Hindawi
International Journal of Aerospace Engineering
Volume 2024, Article ID 1614684, 11 pages
https://doi.org/10.1155/2024/1614684

Research Article

Model of Multi-Algorithmic-Based Optimization of 4D Approach Trajectory under Thunderstorm Weather

Li Lu and Xin Lai

School of Air Traffic Management, Civil Aviation Flight University of China, Guanghan, Sichuan 618307, China

Correspondence should be addressed to Li Lu; 421361599@qq.com

Received 18 October 2023; Revised 29 December 2023; Accepted 16 January 2024; Published 31 January 2024

Academic Editor: Pengyun Chen

Thunderstorms are recognized as perilous meteorological phenomena characterized by irregular and nonlinear movement, posing significant risks to approaching aircraft and necessitating technical methods to ensure safety to the aviation operations. This research specifically addresses the challenges associated with aircraft during the approach segment and introduces a multialgorithmic model focusing on the optimization of 4D approach trajectory. Firstly, the artificial neural network intelligent model was used to predict the thunderstorm movement track. Secondly, the multialgorithmic model combined by the rapidly exploring random tree with artificial potential field was built to plan the trajectory of the approaching aircraft under thunderstorm weather, and then, the mean filter was adopted to smooth the simulated approaching trajectory. Finally, the reliability of the model with a real case study was demonstrated. After optimized simulation by predicting the thunderstorm weather and trajectory-optimized multialgorithmic model mentioned above, the approach trajectory can be outputted successfully, but with some distortions, postprocessing with the mean filter results in a remarkably smooth approach trajectory, providing enhanced feasibility and efficiency for pilots navigating through thunderstorm weather conditions. It is ultimately proved that refined 4D trajectory operations under hazardous weather conditions hold substantial significance in advancing aviation safety and operational effectiveness.

1. Introduction

Flight safety is the cornerstone of the modern civil aviation, and hazardous weather is the main factor that affects the safety of aviation. Therefore, in February 2023, a questionnaire survey was conducted on the impact of different hazardous weather conditions on different flight segments, targeting more than 100 pilots from different domestic airlines and 50 controllers from air traffic systems in China. The result shows that 68.75% of pilots and 63.83% of controllers believe that thunderstorm weather affects flight safety the most; 62.65% of pilots and 89.36% of controllers believe that thunderstorms occur in the approach segment, which is the most dangerous.

Thunderstorms typically form under certain atmospheric conditions characterized by strong convective activity. The key steps for thunderstorm development are that moist air rising makes atmospheric instability, the updraft and downdraft movements contribute to the development of towering cumulonimbus clouds, and the altitude of the thunderstorm cloud can reach to thousands of meters, which pose serious threat to the approaching aircraft.

In aviation meteorology, the main detection method for thunderstorms is usually using aviation weather radar. The color blocks ranging from blue to purple displayed by the radar stand for the intensity of precipitation echoes; usually, yellow, red, and purple echoes indicate moderate to heavy rain in the local area and may be accompanied by severe weather such as lightning and strong winds; the thunderstorm weather echo on airborne radar screen is shown in Figure 1 [1]. If an aircraft is struck by lightning, important equipment such as the fuselage skin and high-frequency or VHF antennas may be damaged. If the aircraft flight into the downburst of thunderstorm weather, it will create more serious safety hazard situation [2].

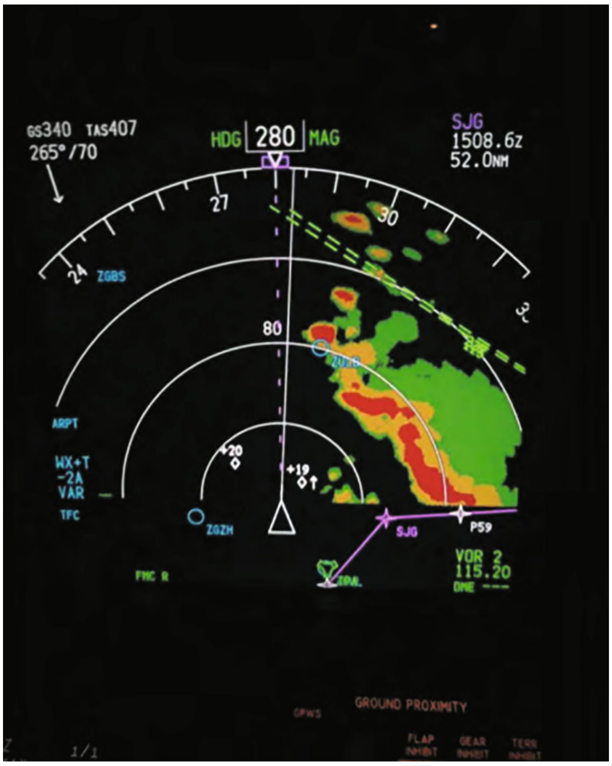


Figure 1: Airborne weather radar echo display interface.

In the past two years, aircraft have suffered frequently from thunderstorms; for instance, Australian Jetstar Airlines and American Airlines, respectively, encountered lightning strikes during approach segment in May 2022 and February 2023, resulting in multiple burning marks on the fuselage, as shown in Figure 2. Thunderstorm weather seriously threatens flight safety and causes economic losses [3].

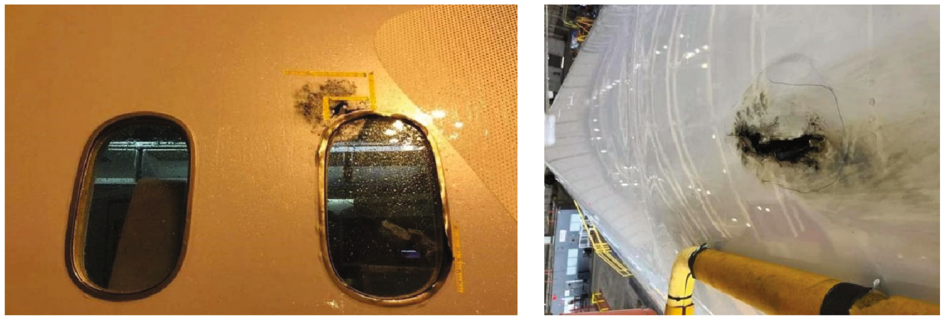
In summary, how to fundamentally ensure the safety of approaching aircraft in thunderstorm weather is the core thinking of this research, which also meets the urgent research needs of China's civil aviation transportation development. Normally, sudden thunderstorm weather occurs into the terminal area, and traditional manual management and flight decision-making are difficult to satisfy the safety requirements.

