decision Tree (GBDT) have demonstrated significant potential in numerous regression prediction tasks, owing to their powerful nonlinear fitting capabilities and excellent predictive performance [5-6]. Among them, the Light Gradient Boosting Machine (LightGBM) is particularly suitable for deployment in resource-constrained or latency-sensitive real-time systems due to its faster training speed, lower memory footprint, and superior processing efficiency [7]. However, despite the widespread application of LightGBM in various fields [8-12], its application to the regression prediction of the entire flight time for high-dynamic autonomous aerial vehicles—a problem characterized by strongly nonlinear dynamics—remains relatively unexplored. Specifically, validating its predictive efficacy in high-dynamic flight scenarios with extremely stringent time constraints is of great significance for assessing the algorithm's applicability in broader intelligent aeronautical missions.

To address this gap and thoroughly examine the performance of the LightGBM algorithm in complex aeronautical prediction tasks, this paper employs a missile—a typical high-dynamic autonomous aerial vehicle—as the experimental subject and proposes a LightGBM-based rapid flight time prediction framework. First, the fundamental principles of LightGBM are systematically introduced. Subsequently, based on an analysis of the factors influencing missile flight time, model features are selected and a regression prediction model is constructed. Finally, its effectiveness is validated through simulation experiments. Experimental results indicate that,

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compared to traditional physics-based numerical methods, the proposed approach maintains prediction accuracy while improving computational speed by several orders of magnitude, achieving real-time prediction at the millisecond level. Furthermore, this paper discusses the potential and the technical pathways for its migration to a broader range of intelligent aeronautical systems.

2. FUNDAMENTALS OF LIGHTGBM

LightGBM was first proposed in 2017 by researchers including Tianqi Chen from Microsoft Research Asia. It quickly gained widespread attention in the machine learning community, becoming a rising star in the field [7]. It is fundamentally an ensemble learning method. Its basic principle aligns with that of the GBDT and the Extreme Gradient Boosting (XGBoost) algorithms, which also use decision trees as base learners. The method employs the negative gradient of the loss function as an approximation of the residual for the current decision tree to fit new trees, constructing a powerful model by combining the predictions of multiple base learners. Compared to XGBoost, LightGBM focuses on optimizing model training speed. It introduces several enhancements, including a histogram-based decision tree algorithm, a leaf-wise growth strategy with depth limitation, Gradient-based One-Side Sampling (GOSS), and Exclusive Feature Bundling (EFB). These improvements endow LightGBM with advantages such as higher training efficiency, lower memory usage, improved accuracy, support for parallel learning, and the capability to handle large-scale data [5-6, 8].

2.1. Improvements and Optimizations in LightGBM

(1) Histogram-based Decision Tree Algorithm. The fundamental concept is to first discretize continuous floating-point feature values into K integers, while constructing a histogram with a width of K. While traversing the data, statistics are accumulated in the histogram using the discretized values as indices. After a single pass through the data, the histogram contains the accumulated feature statistics. The optimal split point is then found by traversing these discretized values in the histogram. The principle of the histogram algorithm is illustrated in Figure **1**. The advantages of this approach are reduced memory usage and lower computational cost, as it eliminates the need for storing pre-sorted results and only requires saving the discretized feature values.

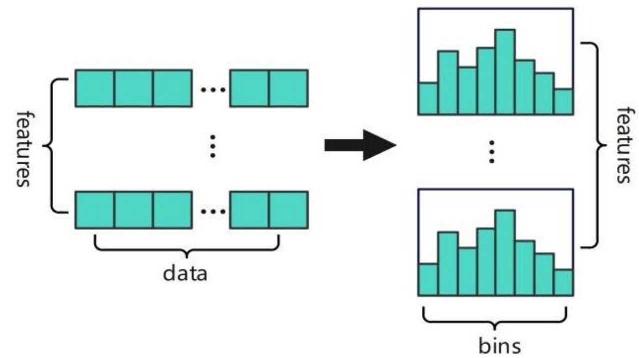


Figure 1: Schematic diagram of the histogram algorithm.

