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# OPTIMIZATION OF MULTI-AIRCRAFT LANDING SCHEDULING BASED ON MACHINE LEARNING WITH QUANTUM ANNEALING UNDER UNCERTAINTY CONDITIONS ON SINGLE AND MULTIPLE RUNS

***The object of this study is multi-aircraft landing scheduling on single and multiple runways, which is an important aspect of modern air traffic management systems. The main problems solved in this research are the complexity of scheduling optimization due to limited runway capacity, the need to maintain a safe distance between aircraft, and the uncertainty of estimated time of arrival (ETA) which is often influenced by external factors such as weather and air traffic density. To overcome these challenges, this research proposes a hybrid approach between Long short-term memory-gradient boosting with the quantum annealing method. the results show that this approach is able to significantly improve the performance of the scheduling system, with an accuracy of 0.93, a precision of 0.91, a recall of 0.90, and an F1 score of 0.91. These values are higher than the model without quantum annealing, which only achieved an accuracy of 0.87, a precision of 0.85, a recall of 0.83, and an F1 score of 0.84. This improvement can be explained by the ability of LSTM-gradient boosting to predict ETA deviation more accurately, as well as the effectiveness of quantum annealing in solving the quadratic unconstrained binary optimization (QUBO) formulation efficiently. The unique feature of this research lies in the application of a hybrid model that combines the power of machine learning and quantum computing, achieving a balance between predictive accuracy and optimization efficiency. These research findings can be applied to air traffic scheduling systems at airports with single or multiple runways. Their implementation has the potential to improve operational efficiency, reduce delays, and enhance flight safety through more precise and adaptive landing time management***

***Keywords: aircraft landing scheduling, LSTM-gradient, quantum annealing, machine learning, optimization, ETA prediction***

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## 1. Introduction

Advances in modern aviation technology demand air traffic management systems that are increasingly efficient, safe, and adaptive to dynamic operational conditions. One of the most complex challenges in this area is scheduling multi-aircraft landings on single and multiple runways. This scheduling process requires optimization that takes into account various variables, such as runway capacity limitations, safe landing times, flight priorities, and uncertainties such as weather changes, air density, and deviations from estimated time of arrival. This uncertainty significantly disrupts airport operational efficiency and has the potential to cause chain delays that impact the entire air transportation system [1, 2]. Flight delays, delayed landings, and queues are real issues frequently encountered in air traffic management. These conditions not only impact passenger comfort but also incur additional costs for airlines, increase fuel consumption, and contribute to higher carbon emissions. In this context, aircraft landing scheduling cannot be viewed as a simple problem, but rather as a complex and dynamic optimization challenge. Therefore, a modern approach based on machine learning technology is needed to help find more effective and adaptive solutions to air traffic dynamics [3, 4].

The main problem in scheduling aircraft landings lies in the limited resources, namely the number of runways available at the airport, while the demand for aircraft landings continues to increase. At airports with a single runway, scheduling complexity is higher because all aircraft must share time and space to land on the same runway. Meanwhile, at airports with multiple runways, although there is greater flexibility, there are still constraints such as safe distance limits between aircraft (separation minima), changing weather conditions, and certain priorities for flight types, such as aircraft experiencing emergencies or international flights with tight schedules. Uncertainty is a factor that significantly affects the effectiveness of landing scheduling. This uncertainty can include extreme weather that causes changes in flight paths, delays in departure from the originating airport, variations in aircraft speed in the air, and even sudden technical factors [5, 6]. These conditions require landing scheduling to adapt in real time while maintaining safety and efficiency. Traditional scheduling methods, which generally use a first-come-first-served (FCFS) approach or simple priority rules, are often unable to handle the complexity of these problems. This results in suboptimal landing schedules, increased aircraft waiting times in the air, and increased operational costs. Therefore, a scheduling model is needed that not only considers the order of aircraft arrivals but also comprehensively considers various other variables, such as runway capacity, time slots, aircraft speed, and uncertainty scenarios [7, 8]. These conditions require landing scheduling to adapt in real time while maintaining safety and efficiency. Traditional scheduling methods, which generally use a first-come-first-served (FCFS) approach or simple priority rules, are often unable to handle the complexity of these problems [9, 10]. This results in suboptimal landing schedules, increased aircraft waiting times in the air, and increased operational costs. Therefore, a scheduling model is needed that not only considers the order of aircraft arrivals but also comprehensively considers various other variables, such as runway capacity, time slots, aircraft speed, and uncertainty scenarios. In the context of aircraft landing scheduling, quantum annealing can be used to find the optimal landing sequence by minimizing total waiting time, maximizing runway utilization efficiency, and reducing the risk of excessive delays [11]. The integration of machine learning with quantum annealing offers significant opportunities to generate more optimal scheduling solutions. Machine learning can be used to predict aircraft arrival times more accurately, while quantum annealing can be used to create the best schedule sequence based on these predictions. In this study, the machine learning algorithm chosen is a combination of long short-term memory (LSTM) and gradient boosting. LSTM is a variant of recurrent neural network (RNN) that is very effective in handling time series data [12]. LSTM is able to remember long-term patterns while capturing short-term dynamics in data, making it very suitable for modeling temporal air traffic behavior. For example, LSTM can learn the relationship between historical arrival schedules and weather factors, aircraft speed, and air traffic density at a given time [13].