2. State of the Art

With the development of civil aviation technology, the impact of thunderstorms on flight safety has received widespread attention. Thunderstorm weather has the characteristics of quick movement and nonlinear changes; hence, accurate movement prediction of thunderstorm plays an important role in the basic theory of this research. Scholars such as Litta et al. [4] and Collins and Tissot [5] believe that the artificial neural network (ANN) model is an effective modeling method for predicting the movement trend of thunderstorm clouds, which can predict the thunderstorm movement in this study. Ivanova [6], Yang et al. [7], and other scholars analyzed the characteristics, movement, modeling methods, constraint conditions, and movement prediction ideas of thunderstorm weather based on historical sample data, demonstrating that 3D spatial modeling is reliable for thunderstorm weather prediction. The above researches made effort to use long-term thunderstorm data samples for processing and conducted detailed analysis on the temperature and water density inside the thunderstorm. However, the thunderstorm appearance is out of sudden; in order to solve the thunderstorm avoidance problem during the approach segment, it is necessary to use short-term thunderstorm data samples to analyze movement. Dunn and Shultis [8] proposed the Monte Carlo model and demonstrated that it has good performance in predicting variable and complex random thunderstorm clouds.

At present, terminal area trajectory optimization is a research focus all around the world, and the existing researches provide many methods to the trajectory optimization for this research. Hentzen et al. [9] elaborated that flight trajectory prediction must be a focus in future research under uncertain and dangerous weather and proposed the application of data statistical models for flight trajectory prediction under uncertain weather. González-Arribas et al. [10] proposed an algorithm for numerical optimal control, which simulates the optimal flight trajectory for different weight aircraft models under moving thunderstorm weather. Zeh et al. [11] sampled 10000 climb tracks and used a neural network model to fit the trajectories of aircraft with different takeoff weights. The results showed that the fitting degree could reach 90% and the algorithm had high accuracy. However, for trajectory optimization under uncertain conditions, using this algorithm has limitations. Juntama et al. [12] proposed a König metric algorithm to evaluate air traffic complexity and optimize 4D trajectories. The results showed that using this method can reduce traffic complexity by more than 95% and save 80 tons of fuel. Liu et al. [13] suggested considering clustering technologies as a trajectory design method. By comparing four optimization models, it was found that the random tree model has the best performance, which also provides ideas for the selection of trajectory optimization models in this research. In the preliminary work, the author proposed the idea of optimizing the approach diversion trajectory by predicting the movement of thunderstorms, analyzing from the longitude and dimension directions. Furthermore, the dynamic window algorithm was used to optimize trajectory of the approaching aircraft by avoiding thunderstorm [14]. The above scholars provided important thinking for this research, but for the optimization of flight dynamic obstacle avoidance trajectory, a simple optimization model is insufficient to meet the requirements and needs to consider the time dimension. This research proposes a kind of combined algorithm to optimize the trajectory of approaching aircraft under thunderstorm weather.

Therefore, research on integrated operational dimensions based on intelligent algorithms still has great potential for development. In 2022, scholars such as Guastavino et al. successfully used machine learning models to predict thunderstorm weather and set up warning systems, which were ultimately published in the journal *Nature* [15]. This achievement provides guidance for the research ideas and methods.



(a) (b)

Figure 2: Aircraft damaged by thunderstorms ((a) Jetstar and (b) American Airlines).

3. Illustration of Multialgorithmic Model

This research is based on the optimization of the 4D approach trajectory under thunderstorm weather. The research process requires the following tasks: first, predicting the movement of thunderstorm clouds; second, optimizing the diversion trajectory; and third, smoothing the trajectory. Based on the above three requirements, this research plans to comprehensively implement the research theme from "points," "lines," and "surfaces," to design a practical and feasible algorithm model, to draw an intuitive and visible optimized approach trajectory, to serve the future goal of intelligent air traffic control for refined operation of four-dimensional flight trajectories, and to implement various indicators for aircraft approach safety in thunderstorm weather.

This research requires computer simulation and mathematical modeling to achieve objectives. MATLAB simulation software has powerful matrix operation and graphic processing capabilities. Therefore, this research is programmed and simulated by MATLAB, and the detailed plan is as follows:

(1) Processing radar echoes of thunderstorm weather at different times, extraction of feature thunderstorm color block data, establishment of thunderstorm data matrices in samples at different times, construction of artificial neural network models, and simulation of thunderstorm cloud movement trends and random thunderstorm cloud point states in the terminal area

(2) When thunderstorm weather occurs, adopt random tree trajectory optimization model, set entry points and runway positions, clarify the constraints of approach flight, and simulate the 4D approach optimization trajectory under the moving thunderstorm cloud

(3) The trajectory is not always very smooth; hence, the filter was used to discard some waypoints with big turning angle to the direction of the trajectory

This research is based on the theoretical knowledge of multiple disciplines such as air traffic management, flight procedure design, and aviation meteorology predicting the movement of thunderstorm and exploring and optimizing flight trajectory when encountering thunderstorm weather during aircraft approach. The overall technical flow map is shown in Figure 3.

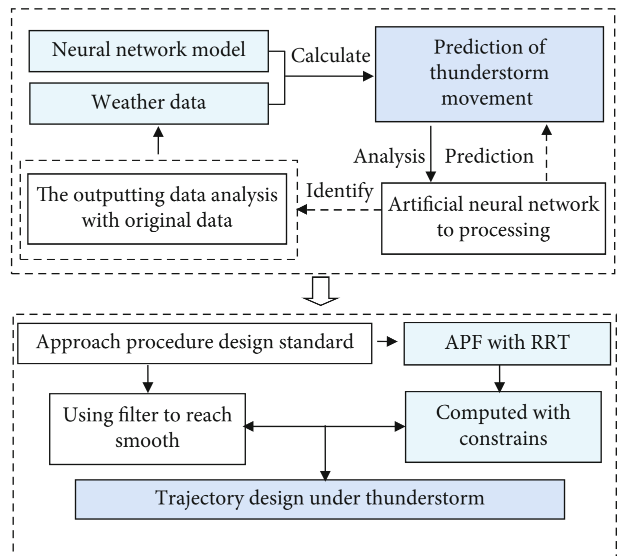


Figure 3: Theoretical research model for trajectory optimization under thunderstorm weather.

3.1. Prediction of Thunderstorm Movement. In this part, this research will extract the color of thunderstorm, analyzing and predicting the short-term movement of thunderstorm. The flow chart of this part is shown in Figure 4.