Furthermore, the histogram algorithm can be accelerated through subtraction. The histogram of a leaf node can be obtained by subtracting the histogram of its sibling node from the histogram of their parent node, which can double the training speed. Typically, constructing a histogram requires traversing all data points on that leaf. However, histogram subtraction only needs to traverse the K bins of the histograms involved. This subtraction process is illustrated in Figure **2**.

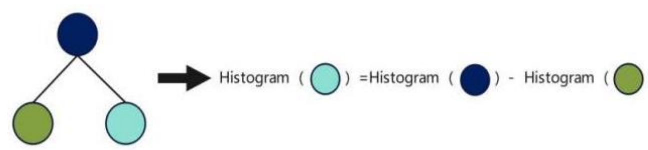


Figure 2: Schematic diagram of subtracting histograms.

(2) Leaf-wise Growth Strategy with Depth Limitation. The fundamental concept of the leaf-wise decision tree growth strategy is to iteratively find and split the leaf with the highest split gain among all current leaves. Compared to the level-wise growth strategy, this approach can achieve greater error reduction and better accuracy for the same number of splits. However, it may result in deeper trees and potential overfitting. Therefore, LightGBM incorporates a maximum depth constraint on top of the leaf-wise strategy to ensure high efficiency while preventing overfitting. The leaf-wise tree growth is illustrated in Figure **3**.

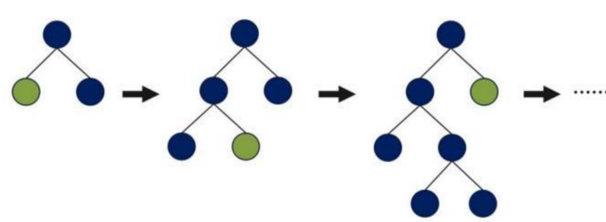


Figure 3: Schematic diagram of the leaf-wise tree growth.

(3) Gradient-based One-Side Sampling (GOSS). According to the definition of information gain calculation, samples with larger gradients have a greater impact on information gain. GOSS first sorts all values of the feature to be split in descending order based on their absolute magnitude and selects the top a data points with the largest absolute values. Then, it randomly selects b data points from the remaining data with smaller gradients. These b data points are subsequently multiplied by a weighting coefficient c. Finally, information gain is calculated using these $a+b$ data points. This approach allows the algorithm to focus more on under-trained samples without significantly altering the distribution of the original dataset. From the perspective of sample reduction, GOSS excludes most samples with small gradients and uses only the remaining samples to compute information gain, making it an algorithm that balances data reduction and accuracy preservation.

(4) Exclusive Feature Bundling (EFB). EFB is an efficient, lossless technique designed to reduce feature dimensionality. Its core idea is to combine multiple approximately mutually exclusive features into a new "bundled feature." This reduces the total number of features the model needs to process without losing the original information.

2.2. Advantages of LightGBM for Missile Flight Time Prediction

For regression problems demanding high precision and efficiency, such as missile flight time prediction, LightGBM offers the following advantages:

(1) High Prediction Accuracy and Efficient Model Convergence. Missile flight time is influenced by the complex coupling of multiple factors, including initial velocity, launch angle, and atmospheric conditions. The depth-limited leaf-wise growth strategy employed by LightGBM can construct decision trees with superior and more refined structures compared to traditional level-wise strategies under the same number of splits. This effectively captures complex nonlinear relationships, leading to higher prediction accuracy. Concurrently, overfitting is effectively prevented by imposing a maximum depth limit.

(2) High Training Efficiency and Low Computational Resource Consumption. The histogram-based decision tree algorithm and GOSS used by LightGBM can significantly enhance training efficiency and reduce machine learning training time while maintaining accuracy. The histogram algorithm itself has low memory overhead. Coupled with the EFB technique which reduces the number of features, memory consumption is notably decreased. This makes it feasible to process large-scale ballistic simulation data on conventional computing equipment.