In the context of aircraft landing scheduling, quantum annealing can be used to find the optimal landing sequence by minimizing total waiting time, maximizing runway utilization efficiency, and reducing the risk of excessive delays. The integration of machine learning with quantum annealing offers significant opportunities to generate more optimal scheduling solutions. Machine learning can be used to predict aircraft arrival times more accurately, while quantum annealing can be used to create the best schedule sequence based on these predictions. In this study, the machine learning algorithm chosen is a combination of long short-term memory (LSTM) and gradient boosting. LSTM is a variant of recurrent Neural network (RNN) that is very effective in handling time series data. LSTM is able to remember long-term patterns while capturing short-term dynamics in data, making it very suitable for modeling temporal air traffic behavior. For example, LSTM can learn the relationship between historical arrival schedules and weather factors, aircraft speed, and air traffic density at a given time. Therefore, research on the development of integration between machine learning models such as LSTM-gradient boosting and quantum annealing-based optimization methods is highly relevant, as it is able to address the need for a scheduling system that is not only accurate in predicting aircraft arrival times, but also efficient in optimizing landing sequences under complex uncertainty conditions. This approach is expected to make a significant contribution to improving airport operational efficiency and overall flight safety.

## 2. Literature review and problem statement

Research [11] produces an integer linear programming (ILP)-based aircraft landing scheduling model that is capable of providing optimal solutions for a limited number of aircraft and is effective in reducing delays and runway conflicts. However, there is an unresolved problem, namely the exponential increase in computational complexity as the number of aircraft and decision variables increases. This condition makes this research relevant but impractical when applied to real-world scenarios with high levels of uncertainty, such as weather changes, arrival time deviations, and dynamic air traffic density. Therefore, one way to overcome this difficulty is to apply a quantum computing-based approach, specifically the quantum annealing method, which is able to streamline the search for optimal solutions through the quadratic unconstrained binary optimization (QUBO) formulation. This approach provides opportunities to accelerate the optimization process, maintain system adaptability on a large scale, and improve the efficiency of multi-aircraft scheduling under conditions of uncertainty.

Research [14] produces a flight scheduling model using metaheuristic algorithms such as genetic algorithm and particle swarm optimization (PSO) which aims to improve the synchronization system in handling weather distance and potential flight length. The results show an increase in efficiency compared to conventional methods such as integer linear programming (ILP). However, there are unresolved issues, namely the relatively long convergence time and the risk of being stuck in a local optimum, which causes the algorithm's performance to decrease when operational conditions change rapidly. As a result, this research becomes impractical to be applied in a real-time scheduling environment that requires adaptive response to flight dynamics. Therefore, one way to overcome these difficulties is to apply a quantum computing-based approach using quantum annealing, which is able to explore the solution space more widely and efficiently, thereby accelerating the convergence process and improving the system's ability to find the global optimal solution under certain conditions.

Research [15] produces a long short-term memory (LSTM)-based machine learning model that focuses on predicting aircraft estimated time of arrival (ETA) with a high degree of accuracy. This model is designed to provide more reliable predictive data to support the decision-making process in flight scheduling systems. However, there is an unresolved problem, namely the limitations of pure LSTM models in optimizing scheduling decisions, especially when there is a surge in the number of aircraft and dynamic changes in operational conditions. This model is only predictive, not optimal, so it cannot directly determine the best landing sequence based on the prediction results. As a result, this research is relevant but impractical when applied independently in complex and uncertain real-time scheduling systems. Therefore, one way to overcome this difficulty is to integrate the quantum annealing method, which is able to convert LSTM prediction results into optimal scheduling decisions in real-time. This integrative approach allows the system to have higher adaptive capabilities, with better computational efficiency in dealing with dynamic air traffic conditions.

Research [16] produces a model that combines machine learning with the gradient boosting algorithm to classify aircraft landing priorities, with the main goal of minimizing potential collisions and accelerating the runway allocation process. The results show quite promising performance in improving operational efficiency and safety. However, there is an unresolved problem, namely the model's limitations in balancing global and local optimality, so that the resulting decisions are often partial and not always consistent with the overall system conditions. As a result, this research is relevant to be impractical to be directly applied in multi-aircraft scheduling systems that require decision consistency across variables and dynamically changing conditions. Therefore, one way to overcome this difficulty is to integrate the quantum annealing method, which has adaptive capabilities in optimizing complex combinatorial problems through a single annealing process. This approach allows for the achievement of more holistic and efficient solutions, while maintaining decision stability in large-scale flight scheduling systems.

Research [17] produces a stochastic programming-based approach model designed to accommodate various forms of operational uncertainty, such as variations in wind direction and speed, changes in aircraft technical conditions, and air traffic dynamics. The main objective of this research is to improve the reliability of landing schedules through probabilistic modeling that considers various possible scenarios. The results show an increase in schedule stability and reliability compared to the deterministic approach. However, there is an unresolved problem, namely the very high computational cost because the model must evaluate a large number of uncertainty scenarios simultaneously. This complexity makes this research relevant but impractical when applied to a real-scale operation, where computation time must be fast and the system response must be adaptive to changing conditions in real time. Therefore, one way to overcome this difficulty is to apply the quantum annealing method, which is able to accelerate the optimization process in a large probabilistic space while maintaining computational efficiency. This approach allows the scheduling system to be more adaptive to various dynamic conditions, while reducing the computational load without sacrificing the accuracy or reliability of the optimization results.

Research [18] produces a dual-runway scheduling optimization model using heuristic algorithms such as Tabu Search and Simulated Annealing, which aims to accelerate the solution search process compared to conventional deterministic methods. The results show quite good performance in medium-scale cases, where computational efficiency is increased and the resulting solution meets the operational constraints of the system. However, there is an unresolved problem, namely a significant decrease in algorithm performance when the system scale is enlarged, because the heuristic model is still prone to stagnation at sub-optimal solutions. This makes this research relevant to be impractical for application in large-scale multi-aircraft scheduling systems that require broader solution exploration capabilities and adaptability to dynamic conditions. Therefore, one way to overcome this difficulty is to apply a quantum annealing-based approach, which has a similar principle to Simulated Annealing but is based on quantum mechanics, so it is able to break through local energy limits to find optimal global solutions. This approach provides higher adaptive capabilities and better optimization efficiency in solving complex scheduling problems in dual-runway systems.