Before extracting thunderstorm from radar echoes, it is necessary to convert colors from RGB space to HSV, which is more capable of perceiving color changes and accurately extracting feature thunderstorm color blocks. The result of the processed thunderstorm is shown in Figure 5.

Combining the extracted thunderstorm feature color blocks, further data processing is needed; then, before creating a thunderstorm matrix, the scope of thunderstorms should be determined; hence, drawing the envelope of the thunderstorm is the blue dots shown as Figure 6.

Figure 6 shows the thunderstorm area of terminal at a certain time from the radar echo, after confining the scope

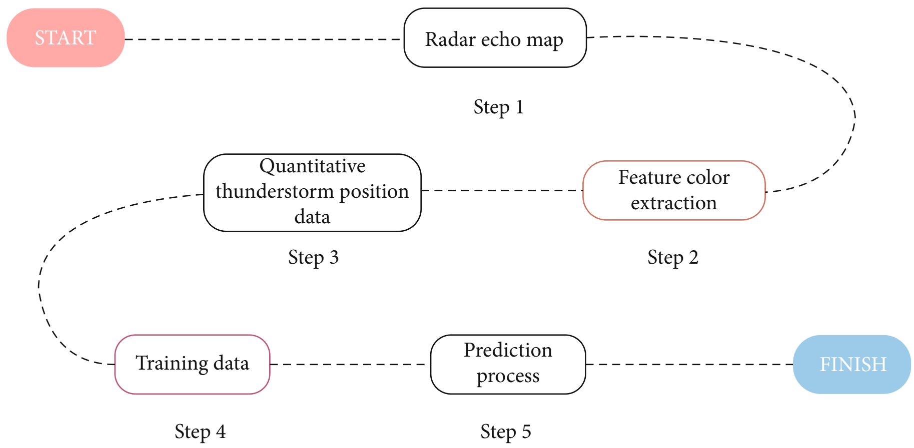


FIGURE 4: Flow chart of thunderstorm movement.

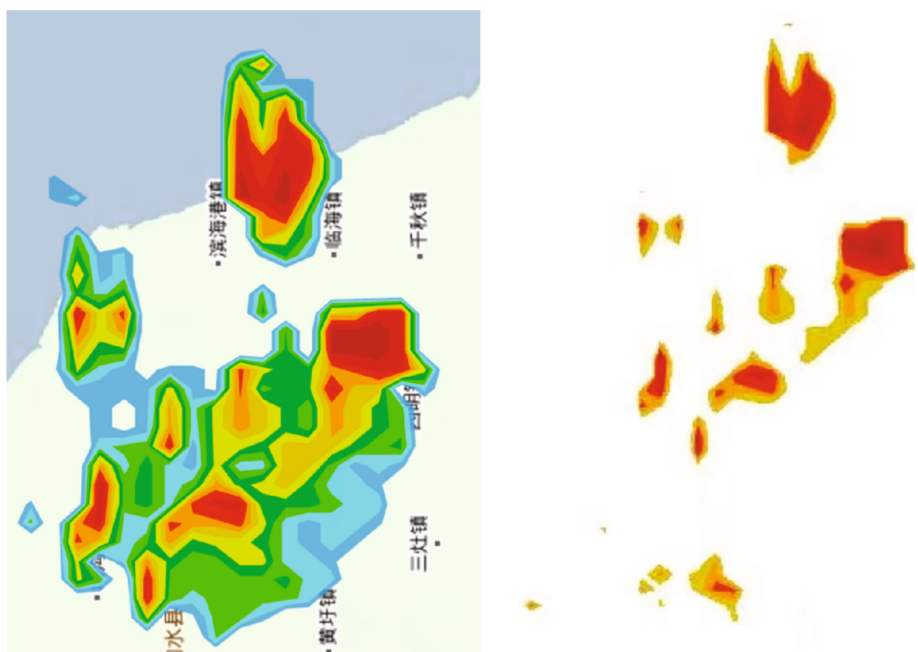


FIGURE 5: The extracted feature color blocks of thunderstorm.

of the thunderstorm; the data can be depicted by a matrix shown as follows:

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix}. \quad (1)$$

From formula (1), the terminal area can be regarded as X, m represents the longitude serial number, and n represents the latitude serial number. If thunderstorm occurs in one position, a value of 1 can be assigned; otherwise, it is 0.

3.2. Thunderstorm Movement Prediction Model. After setting up the thunderstorm data matrix, the appropriate thunderstorm predicted model should be adopted; meteorological prediction always acquires many different algorithms and methods, which include numerical weather prediction model (NWP), GFS (global forecast system), and artificial neural networks (ANN). Among the above models, ANN can adapt to different data structures and automatically learn complex relationships between input features, which has the ability to simulate nonlinear relationships in meteorological systems. Therefore, this research adopts ANN to predict the short-term and complex movement of thunderstorm. The flow chart is shown in Figure 7 for the model to do sample data processing [16–18].

Among them, $\boldsymbol{X}_s(\boldsymbol{t})$ is the input data of sampled thunderstorm, processed by several neurons, and output $\boldsymbol{Y}_r(\boldsymbol{t}+\mathbf{1})$ is the predicted thunderstorm matrix; the model is expressed as follows:

$$\boldsymbol{Y}_r(\boldsymbol{t}+\mathbf{1}) = \sum_{i=1}^{k} \boldsymbol{v}_{r,k} \times g\left(\sum_{j=1}^{s} \boldsymbol{w}_{k,s} \times \boldsymbol{X}_s(\boldsymbol{t})\right). \quad (2)$$

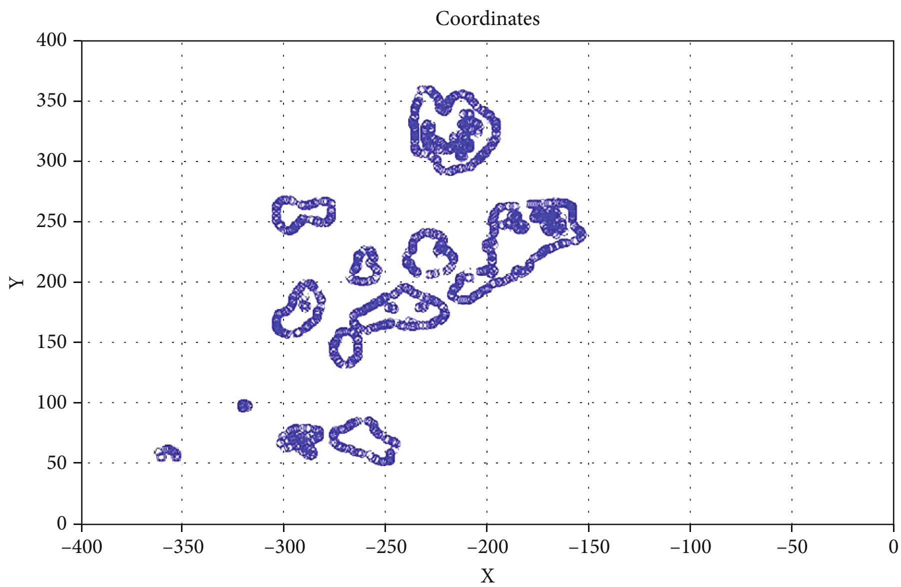


Figure 6: The envelope of the thunderstorm.