(3) Model Interpretability for Assisting Physical Analysis and Design. LightGBM's built-in feature importance evaluation function can quantify the contribution of each input variable to the missile flight time and rank the importance of various features influencing it. This aids engineers in understanding the primary and secondary factors affecting flight time, providing valuable insights for physical analysis and design considerations.

3. FEATURE SELECTION FOR THE MISSILE FLIGHT TIME PREDICTION MODEL

According to missile ballistics, under standard conditions, the total flight time of a missile is a deterministic function of the launch point's longitude, latitude, and altitude, as well as the target point's longitude, latitude, and altitude [4]. The standard ballistic initial calculation data for a missile includes six parameters: launch point longitude λ_0, launch point latitude B_0, launch point altitude H_0, target point longitude λ_m, target point latitude B_m, and target point altitude H_m. Since the Earth is a rotating ellipsoid, the main factors influencing missile flight time can be simplified to five parameters through coordinate transformation: launch point latitude B_0, geodesic distance between the launch and target points L_d, geodetic azimuth between the launch and target points A_d, launch point altitude H_0, and target point altitude H_m [2-3].

3.1. Launch Point Latitude

Variations in launch point latitude B_0 affect missile flight time due to changes in the Earth's gravitational field and its rotational linear velocity, with the combined effect being related to the geodetic azimuth A_d. When the geodetic azimuth is $0^\circ \sim 180^\circ$, an increase in launch point latitude leads to a decrease in flight time; when the geodetic azimuth is $180^\circ \sim 360^\circ$, an increase in launch point latitude results in an increase in flight time. Details are illustrated in Figure **4**.

3.2. Missile Range

For medium to long-range ballistic missiles, a larger range corresponds to a longer flight time, with the relationship between flight time and range being approximately linear, as detailed in Figure **5**. For short-range ballistic missiles, when the range is relatively small, the total flight time for a shorter range might actually be longer than that for a slightly larger range. This can occur because, to ensure the missile's active phase burnout occurs outside the dense atmosphere, the trajectory for a very short range may necessitate specific adjustments that impact the total time of flight.

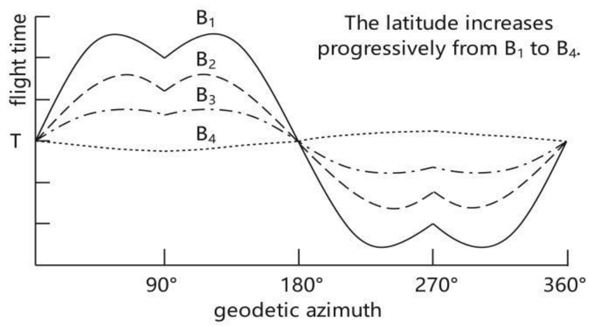


Figure 4: Schematic diagram of the flight time changes with the geodetic azimuth and the latitude of the launch site.

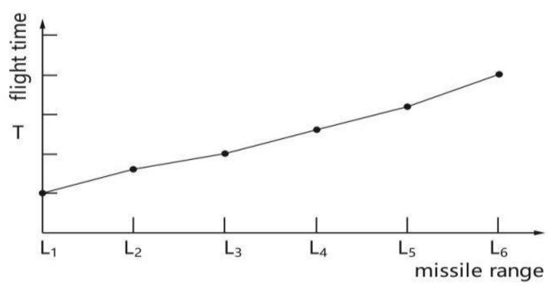


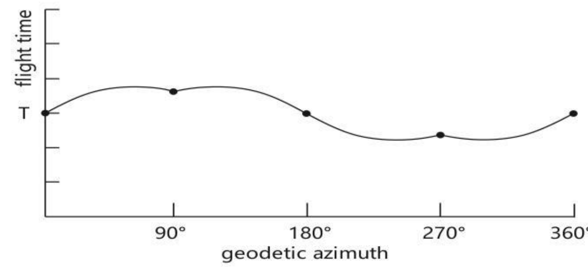
Figure 5: Schematic diagram of the variation of flight time of medium and long-range missiles with range.