Research [19] produces a model that combines a deep learning approach with an air traffic prediction system with the primary goal of reducing flight delays. This model is designed to be able to predict aircraft queues more accurately, so that the scheduling decision-making process can be carried out more timely and efficiently. The results show a high level of prediction accuracy, which provides a strong basis for planning landing and departure schedules. However, there is an unresolved problem, namely the difficulty in integrating the prediction results with the scheduling optimization process, because the model tends to be passive and less adaptive to changing real-time conditions. This makes this research relevant but impractical when directly applied in complex and dynamic air traffic control systems. Therefore, one way to overcome this difficulty is to integrate the quantum annealing method, which is able to bridge the gap between data-based prediction results and the schedule optimization process through an adaptive quadratic unconstrained binary optimization (QUBO) formulation. This approach allows the system to transform dynamic predictions into optimal scheduling decisions in real-time, while simultaneously improving efficiency and responsiveness in modern air traffic management.

## 3. The aim and the objectives of the study

The aim of this study is to optimize multi-aircraft landing scheduling under uncertainty conditions, both on single and multiple runways, using a hybrid long short-term memory (LSTM) and gradient boosting-based machine learning approach integrated with quantum annealing techniques.

To achieve this aim, the following objectives were accomplished:

– to solve an optimization problem using quantum annealing techniques;

– to apply of a hybrid LSTM-gradient boosting model;

– to comparison of model performance results.

## 4. Materials and methods

The object of this study is multi-aircraft landing scheduling on single and multiple runways, which is an important aspect of modern air traffic management systems. The hypothesis of this research will make predictions in multi-aircraft landing scheduling. Assumptions in this context, a machine learning model approach will be used to predict and optimize multi-aircraft landing scheduling under uncertain conditions, both on single and multiple runways. The simplification accepted in this section is a hybrid algorithm that will be applied that combines long and short-term memory (LSTM) to capture temporal patterns from air traffic data with gradient boosting to improve generalization and strengthen the prediction results. This combination is expected to produce an accurate model in estimating optimal landing times, reducing potential schedule conflicts, and increasing runway utilization efficiency. This research will use flight operational data that includes key parameters such as actual and estimated arrival times, aircraft speed, runway capacity, available time slots, weather conditions, and landing priority levels. Data is collected from historical flight records and operational reports from airlines and airport authorities. In the optimization process, the quantum annealing approach will be applied to solve combinatorial optimization problems related to complex aircraft landing sequences. quantum annealing is used as a mechanism to find a schedule solution that is close to optimal by minimizing total delays, maximizing operational safety, and considering runway capacity constraints. The selection of theoretical and experimental research methods in this study is based on the need to combine a strong conceptual foundation with measurable empirical evidence. The theoretical approach is used to build a hybrid machine learning-based multi-aircraft landing scheduling predictive model that combines long short-term memory (LSTM) and gradient boosting to capture temporal patterns and improve prediction accuracy. Meanwhile, the experimental approach is applied by testing the model using historical flight data that reflects real operational conditions such as weather, runway capacity, and landing priority. The paper device used in the study is a laptop with a Core i3 processor, while for software, Google Collaboratory is used. Evaluation techniques used in this study include f1 score, precision, and recall to assess the performance of landing time predictions, as well as measuring scheduling quality. This study will begin with the design of a hybrid LSTM-gradient boosting model architecture integrated with the quantum annealing optimization mechanism as shown in Fig. 1.

Fig. 1 explains that in making predictions, a machine learning model using the hybrid LSTM-XGBoost algorithm, in this context, requires well-structured data. This problem is mathematically known as the Aircraft Landing Scheduling Problem (ALSP), which can be classified as a combinatorial optimization problem and is NP-Hard, meaning that the computation time grows exponentially with the number of aircraft. To represent this problem quantitatively, it is assumed that there is a symbol with $N$ the plane that is scheduled to land on $R$ runway. Every plane $i$ has an ideal landing time $T_i$, as well as a minimum time limit $E_i$ and maximum $L_i$ which are permitted to land. In addition, between each pair of aircraft $i$ and $j$. There is a minimum landing time interval $S_{ij}$. If both use the same runway, to maintain safety and avoid residual turbulence. The main decision variables in this formulation are, which has a value of 1 if the plane $i$ scheduled to land on time $t$ on the runway $r$, and 0 otherwise. Thus, the actual landing time of the aircraft $i$, symbolized as $A_i$, can be expressed by equation (1)

$$A_i = \sum_{t,r} t \cdot x_{i,t,r}. \quad (1)$$

From equation (1), there is an objective to minimize the total squared deviation between the actual appearance time and the ideal appearance time of each aircraft with the symbols $x_{i,t,r}$ which are the $i$ entity that lands, the symbol $t$ for time while the symbol $r$ for the runway by considering a certain priority weight $P_i$, so that the objective function is written in equation (2)

$$\min \sum_{i=1}^{N} P_i \cdot \left(A_i - T_i\right)^2. \quad (2)$$

In equation (2), there is an objective function that not only pursues time efficiency, but also takes into account the importance of each aircraft (for example, military aircraft, VIPs, or aircraft with critical fuel).