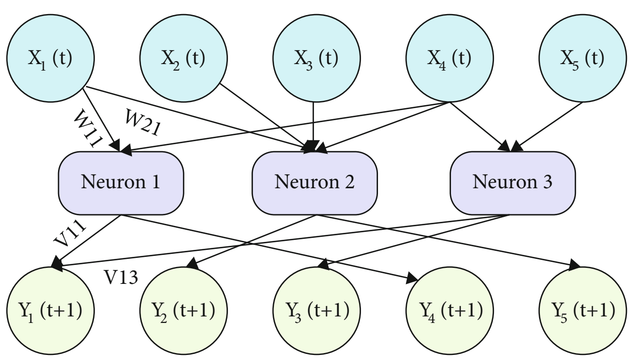


Figure 7: The artificial neural network function model.

r represents the r-ranked thunderstorm data in the predicted output at time $t+1$, s represents the s-ranked thunderstorm data point in the input, k represents the number of neurons, and $\boldsymbol{w}_{k,s}$ and $\boldsymbol{v}_{r,k}$, respectively, represent the weights of input and output calculation. Due to the nonlinear movement of thunderstorms, optimization is needed in the processing to avoid excessive positive and negative deviations. Therefore, in this research, adding a nonlinear activation function $g = 1/(1+e^{-x})$ can make the results more reliable.

The corresponding thunderstorm is $X = \{X_1, X_2, \cdots, X_i\}$ at different times $t = \{T_1, T_2, \cdots T_i\}$; as for future times $t = \{T_{i+1}, T_{i+2}, \cdots, T_{\text{pred}}\}$, based on the above principles, the prediction matrix of thunderstorm data $Y = \{Y_{i+1}, Y_{i+2}, \cdots, Y_{\text{pred}}\}$ at different future times can be output.

3.3. Optimization of 4D Approach Trajectory under Thunderstorm Weather. The movement of thunderstorm can be seen as four-dimensional moving obstacles. This research includes two steps, setting constraints and establishing the trajectory optimization algorithm model. The process implementation is shown in Figure 8.

L(nm), turning angle of each segmentθ(°), descent gradientGr(%), and true air speedTAS(km/h). This research focuses on three flight approach segments: initial approach, intermediate approach, and final approach. The specific constraints are set as shown in the following:

$$\text{Constraints} = \begin{cases} \theta \in (0{,}120), \text{TAS} \in (300{,}450) & (\text{arrival segment}), \\ \theta \in (0, 30), \text{TAS} \in (250{,}350), L \in (10, 20) & (\text{intermediate segment}), \\ \theta \in (0, 15), \text{TAS} \in (220{,}300), L \in (5, 15) & (\text{approach segment}). \end{cases} \quad (3)$$

In this research, the used multiple algorithmic model will have a better performance. For instance, setting obstacles in the statement, respectively, rapidly exploring random tree, artificial potential field algorithm, and multiple algorithmic model (RRT and APF combined) were used to test the performance. The result is shown in Figure 9.

Figure 9 shows that the multiple algorithmic model has a better performance due to trajectory length and elapsed time advantages; therefore, in this research, the RRT and APF combined algorithm was adopted [19, 20]. The artificial potential field algorithm mainly solves the obstacle avoidance problem of dynamic obstacles; by this way, it can create

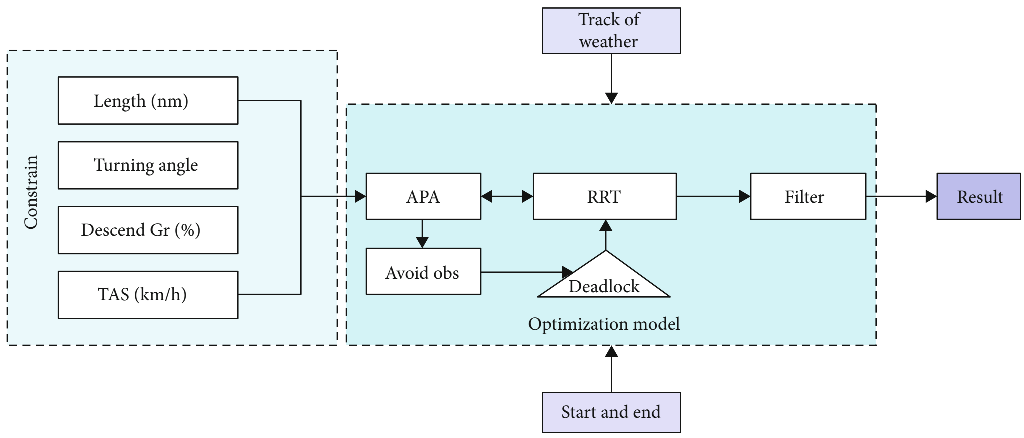


Figure 8: The process of approaching trajectory prediction.