3.3. Geodetic Azimuth

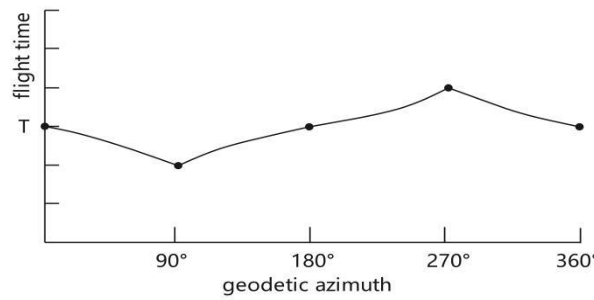
The influence of the geodetic azimuth A_d on missile flight time is primarily caused by the Coriolis acceleration resulting from the Earth's rotation. When the launch point is located in low-latitude regions, the variation of flight time with the A_d approximately follows a sinusoidal curve, as specifically shown in Figure **6**(**a**). When the launch point is in high-latitude regions, the variation of flight time with the A_d gradually deviates from a sinusoidal curve but remains a periodic function, as detailed in Figure **6**(**b**).

3.4. Launch Point Altitude and Target Point Altitude

Research in literature [3] indicates that launch point altitude and target point altitude have a minor impact on parameters such as the flight path angle and aiming azimuth, and their influence on the total flight time is negligible.



(**a**)



(**b**)

Figure 6: Schematic diagram of the variation of missile flight time with the azimuth.

Consequently, for the model in this paper, the input features are selected as launch point latitude B_0, missile range L_d, and geodetic azimuth A_d, while the output feature is missile flight time T. The process of feature selection for the missile flight time prediction model is illustrated in Figure **7**.

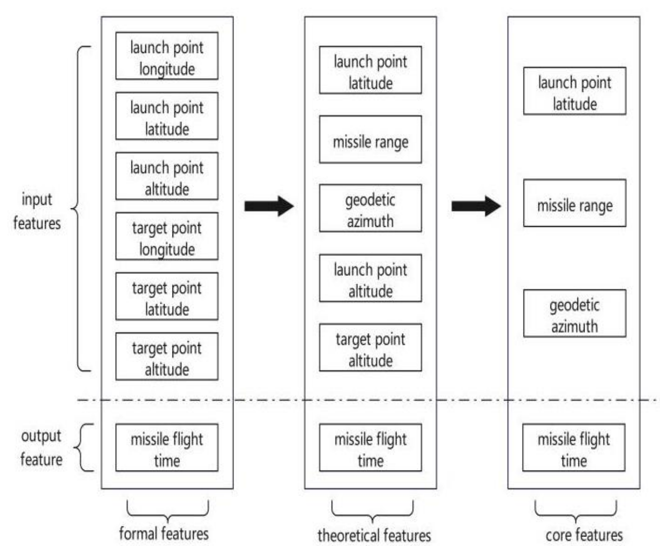


Figure 7: Block diagram of the feature selection process.

4. RAPID PREDICTION METHOD FOR MISSILE FLIGHT TIME BASED ON LIGHTGBM

4.1. Model Development Environment and Procedure

The system configuration for this paper is as follows: the operating system is Windows 10, the processor is an Intel® Core™ i7-4702MQ @ 2.20GHz, the programming language is Python 3.10.18, and the LightGBM 4.6.0 package is employed to build the prediction model. The training workflow for the prediction model is illustrated in Figure **8**.