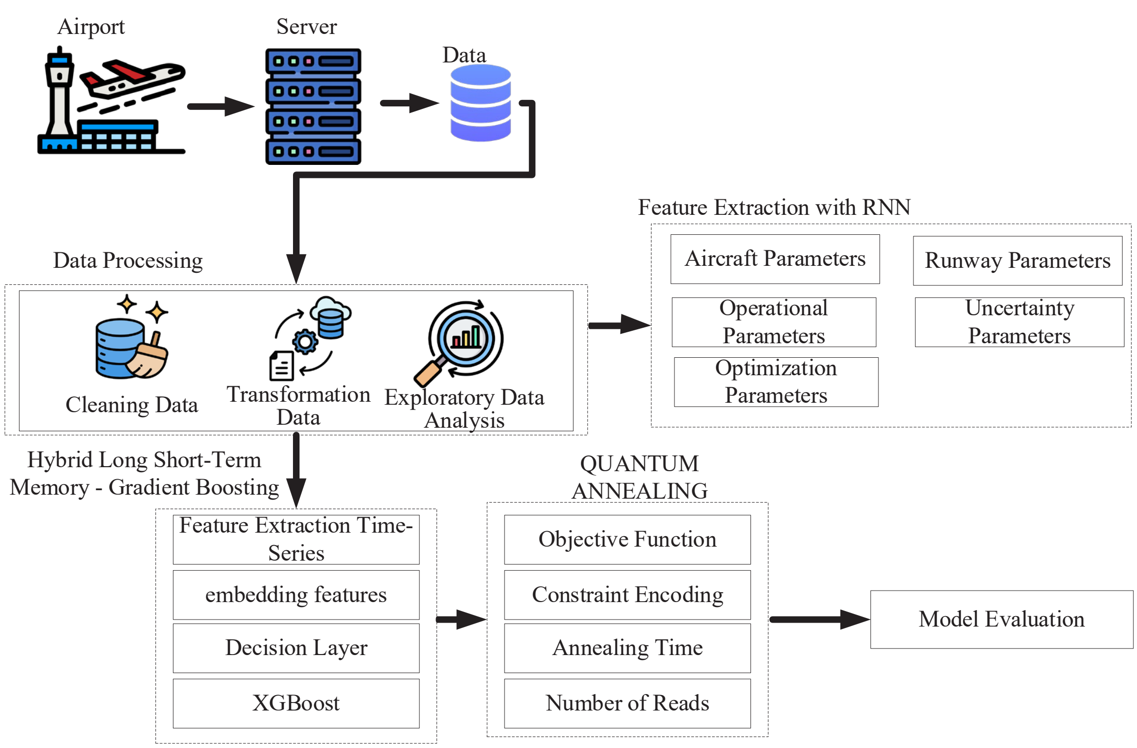


Fig. 1. Architectural framework

## 5. Results optimization of multi-aircraft landing scheduling based on machine learning

### 5. 1. To solve an optimization problem using quantum annealing techniques

The application of quantum annealing in this study aims to improve multi-aircraft landing scheduling. In the process, quantum annealing is used to solve combinatorial optimization problems that arise due to the large number of aircraft that must be scheduled simultaneously, taking into account runway limitations, minimum time intervals between aircraft, and uncertainty in actual arrival times. This scheduling problem formulation is translated into the form of quadratic unconstrained binary optimization (QUBO), where each binary variable represents a decision whether an aircraft lands at a certain time slot. To ensure the solution obtained is operationally feasible and safe, this mathematical formulation is limited by several constraints. First, each aircraft can only be scheduled once at a time on one runway according to equation (3)

$$\sum_{t,r} x_{i,t,r} = 1 \quad \forall i \in \{1,\ldots,N\}, \tag{3}$$

Second, the scheduled landing time must be within the permitted range, namely between $E_i$ and $L_i$. This can be implemented by disabling the variable $x_{i,t,y}$ for times outside that range. Third, to avoid conflict and maintain a safe distance between two aircraft landing on the same runway, each pair of aircraft $I$ and $j$ scheduled close together must meet the minimum time separation requirement $S_{ij}$ according to equation (4)

$$x_{i,t,r} + x_{j,t',r} \le 1 \ \text{ if } \ \left|t - t'\right| < S_{ij}. \tag{4}$$

This constraint ensures that no violations of air safety protocols occur. Additionally, to facilitate processing with the quantum annealing method, additional variables can be used. $y_{ij} \in \{0, 1)$ which states whether the plane $i$ landed before the plane $j$, so that it develops into equation (5)

$$y_{ij} + y_{ji} = 1 \quad \forall i \ne j, \tag{5}$$

The uncertainty will then be processed using machine learning. In real-world conditions, factors such as weather, changes in air routes, or traffic congestion can cause fluctuations in actual arrival times. To address this, a machine learning-based predictive approach with a hybrid long short-term memory – gradient boosting algorithm is used to estimate the deviation value of arrival times. $S_i$ against the ideal time $T_i$. Thus, the target landing time can be revised to $T_i = T_i + S_i$, and the optimization model turns into equation (6)

$$\min \sum_{i=1}^{N} P_i \cdot \left(A_i - \tilde{T}_i\right)^2. \tag{6}$$

Statistically, $S_i$, can be modeled as a random variable that follows a Gaussian distribution $S_i \sim N\left(0, \alpha_i^2\right)$. The updated mathematical formulation is transformed into a quadratic unconstrained binary optimization (QUBO) form which is suitable for solving with the quantum annealing approach. In QUBO form, all objective functions and constraints are encoded into a symmetric matrix $Q$, so the problem can be stated in equation (7)

$$\min_{x \in \{0,1\}^n} x^T Q x. \tag{7}$$

Binary vector $x$ consists of all decision variables $x_{i,t,r}$, and the elements in the matrix $Q$ Encode penalties for time deviations, schedule rule violations, and runway conflicts. Penalties for constraint violations such as double schedules or insufficient time gaps are assigned high weights to certain elements of the matrix $Q$, Thus, the optimal solution will naturally avoid invalid configurations. Embedding QUBO into a quantum annealing machine allows for global solution exploration with higher efficiency than classical techniques, especially for large solution spaces. This can be seen in Fig. 2.