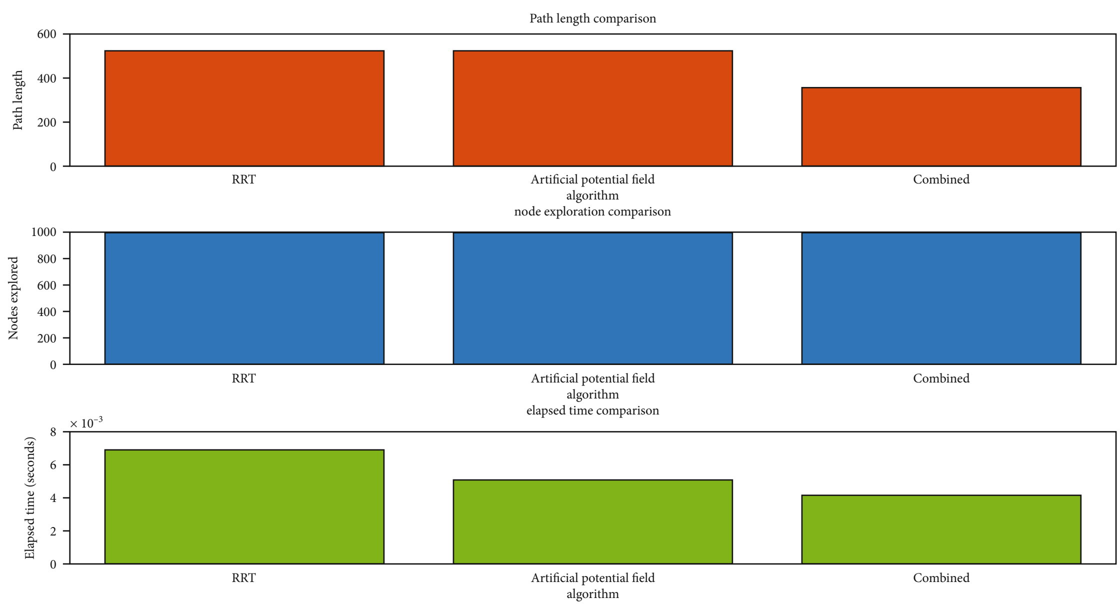


Figure 9: The performance test of three algorithms.

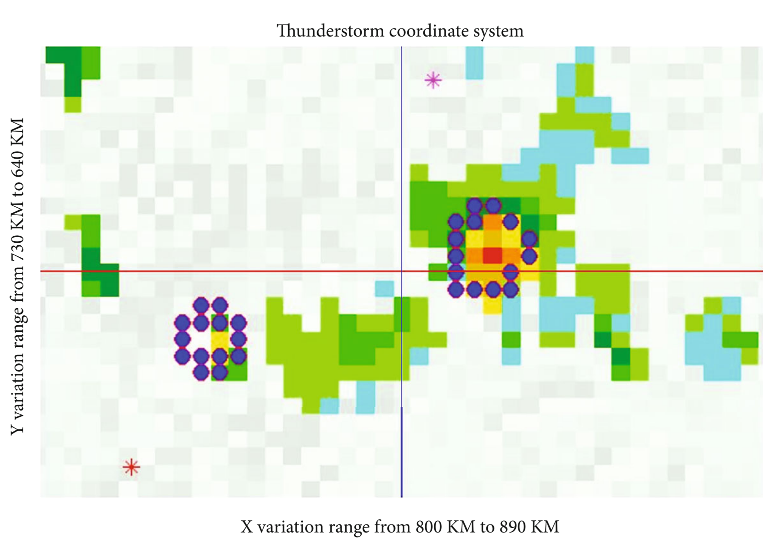


Figure 10: Simulation area of thunderstorm echo map.

Table 1: The thunderstorm dataset (km).

Initial X value	Initial Y value	Predicted X value (24 min)	Predicted Y value (24 min)
826.0	692.5	827.48	687.50
828.0	692.5	829.50	687.50
826.0	694.9	827.48	689.90
828.0	694.9	829.50	689.90
826.0	700	827.48	695.00
828.0	700	829.50	695.00
826.0	705.4	827.48	700.40
828.0	705.4	829.50	700.40
821.5	676	822.98	671.00
821.5	694	822.98	689.00
821.5	700	822.98	695.00
830.5	676	831.98	671.00
830.5	694	831.98	689.00
830.5	700	831.98	695.00

the attractive and repulsive forces generated by the external environment on the aircraft and under the relative mutual exclusion relationship with thunderstorm, ultimately completing the conflict-free optimization between the aircraft and thunderstorms. The destination airport generates attraction on the aircraft, while thunderstorm generates repulsion on the aircraft; formulas (4)–(6) are shown as follows:

$$\boldsymbol{F}_{\boldsymbol{att}} = \mu \times dg \times \boldsymbol{n}_{\boldsymbol{rg}}, \tag{4}$$

$$\begin{aligned} \boldsymbol{\eta}_{\boldsymbol{rep}} &= \varepsilon \times R \times dg \times \left(\frac{1}{d} - \frac{1}{\rho}\right)^2 \times \boldsymbol{n}_{\mathrm{or}} \\ &\quad - \varepsilon \times R \times \left(\frac{1}{d} - \frac{1}{\rho}\right) \times \frac{dg^2}{d^2} \times \boldsymbol{n}_{\boldsymbol{rg}}, \end{aligned} \tag{5}$$

$$\begin{cases} \boldsymbol{F}_{\boldsymbol{rep}} = 10 \times \boldsymbol{\eta}_{\boldsymbol{rep}} & (d \in [\tau, 2\tau)), \\ \boldsymbol{F}_{\boldsymbol{rep}} = 100 \times \boldsymbol{\eta}_{\boldsymbol{rep}} & (d \in (0, \tau)), \\ \boldsymbol{F}_{\boldsymbol{rep}} = 0 & (\text{other condition}). \end{cases} \tag{6}$$

Among them, μ and e represent the coefficients of attraction and repulsion; R represents the range of repulsive force action; dg represents the square of the distance between the target or obstacle and the aircraft; $\boldsymbol{\eta}_{\boldsymbol{rep}}$ represents a unit repulsion; the closer the aircraft is to the thunderstorm cloud, the greater the repulsive force generated; d represents the aircraft step size; ρ represents the effective distance of repulsion; $\boldsymbol{n}_{\mathrm{or}}$ and $\boldsymbol{n}_{\boldsymbol{rg}}$ represent a mutually exclusive constant.

When the simulation environment detects that the flight trajectory is in a deadlock state, the rapidly exploring random tree algorithm can be used for reference; this algorithm is used to find the optimal trajectory in complex environments, initialize the starting point, and randomly select adjacent nodes from the established state space. If there are obstacles in the trajectory planning process, the next path node will be changed. After multiple iterations, an optimal trajectory can be obtained. Imaging that the aircraft is in

Table 2: Procedure data setting.

	Length (km)	Gradient (%)	Turning angle (°)
Initial approach	20	4%	0 to 120
Intermediate approach	15	0	0 to 30
Final approach	10	5.2%	0

Table 3: Simulating data setting.