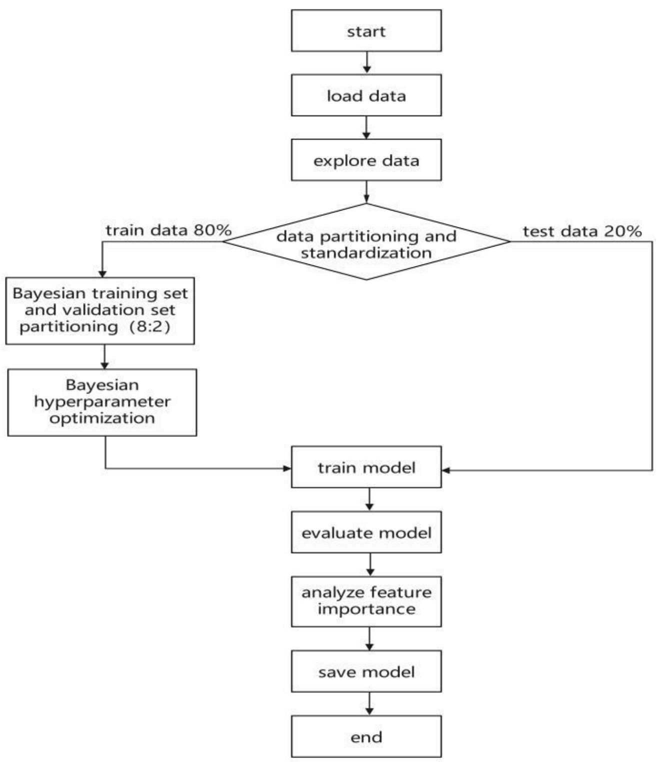


Figure 8: Block diagram of the predictive model training process.

4.2. Dataset Source and Partition

This paper employs a ballistic simulation software to generate 29,791 trajectories under varying conditions of launch point latitude B_0, missile range L_d, and geodetic azimuth A_d within the specified range envelope, following a discrete sampling rule. The corresponding flight time for each case is obtained. For model construction, this dataset of 29,791 samples serves as the training data for LightGBM. The dataset is partitioned into training and testing sets at an 80/20 ratio. The training set is used for model fitting, while the testing set is reserved for model evaluation.

4.3. Hyperparameter Optimization

The LightGBM algorithm encompasses numerous adjustable hyperparameters. Appropriate parameter settings can enhance both the training speed and prediction accuracy of the model. While the commonly used grid search method can find the best-performing parameters by exhaustively iterating through candidate combinations, it suffers from high computational cost and low search efficiency. This paper utilizes the BayesianOptimization library to perform Bayesian optimization [13] for selecting optimal parameters. This approach can find a relatively good hyperparameter combination within a limited timeframe. After 30 search iterations, a relatively optimal set of hyperparameters was identified. The total search time was 51.52 s. The optimal hyperparameter combination is presented in Table **1**.

Table 1: Optimal Combination of Hyperparameters.

Hyperparameter	Value
num_leaves	66
max_depth	15
learning_rate	0.3
feature_fraction	0.5
bagging_fraction	1.0
bagging_freq	10
lambda_l1	0.0
lambda_l2	0.0
min_data_in_leaf	10

5. SIMULATION EXPERIMENTS AND RESULTS ANALYSIS

5.1. Evaluation of Model Prediction Results

The optimal hyperparameters were input into the LightGBM model, yielding a Bayesian-optimized missile flight time prediction model. The model's predictive performance was then evaluated using the testing set, with an early stopping mechanism employed (maximum iterations: 1000). The final model prediction results showed a coefficient of determination (R^2) of 0.999, a Mean Absolute Error (MAE) of 0.0001, a Root Mean Square Error (RMSE) of 0.0001, and a model training time of 1.61 s.

Figure **9** presents the scatter plot of predicted versus actual values, showing the points tightly clustered around the diagonal line. Figure **10** displays the residual plot, where the residual points are randomly distributed above and below the zero line. Figure **11** compares predicted and true values for 50 randomly selected data groups, demonstrating nearly perfect overlap. Figures **12** and **13** show the training curves for MAE and RMSE, respectively, indicating that both the training and testing set curves rapidly decrease before stabilizing. Collectively, these five figures illustrate the excellent performance of the prediction model from different perspectives.