Fig. 2 will represent a flow graph model used to model the multi-aircraft landing scheduling process on a runway. Each circle or node in the figure represents a decision point, where $k_1$ be the starting point that describes the beginning of the landing schedule and $k_3$ becomes the end point that indicates that the entire scheduling process has been completed. Node *I, II, III, III* and *IV* are transition phases that represent time slots or specific conditions in the aircraft landing sequence. Arrows or edges connecting nodes are labeled with pairs of values, for example (0,0), (1,2), (3,5) and so on, which indicate the minimum and maximum time limits or gap parameters that must be met between consecutive landings of aircraft. For example, the edge of a node *I* towards the node *II* with labels (1,2) shows that the distance between landings in the slot is at least one time unit and at most two time units.

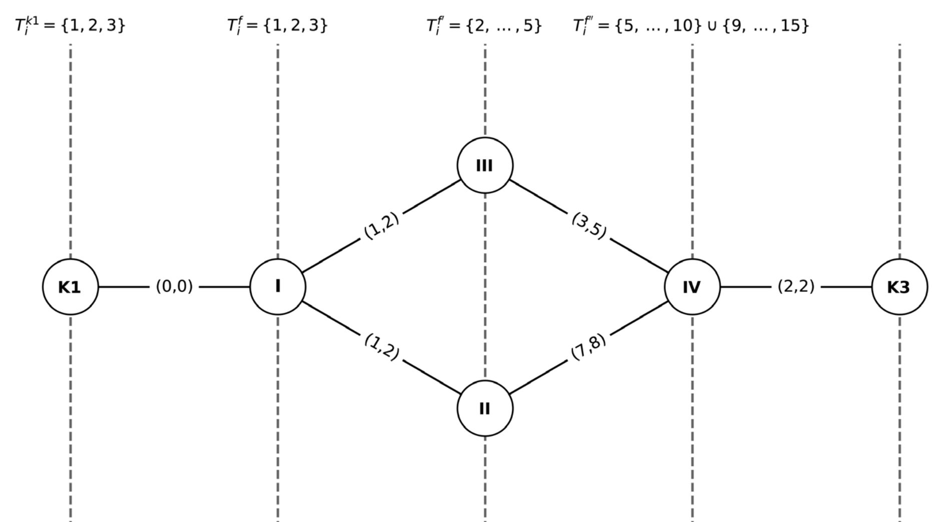


Fig. 2. Graph quantum annealing in hybrid models

In addition, the figure is also equipped with dotted lines that divide the graph into several parts, each labeled with a time set such as $T_f^I = \{1,2,3\}$, $T_f^{II} = \{2,....5\}$ to $T_f^{k3} = \{7,...15\}$. This set represents the allowable time range for each landing phase, so scheduling takes into account not only the sequence of aircraft but also the constraints of safe time intervals. Thus, the figure as a whole provides a visual representation of how timing rules, slot constraints, and transitions between phases are integrated into a mathematical model to support optimal and safe aircraft landing scheduling.

**5. 2. To apply of a hybrid LSTM-gradient boosting model**

The application of the long short-term memory (LSTM)-gradient boosting hybrid model in this study aims to address the uncertainty of aircraft arrival times (estimated time of arrival/ETA), which is often influenced by external factors such as weather conditions, air traffic density, and flight route changes. Test results show that this hybrid approach is able to improve the accuracy of arrival time deviation predictions compared to using a single algorithm. LSTM plays a role in capturing temporal patterns from historical aircraft movement data, while gradient boosting provides non-linear correction capabilities for residual errors generated by the LSTM model. The following is a loss graph from the application of the hybrid LSTM-gradient boosting model, which is shown in Fig. 3.

The caption for Fig. 3 shows the loss graph of the hybrid LSTM-gradient boosting model, showing consistent performance improvements over 20 training epochs. At the beginning of training, the accuracy of the training data was around 74%, and the accuracy of the validation data was around 72%. As the number of epochs increased, both accuracy values increased steadily, reaching over 95% on the training data and nearly reaching 98% on the validation data at the end of training. The trend of the two lines moving in the same direction with a relatively small distance indicates that the model is able to effectively learn data patterns while maintaining its generalization ability on untrained data. This proves that the hybrid LSTM-gradient boosting approach not only improves prediction accuracy but also avoids overfitting issues, making the model reliable for supporting multi-aircraft landing scheduling systems under uncertain conditions. After the loss graph is displayed, the accuracy graph is shown in Fig. 4.