Parameters	Value
TAS	380 km/h
The distance avoided from thunderstorm	1 km
The radius distance of $\boldsymbol{F}_{\boldsymbol{rep}}$	5 km
Direct proportion value of $\boldsymbol{F}_{\boldsymbol{rep}}$	3000000
Direct proportion value of $\boldsymbol{F}_{\boldsymbol{att}}$	6000000
Time period	24 minutes
$\boldsymbol{w}_{k,s}$	$\frac{20 \times s}{k+s}$
$\boldsymbol{v}_{r,k}$	$\frac{r}{k+r}$
Time step	0.5 seconds

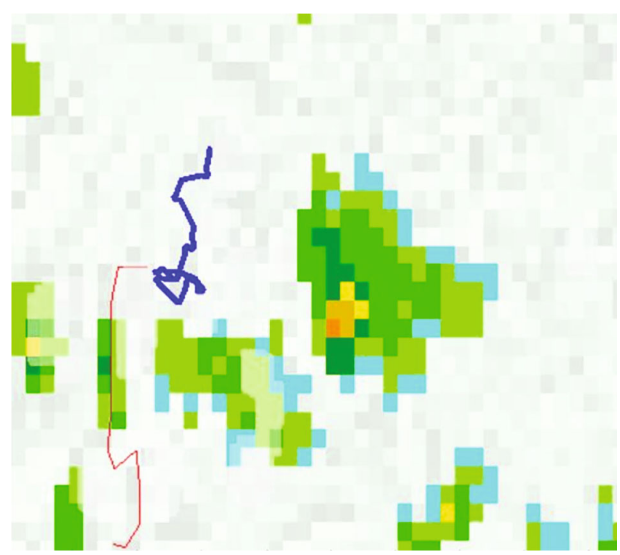


Figure 11: The processing of trajectory prediction.

the position $p_n = (x_n, y_n)$, the next point is the nearest without obstacle; assuming $p_{n+1} = (x_{n+1}, y_{n+1})$, the length of every step can be expressed by the following:

$$L_{n+1} = \sqrt{(x_{n+1} - x_n)^2 + (y_{n+1} - y_n)^2}. \tag{7}$$

When n approaches infinity, it can be assumed that $\overline{v_n}$ follows a uniform distribution, and formula (8) is

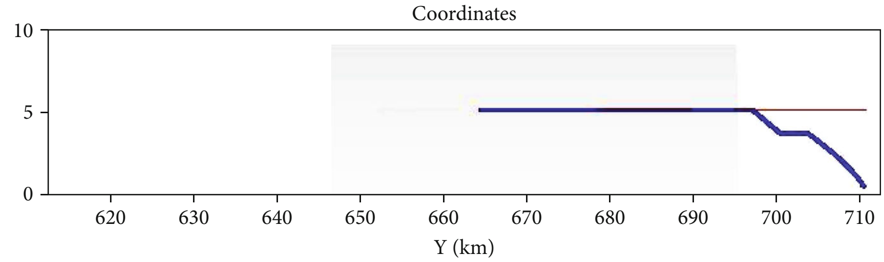


Figure 12: The profile trajectory.

$$\overline{v_n} = \frac{d(p_{n+1} - p_n)}{dt}. \quad (8)$$

For RRT optimization theory, the most optimum trajectory is the shortest sum of steps after iterative operation; formula (9) is

$$\begin{cases} L_{\text{total}} = \min \sum_{n=0}^{\text{iterations}} L_{n+1}, p_n + \bar{v}t \neq p_{\text{storm}} + \overline{v_o}t, \\ p_{n+1} \text{ is not available}, p_n + \bar{v}t = p_{\text{storm}} + \overline{v_o}t. \end{cases} \quad (9)$$

4. Case Study

This research provides an example in southwest of China. Due to the geography, the weather in this area is always stormy and cloudy with a lot of turbulence. The weather data is obtained in the national weather Internet in June 6, 2023. The original and processed thunderstorm is shown in Figure 10; the blue dots around the thunderstorm are the envelope of the thunderstorm.

The thunderstorm has been processed into blue dots, and the red and yellow thunderstorm color blocks of thunderstorm are enclosed with the blue marking dots, as can be seen in Figure 10. With the limitation of the paper, the left thunderstorm datasets of Figure 10 provided by MATLAB with X and Y coordinates are shown in Table 1; there are 14 dots.

After the initial datasets are processed by the artificial neural network function model with 24 min time period, the data of the left thunderstorm of Figure 10 is predicted which can be seen as Table 1. The positions of every blue marking dots have been changed, and it depicts that the thunderstorm is moving northward.

Then, for simulating the appropriate flight trajectory, according to the standard of flight procedure design, the setting of the approach procedure data is given in Table 2.

Finally, the simulating datasets are shown in Table 3; with these data, the appropriate approach trajectory can be artificially designed by MATLAB programming.

5. Results

With the simulation, the length and width of the map are 2150 km and 2000 km, imaging that the position of arrival point is 864.35 and 661.76 with altitude 5000 m; the destination airport is 842.96 and 723.38 with altitude 0 m, imaging

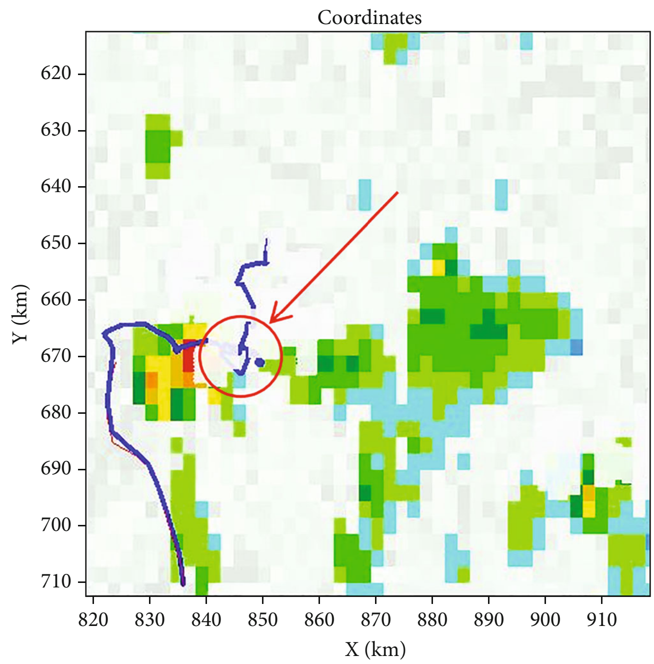


Figure 13: The results of trajectory prediction.

that the elevation of airport is 0 m. As seen from the simulation result shown in Figure 11, the red line gives the dynamic obstacle-avoidance guidance produced by artificial potential field algorithm firstly than the blue line which is decided by RRT algorithm if the processing is fallen into deadlock.