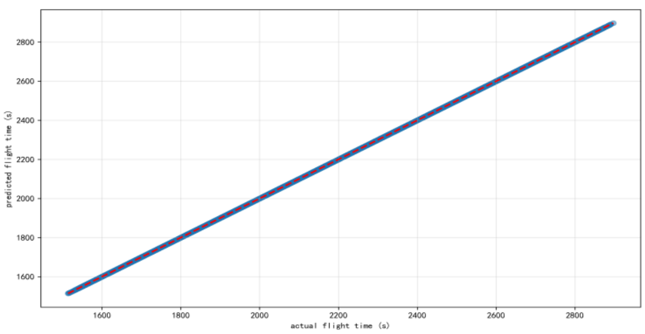


Figure 9: Scatter plot of predicted and actual values.

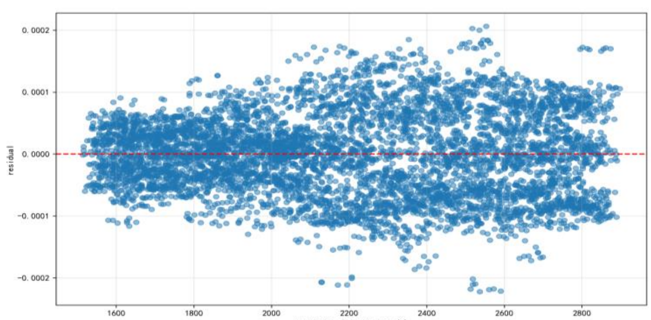


Figure 10: Residual plot of predicted and actual values.

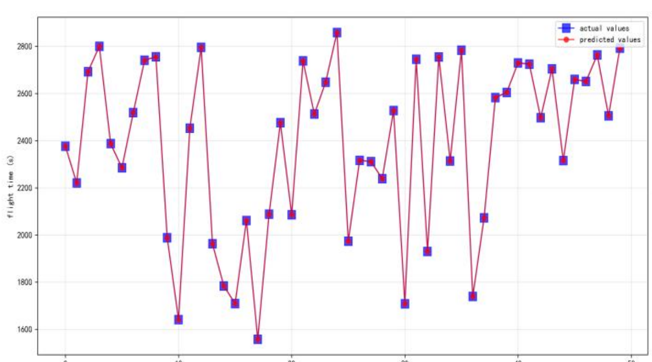


Figure 11: Comparison chart between predicted and actual values of 50 random data sets.

LightGBM also provides a feature importance analysis function. As analyzed by the model and shown in Figure **14**, the variation in missile range is the primary factor influencing flight time, accounting for 99.39% of the importance. This is followed by the geodetic azimuth and the launch point latitude, contributing 0.51% and 0.1%, respectively.

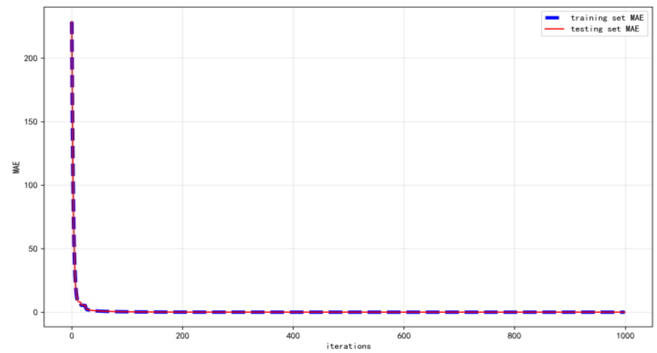


Figure 12: MAE training curve.