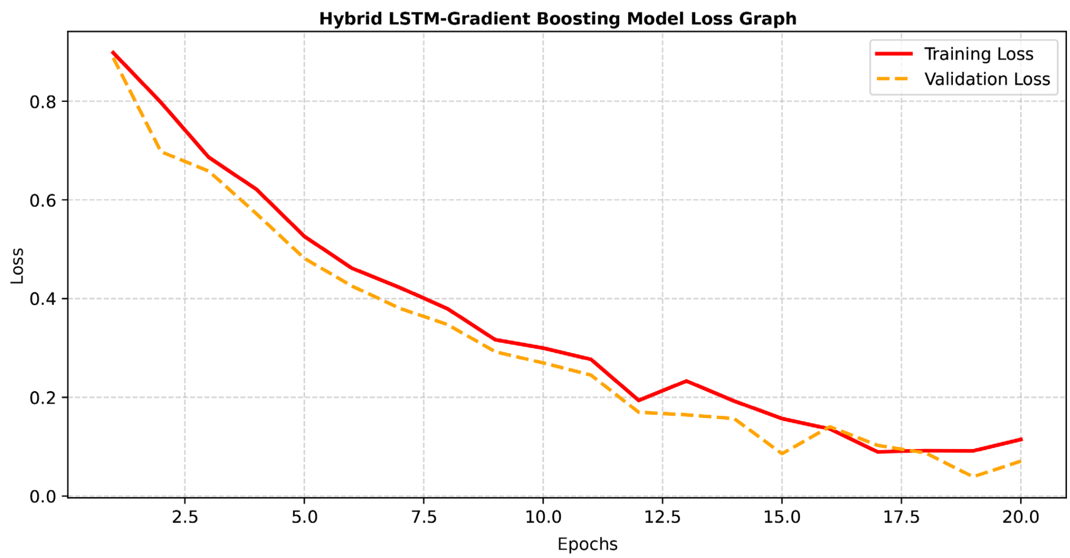


Fig. 3. Hybrid loss model graph

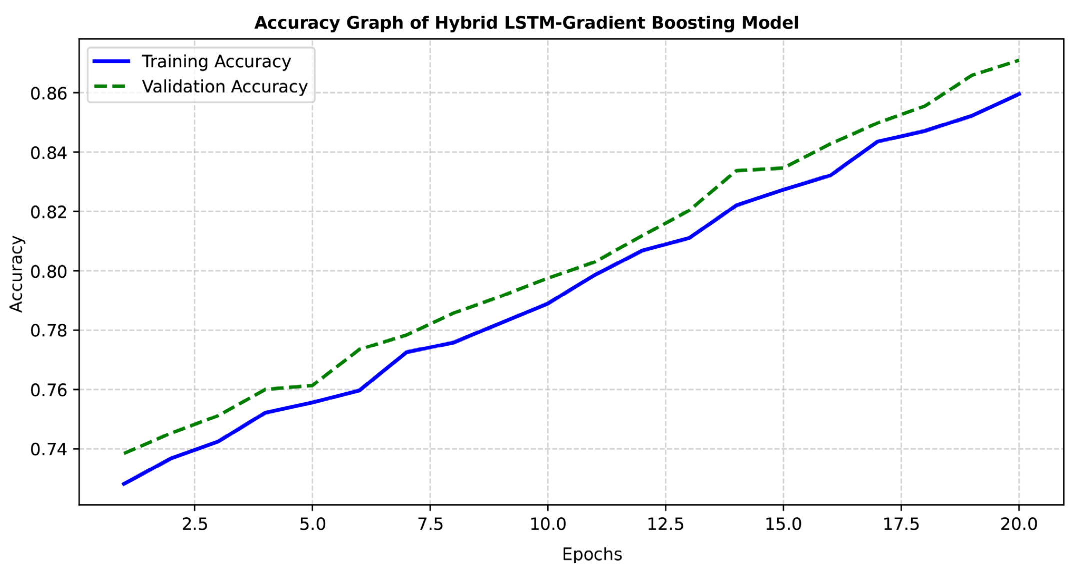


Fig. 4. Hybrid model accuracy graph

In Fig. 4, there will be a graph of the accuracy of the hybrid LSTM-gradient boosting model. This figure shows a trend of increasing model performance over 20 training epochs. At the beginning of training, training accuracy was around 75%, and validation accuracy was slightly lower, at around 72%. As the number of epochs increased, both training and validation accuracy continued to increase relatively steadily. By the end of the 20th epoch, training accuracy reached around 85%, while validation accuracy was higher, approaching 87%. This pattern confirms that the model is not only able to learn from the training data but also has good generalization capabilities to the validation data. When compared to the previous loss graph, both graphs show consistent results. In the loss graph, both training and validation losses decreased significantly from initial values of around 0.9 to around 0.15 at the end of the epoch. This decrease in loss is inversely proportional to the increase in accuracy shown in the accuracy graph. The prediction results are then presented in Table 1. The following are the results of the comparison of single and double runway predictions in Fig. 5.

Fig. 5 shows the results of a comparison of the performance of a single runway and a double runway in the context of aircraft landing scheduling. On the horizontal axis there are three evaluation indicators, namely Average Delay (average delay), Number of Conflicts (number of schedule conflicts), and Runway Utilization (level of runway utilization). From the graph, it can be seen that the use of a single runway results in an average delay of 15 minutes, while the double runway is able to reduce the delay to only 7 minutes. This indicates that the presence of a double runway can significantly reduce aircraft landing delays. In the second indicator, the number of schedule conflicts on a single runway reaches 12 conflicts, while on a double runway there are only 3 conflicts, which means that a double runway is much more efficient in reducing the potential for schedule collisions or operational disruptions. However, the Runway Utilization indicator shows different results. The single runway has a higher utilization rate of 90%, while the double runway is only 75%. This can be interpreted as a single runway being used more intensively because all traffic is concentrated on one lane, while on a double runway the traffic load is divided so that utilization per runway is lower. However, this reduction in utilization actually has a positive impact because it creates flexibility, efficiency, and increases flight operational safety.