Finally, as Figure 12 shows, the profile of trajectory shows a very excellent performance for three approach segments; thus, the result meets the requirements for the gradient and the structure of the approach flight procedure.

However, the trajectory of the simulation shown in Figure 13 is very tortuous and not smooth for flight operation, shown as the arrow points in the trajectory part in a red circle in Figure 13; a smooth trajectory should meet the requirements that every turning corner of the flight trajectory should not exceed to 120°; however, in Figure 13, there are two or more turns exceeding 180° within 10-kilometer radius. The reason-result in this situation is that the thunderstorm presents nonlinear change; when the predicted thunderstorm appears suddenly in front of the aircraft, the trajectory will torch together to avoid the thunderstorm.

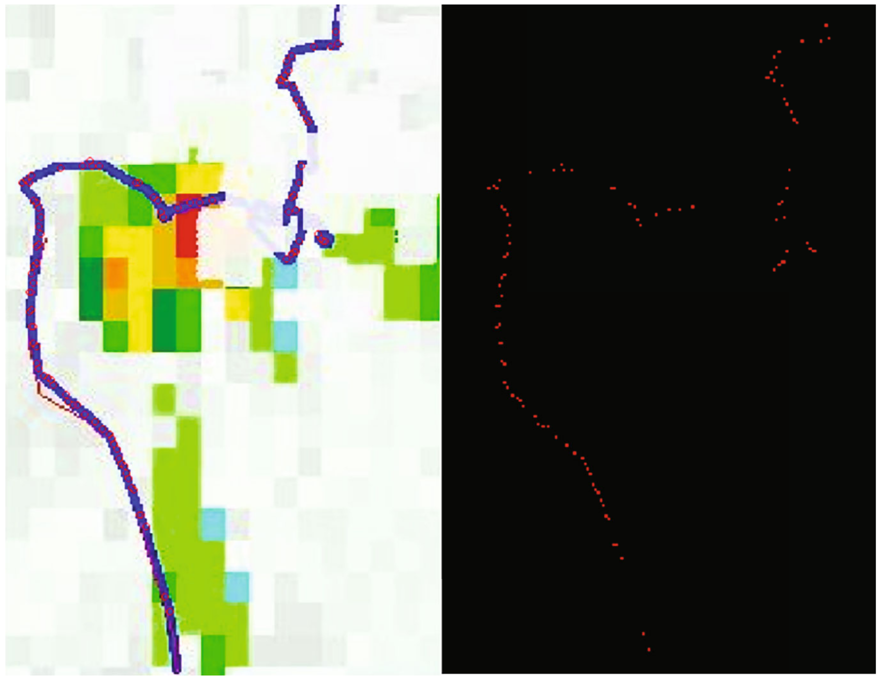


Figure 14: The dots sampled from the simulated trajectory.

However, in reality, the trajectory of approach is relatively smooth because it is convenient for pilot to operate the aircraft. In addition, approach flight stage is so critical that it needs smooth trajectory to make sure for the safety of aircraft. In order to deal with this problem, optimize the trajectory in the further step, this research will adopt a kind of filter to smooth the simulated approach trajectory.

At first, the trajectory was sampled into 100 dots. Figure 14 shows that the red point is the sampled dots and every dot has its own coordinate.

Then, this research adopts the mean filter to extract the available dots to smooth the trajectory; this kind of filter is usually used in image processing and signal processing; the principle of this step is to replace the value of the target dot with the average value of chaotic dots, thus achieving smoothing and reducing noise.

The core idea of the mean filter is to check each dot of the original trajectory during the filtering process to decide whether it is beneficial for smoothness. Assume that the target dot is at the center of a round sliding window, and then, calculate the average value of all dots which can be depicted as$p_i = (x_i, y_i)$within the window and use it as the new value of the target dot. The thinking can be depicted as follows:

$$\bar{p} = \left(\frac{\sum_i^k x_i}{k}, \frac{\sum_i^k y_i}{k} \right). \tag{10}$$

Among them, $\sum_i^k x_i/k$ and $\sum_i^k y_i/k$ represent the average of x and y value in the window, respectively, and k represents the number of the dots; this method can calculate the average value of the dots inside the sliding window.

With the sliding window application of the mean filter, the trajectory can be divided into several rounding areas with the radius of 2.5 km. Figure 15 shows that the center of red circle is the target dot and other dots have been discarded.

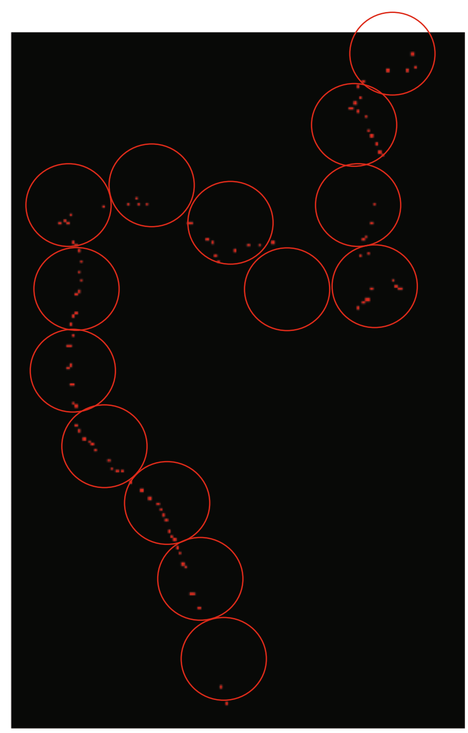


Figure 15: The sliding window used to filter the disordered dots.

Connecting all the average dots with the blue line, Figure 16 can be obtained. The blue line is the optimized trajectory. Finally, the trajectory seems very smooth, and each turning corner can be joined well together with different

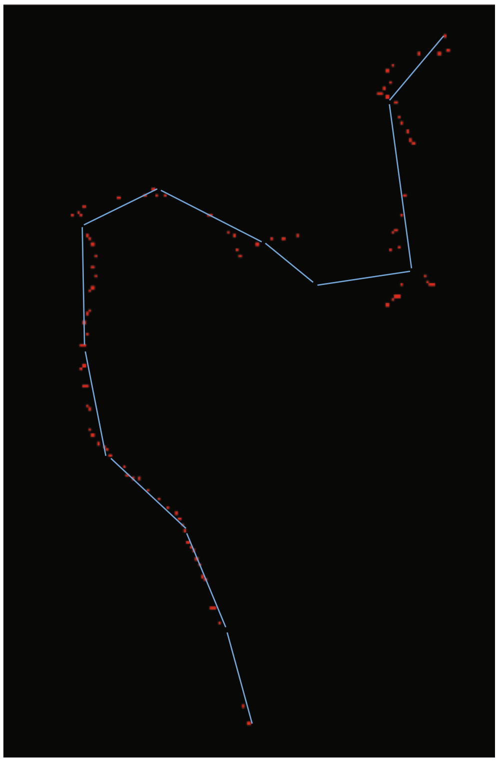


Figure 16: The optimized 4D trajectory under thunderstorm weather.

approaching segments; it means that the filter is necessary for the trajectory optimization in this research.