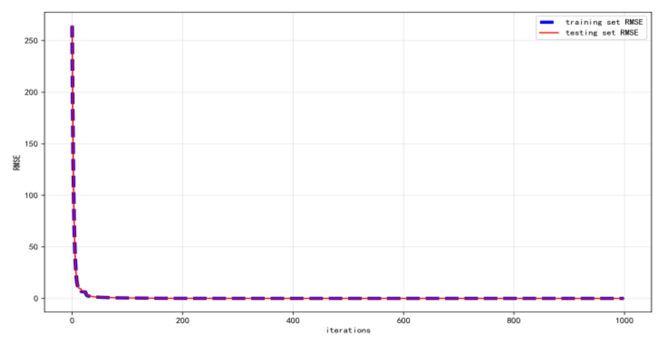


Figure 13: RMSE training curve.

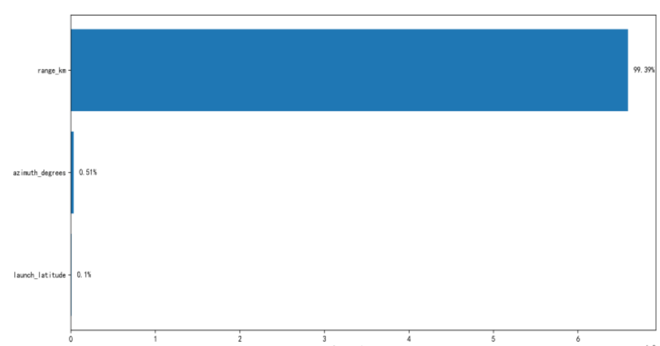


Figure 14: Bar chart of feature importance analysis.

5.2. Comparative Analysis of Prediction Results from Different Models

To demonstrate the advantages of the LightGBM algorithm in predicting missile flight time, the LightGBM model was compared and analyzed against the BP Neural Network model [3, 14], the Random Forest model [15], and the XGBoost model [16]. Tables **2**, **3**, and **4** present the hyperparameter settings for the BP

Neural Network, Random Forest, and XGBoost models, respectively.

Table 2: Hyperparameters of BP Neural Network.

Hyperparameter	Value
hidden_layer_sizes	(100,50,25)
activation	relu
solver	adam
alpha	0.0001
batch_size	128
learning_rate	adaptive
learning_rate_init	0.001
max_iter	1000
early_stopping	True
validation_fraction	0.1
n_iter_no_change	50

Table 3: Hyperparameters of Random Forest.

Hyperparameter	Value
n_estimators	800
max_depth	30
min_samples_split	2
min_samples_leaf	1
max_features	0.8
bootstrap	True
n_jobs	-1

Table 4: Hyperparameters of XGBoost.

Hyperparameter	Value
max_depth	12
learning_rate	0.1
n_estimators	1000
subsample	0.8
colsample_bytree	0.8
reg_alpha	0.01
reg_lambda	0.01
min_child_weight	5

Based on the calculations, the performance metrics of the four prediction models are shown in Table **5**. A comparative analysis of the prediction results indicates that the R^2 for all four models is close to 1, suggesting excellent fitting performance on the given dataset by each model. Notably, compared to the other three algorithms, the LightGBM algorithm achieves a lower MAE and RMSE, while also requiring less training time. Consequently, in terms of model performance ranking, LightGBM demonstrates the best results, followed by XGBoost, then the BP Neural Network and Random Forest.

Table 5: Performance comparison of four prediction models.

Model	MAE	RMSE	R^2	Training Time (s)
BP Neural Network	0.6443	0.8613	0.993	20.47
Random Forest	0.9256	1.3318	0.986	7.21
XGBoost	0.0021	0.0024	0.998	4.51
LightGBM	0.0001	0.0001	0.999	1.61

5.3. Rapid Prediction of Missile Flight Time

Based on the pre-trained LightGBM model, rapid prediction of missile flight time was conducted. Experimental results indicate that the prediction for a single missile took 2 ms. The total time for a batch prediction of 200 missiles was 6 ms, resulting in an average prediction time of 0.03 ms per missile. However, if traditional numerical integration methods are employed, predicting the flight time of a single missile typically requires on the order of minutes. This clearly demonstrates that the method proposed in this study achieves an improvement in prediction efficiency by orders of magnitude, effectively meeting the timeliness requirements for missile flight time prediction.