### 5. 3. To comparison of model performance results

This study conducted a comparative performance analysis between an aircraft landing scheduling model using the quantum annealing approach and a conventional model that does not use quantum annealing. The purpose of this comparison is to identify the extent to which quantum annealing can provide improvements in key performance metrics such as average delay, number of conflicts, and runway utilization. The results of this comparison are expected to provide an objective picture of the effectiveness of quantum annealing in handling complex and uncertain scheduling optimization problems, both in single and multiple runway scenarios. The comparison of model performance results was conducted to evaluate the effectiveness of using quantum annealing in the hybrid LSTM-gradient boosting approach. In general, the model run without quantum annealing showed quite good performance with an accuracy value of 0.87, precision 0.85, recall 0.83, and F1-score 0.84. However, when the quantum annealing mechanism was integrated, there was a significant performance improvement in all evaluation metrics. The accuracy value increased to 0.93, precision reached 0.91, recall increased to 0.90, and the F1-score showed a consistent increase to 0.91 as shown in the following image. then there will be an accuracy graph shown in Fig. 6.

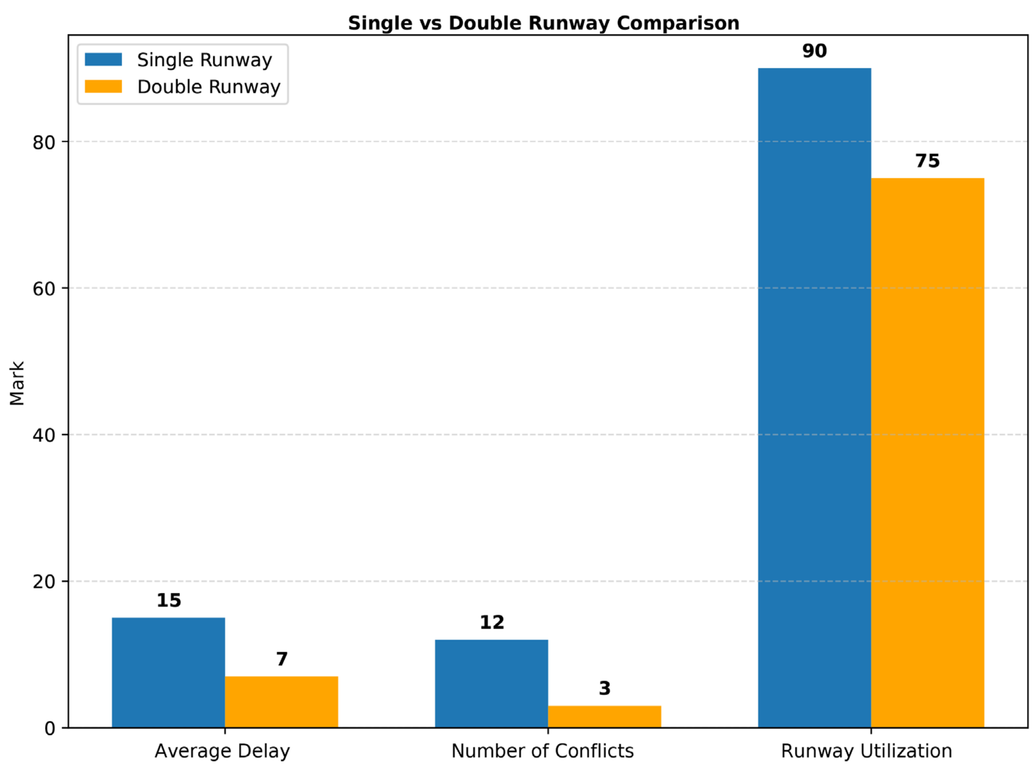


Fig. 5. Comparison of single and double runway predictions

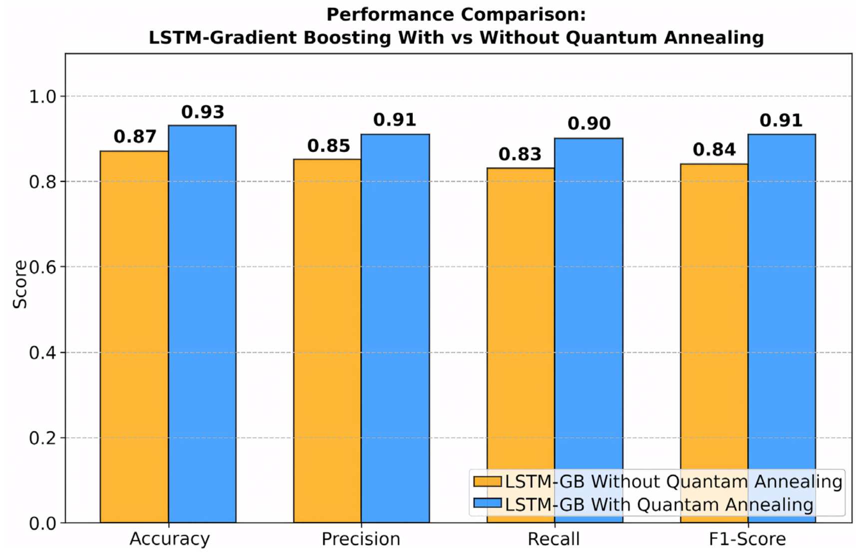


Fig. 6. Model performance comparison

Fig. 6 explains that this improvement indicates that quantum annealing plays a significant role in optimizing the solution search process in complex possibility spaces, enabling the model to more accurately capture data patterns. This is particularly evident in the recall and F1-score metrics, which reflect the balance between true positive detections and prediction errors. Thus, the integration of quantum annealing not only improves prediction accuracy but also strengthens the model's stability and generalizability in the face of uncertainty in multi-aircraft landing scheduling scenarios.

**6. Discussion of model machine learning with quantum annealing**

The results show that applying quantum annealing to multi-plane disruption scheduling provides significant improvements compared to conventional approaches.