6. Conclusion

Thunderstorm weather always occurs in the terminal area with a relatively low altitude; by the way, when aircraft approach at a low flight level, it easily encounters danger. This research is based on this background, adopting multiple algorithmic model to process the approach trajectory optimization. Firstly, artificial neural network was used to predict thunderstorm movement, and then, artificial potential field algorithm was combined with rapidly random tree method to design the approaching trajectory of aircraft; the results are not very ideal due to the thunderstorm's nonlinear movement, and the original trajectory is very distorted; thus, this research adopts the mean filter to smooth the approaching trajectory, the disordered dots are filtered out, and ultimately, the trajectory turns to be more smooth and more practical for pilot to operate during thunderstorm weather.

However, this research still has some further work to be done; for example, the filter only selects the sampled dots within the two-dimensional planar, and the altitude change is not taken into account; therefore, this part will be addressed in the further research.

Data Availability

The data that support the findings of this study are available.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

This research is supported by the (1) China Scholarship Council (Grant No. 202108510115) and (2) Research on Feature Extraction and Event Correlation of Aviation Intelligence Information in Big Data Environment (2023 Central University Level Key Projects) (Grant No. ZJ2023-003).

References

[1] Z. Ruilei, "Interpretation of radar intensity echo map in meteorological science popularization," *East China Meteorological Service*, vol. 14, 2020https://mp.weixin.qq.com/s/JJz5O5_WWSYHLCYuWRfDMw.

[2] H. Guangqin, L. Li, H. Jingyu, and M. Xin, "Research on flight diversion decision under thunderstorm weather based on least squares method," *Safety and Environmental Engineering*, vol. 4, no. 26, pp. 171–176, 2019.

[3] "Anonymity. American Airlines' aircraft was hit by thunderstorms and penetrated the fuselage skin," Civil aviation matters. February 26, 2023. http://www.aero.cn/2023/0225/145963.html.

[4] A. J. Litta, S. M. Idicula, and C. N. Francis, "Artificial neural network model for the prediction of thunderstorms over Kolkata," *International Journal of Computer Applications*, vol. 50, no. 11, pp. 51–55, 2012.

[5] W. G. Collins and P. Tissot, "Thunderstorm predictions using artificial neural networks," in *Artificial Neural Networks-Models and Applications*, IntechOpen, 2016.

[6] A. R. Ivanova, "International practices of thunderstorm nowcasting," *Russian Meteorology and Hydrology*, vol. 44, no. 11, pp. 756–763, 2019.

[7] X. Yang, H. Xing, W. Xu, and X. Ji, "A moving path tracking method of the thunderstorm cloud based on the three-dimensional atmospheric electric field apparatus," *Journal of Sensors*, vol. 2021, Article ID 8856033, 13 pages, 2021.

[8] W. L. Dunn and J. K. Shultis, *Exploring Monte Carlo methods*, Elsevier, 2023.

[9] D. Hentzen, M. Kamgarpour, M. Soler, and D. González-Arribas, "On maximizing safety in stochastic aircraft trajectory planning with uncertain thunderstorm development," *Aerospace Science and Technology*, vol. 79, pp. 543–553, 2018.

[10] D. González-Arribas, M. Soler, M. Sanjurjo-Rivo, M. Kamgarpour, and J. Simarro, "Robust aircraft trajectory planning under uncertain convective environments with optimal control and rapidly developing thunderstorms," *Aerospace Science and Technology*, vol. 89, pp. 445–459, 2019.

[11] T. Zeh, J. Rosenow, R. Alligier, and H. Fricke, "Prediction of the propagation of trajectory uncertainty for climbing aircraft," in *2020 AIAA/IEEE 39th Digital Avionics Systems Conference (DASC)*, pp. 1–9, San Antonio, TX, USA, 2020.

[12] P. Juntama, S. Chaimatanan, S. Alam, and D. Delahaye, "A distributed metaheuristic approach for complexity reduction in air traffic for strategic 4D trajectory optimization," in *2020 International Conference on Artificial Intelligence and Data*

Analytics for Air Transportation (AIDA-AT), pp. 1–9, Singapore, 2020.

[13] Y. Liu, M. Hansen, D. J. Lovell, and M. O. Ball, "Predicting aircraft trajectory choice-a nominal route approach," in *Proc of the International Conference for Research in Air Transportation*, Spain, 2018.

[14] L. Lu and C. Liu, "Research on trajectory planning in thunderstorm weather based on dynamic window algorithm during approach segment," *Scientific Programming*, vol. 2022, Article ID 7031928, 10 pages, 2022.

[15] S. Guastavino, M. Piana, M. Tizzi et al., "Prediction of severe thunderstorm events with ensemble deep learning and radar data," *Scientific Reports*, vol. 12, no. 1, article 20049, 2022.

[16] J. Guo, W. Wang, Y. Tang, Y. Zhang, and H. Zhuge, "A CNN-Bi_LSTM parallel network approach for train travel time prediction," *Knowledge-Based Systems*, vol. 256, article 109796, 2022.

[17] A. Yasar and M. M. Saritas, "Performance analysis of ANN and Naive Bayes classification algorithm for data classification," *International Journal of Intelligent Systems and Applications In Engineering*, vol. 7, no. 2, pp. 88–91, 2019.

[18] J. Zhang, Z. Xu, Y. Li, and S. Jiang, "Framework for the integration of assembly modeling and simulation based on assembly feature pair," *The International Journal of Advanced Manufacturing Technology*, vol. 78, no. 5-8, pp. 765–780, 2015.

[19] S. Wang, Z. Bao, J. S. Culpepper, and G. Cong, "A survey on trajectory data management, analytics, and learning," *ACM Computing Surveys (CSUR)*, vol. 54, no. 2, pp. 1–36, 2021.

[20] D. Niculescu and B. Nath, "Trajectory based forwarding and its applications," in *Proceedings of the 9th annual international conference on Mobile computing and networking*, pp. 260–272, New York, 2003.