6. PRACTICAL IMPLICATIONS AND GENERALIZABILITY DISCUSSION

The experiment demonstrates that the flight time prediction model for high-dynamic autonomous aerial vehicles, built upon LightGBM, achieves millisecond-level prediction response while maintaining high predictive accuracy. This "instantaneous" computational capability allows it to be seamlessly integrated into online aerospace mission planning systems or onboard real-time decision-making systems. In dynamic and uncertain environments, aerial vehicles can leverage this capability for instantaneous evaluation and optimization of numerous candidate trajectories, enabling adaptive online re-planning, thereby significantly enhancing the system's autonomy and agility. Furthermore, the model's lightweight nature places minimal demands on hardware computing power, serving as an efficient alternative to high-energy-consumption physical simulation models. Its application in scenarios such as large-scale airspace scheduling or dense swarm simulation can substantially reduce the computational energy consumption of central servers. This directly aligns with the pursuit of "computational sustainability" and "green computing" in the development of intelligent aeronautics.

Although this paper employs a typical high-dynamic autonomous aerial vehicle as the validation platform, the proposed LightGBM prediction framework is fundamentally a general-purpose, data-driven mapping model with strong methodological extensibility, allowing for migration to various intelligent aeronautical prediction tasks. One direct application is the prediction of the Estimated Time of Arrival (ETA) in civil aviation. The key to successfully migrating this framework to such a scenario lies in the adaptation of feature engineering and data pipelines: the input features need to be expanded to encompass multi-source information including real-time weather, air traffic control instructions, aircraft performance, and route structure. Concurrently, an automated data processing pipeline should be constructed based on historical flight data (e.g., ADS-B records). Through processes of cleaning, alignment, and feature extraction, high-quality "state-time" training samples can be generated. This process enables the model to learn the comprehensive impact of complex operational environments on flight time, providing more accurate and rapid decision support for airport arrival management and air traffic flow prediction. This demonstrates the potential for extending the proposed method from a specific validation case to a broader range of intelligent aeronautical applications.

7. CONCLUSION

To address the urgent need for real-time and accurate flight time prediction in intelligent aeronautical systems, as well as the inherent limitations of traditional methods in computational efficiency and real-time performance, this paper proposed and validated a rapid prediction framework based on LightGBM. The core contributions of this study can be summarized as follows:

(1) An efficient and generalizable prediction framework was constructed. This framework transforms the complex mapping problem of a flight dynamic system into a trainable data regression task, providing a novel technical pathway for the rapid prediction of flight time.

(2) The algorithm's performance was validated in a high-dynamic scenario. Experimental results demonstrate that, compared to traditional physics-based numerical methods, the proposed framework maintains prediction accuracy while reducing the time required for a single prediction by approximately 2 orders of magnitude, achieving millisecond-level efficient inference capability.

(3) Broad application potential and sustainability value were elucidated. The framework's lightweight nature and high inference speed enable its seamless integration into online aerospace mission planning systems, onboard real-time decision-making systems, or large-scale airspace scheduling platforms. Furthermore, by significantly reducing the computational energy consumption for trajectory pre-simulation and planning, it offers algorithmic support for green aeronautical operations from the perspective of "computational sustainability." This paper also details the specific technical pathways for extending this framework to broader intelligent aeronautical fields, such as the ETA prediction in civil aviation.

In summary, the core value of this paper lies in the innovative application of the LightGBM algorithm to the rapid prediction of flight time—a key aeronautical performance metric. Through a high-dynamic validation case, it demonstrates the significant advantages of this data-driven approach in terms of accuracy, speed, and energy efficiency, providing a powerful algorithmic tool for developing next-generation intelligent, real-time, and efficient aeronautical systems.

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