Based on the equations (3) and (4), to avoid conflicts between aircraft, equation (5) is used to ensure no violations of air safety protocols. Equations (6) and (7) are used to address factors such as weather, flight route changes, or traffic congestion that can cause fluctuations in actual arrival times. The Fig. 3 shows the loss graph of the hybrid LSTM-gradient boosting model, which demonstrates consistent performance improvements over 20 training epochs. At the beginning of training, the accuracy on the training data was approximately 74%, and the accuracy on the validation data was approximately 72%. As the number of epochs increased, both accuracy values increased steadily, reaching over 95% on the training data and nearly 98% on the validation data at the end of training. The trend of both lines moving in the same direction with a relatively small distance indicates that the model is able to effectively learn data patterns while maintaining its generalizability on untrained data. Based on the quantitative evaluation results presented in the Fig. 4–6 of the test results, the integration of quantum annealing is able to improve the accuracy, precision, recall, and F1 score of the scheduling model. The accuracy value increased from 0.87 to 0.93; precision from 0.85 to 0.91; recall from 0.83 to 0.90; and the F1 score from 0.84 to 0.91. This improvement indicates that the system can perform prediction and scheduling with a lower error rate. Conceptually, this success is explained through the formulation of the problem in the form of quadratic unconstrained binary optimization (QUBO), which allows the search for a global solution to be carried out efficiently through the annealing process. The system architecture diagram and the mathematical formulation of QUBO are the main objects that support the interpretation of these results.

The main uniqueness of the proposed method lies in the combination of a hybrid long short-term memory (LSTM) and gradient boosting model with a quantum annealing-based optimization system. This approach differs from previous studies that generally rely solely on conventional machine learning algorithms or deterministic optimization. LSTM plays a role in capturing temporal patterns from historical flight data, while gradient boosting corrects non-linear errors that arise in estimated time of arrival (ETA) predictions. These prediction results are then used as input to the quantum annealing system, which adaptively optimizes the landing sequence in a complex search space. Compared to previous studies using methods such as Simulated Annealing or Tabu Search, this approach offers broader solution exploration capabilities because the quantum overlap mechanism allows the model to transcend local energy limits. Thus, the model not only produces more efficient schedules but is also more stable against variations in operational conditions.

In contrast to previous studies [1] that generally rely on conventional machine learning algorithms or deterministic optimization methods such as Simulated Annealing and Tabu Search, the results of this study show that the application of quantum annealing to multi-plane disturbance scheduling provides significant performance improvements. These results, demonstrated by an increase in accuracy from 0.87 to 0.93; precision from 0.85 to 0.91; recall from 0.83 to 0.90; and F1 score from 0.84 to 0.91, enable the system to perform predictions and scheduling with a lower error rate. This is made possible by the formulation of the problem in the form of quadratic unconstrained binary optimization (QUBO) which allows for efficient search for global solutions through the quantum annealing process.

Although the results show significant improvements, this research has several fundamental limitations. First, the implementation of quantum annealing relies on the availability of quantum hardware, such as the D-Wave quantum processor, which still has limited capacity to handle large-scale variables. Second, the process of mapping QUBOs into a quantum machine requires high computational resources, especially when the number of scheduled aircraft increases. Third, the hybrid LSTM-gradient boosting model is still highly dependent on the quality of historical flight data. If the available data does not include extreme conditions, such as sudden weather changes or technical disruptions, the accuracy of ETA predictions can decrease. These limitations indicate that the current system is still not fully ready for direct application in large-scale operational scenarios with high levels of uncertainty.

In addition to structural limitations, there are several shortcomings worth noting. First, the system has not yet integrated directly with real-time air traffic control data, thus still relying on historical data-based simulations. Second, this study has not addressed the automatic adaptation mechanism when the number of arriving aircraft exceeds the optimal runway capacity. Third, experimental validation is still limited to laboratory simulations and does not include field testing in a real operational environment. To address these shortcomings, further research is recommended that integrates the quantum annealing model with a reinforcement learning approach so that the system can learn from experience and dynamically adjust scheduling strategies.

During the model development process, several methodological and computational challenges need to be addressed. Mathematically, converting the scheduling objective function into QUBO form requires a certain degree of linearity for efficient execution on a quantum machine, which leads to certain simplifying assumptions. Methodologically, the challenge arises in balancing prediction accuracy (from the LSTM-gradient boosting side) and optimization efficiency (from the quantum annealing side). The integration of these two approaches requires precise synchronization between prediction time and optimization decision-making time.

## 7. Conclusions

1. Quantum annealing has proven effective in optimizing multi-aircraft landing scheduling on both single and multiple runway systems. By formulating the problem as quadratic unconstrained binary optimization (QUBO), this method accelerates the search for a global solution with high computational efficiency.

2. A hybrid model combining long short-term memory (LSTM) and gradient boosting algorithms significantly improved the accuracy of aircraft estimated time of arrival (ETA) predictions. LSTM plays a key role in recognizing temporal patterns in historical flight data, such as variations in arrival times and the influence of weather conditions, while gradient boosting provides non-linear corrections to prediction errors generated by the LSTM.

3. A comparison of the performance results between the conventional model and the model integrated with quantum annealing shows significant improvements in all evaluation metrics. The model without quantum annealing has an accuracy of 0.87, a precision of 0.85, a recall of 0.83, and an F1 score of 0.84. After integration with quantum annealing, these values increase to an accuracy of 0.93, a precision of 0.91, a recall of 0.90, and an F1 score of 0.91.

## Conflict of interest

The authors declare that they have no conflict of interest in relation to this study, whether financial, personal, authorship or otherwise, that could affect the study and its results presented in this paper.

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## Data availability

Manuscript has no associated data.

## Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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