International Journal of Aviation Science and Engineering
e-ISSN: 2715-6958 p-ISSN: 2721-5342

AVIA

Original Article

Clustering and BiLSTM Network for Aircraft Trajectory Prediction Model

Javen Sembiring [1], M A Fauzan [1], Khairul Ummah [1,*], Fadil Hamdani [2] and Joy R P Djuansjah [3]

[1] Faculty of Mechanical and Aerospace Engineering, Institut Teknologi Bandung, Jalan Ganesha 10, Bandung 40123, Indonesia
[2] Department of Electrical Engineering, Faculty of Engineering, Universitas Lampung, Jl. Prof. Soemantri Brojonegoro no. 1, Bandar Lampung 35143, Indonesia
[3] Department of Mechanical Engineering, Faculty of Engineering, Al Imam Mohammad Ibn Saud Islamic University, P.O. Box 90950, Riyadh 11623, Saudi Arabia
* Correspondence: khairul@ae.ftmd.itb.ac.id

Received: 2 October 2023; Accepted: 12 November 2023; Published: 1 December 2023

The increasing demand for air travel requires the development of more accurate aircraft trajectory prediction methods to optimize airspace utilization and enhance safety. This paper presents a hybrid approach for single-flight-route trajectory prediction that employs the K-means clustering and Bidirectional Long Short-Term Memory (BiLSTM) networks. The primary objective is to develop a deep learning model that effectively predicts aircraft trajectories. Additionally, this research investigates the influence of trajectory clustering on prediction accuracy. To fulfill the objectives, a four-step methodology: data preprocessing, model construction, validation testing, and analysis is employed. Real-world historical flight data is used to train the BiLSTM model after being clustered with K-means. The model's performance is evaluated using randomized enroute flight data and various metrics like mean squared error and root mean squared error. This research is successful in accurately predicting the flight and the clustering process was proven to increase prediction accuracy by 15 percent in latitude, and 10 percent in longitude.

Keywords: trajectory prediction; k-mean clustering; BiLSTM network

---

1. Introduction

The commercial aviation industry has witnessed significant growth since the late 1980s, becoming a preferred mode of long-distance travel for many. Factors contributing to this rise in popularity include convenience, comfort, safety, and the ability to traverse vast distances in a relatively short time frame. This trend is reflected in data from the International Air Transport Association (IATA), which indicates a steady increase in air passenger numbers. In 2019, airlines worldwide carried over 4.5 billion passengers, representing a remarkable 61% growth compared to a decade prior [1]. This statistic underscores the rapid expansion of the aviation sector. This surge in flight operations poses challenges for air traffic flow management, as crowded airspace can lead to delays, inefficiencies, and potential safety risks.

To maintain safe, efficient, and predictable air travel, the need for trajectory pre-diction has become increasingly paramount. Creating an accurate prediction model will allow a more immediate adjustment to accommodate unforeseen variables and dynamic changes in flight path such as weather conditions, air traffic, and emergencies as they provide flight operators valuable insights to adapt to these conditions.

Traditionally, trajectory prediction in aviation has relied on complex methods, including Kalman filters and sophisticated airspace and flight dynamic models. These approaches, while effective, are often resource-intensive and require a deep under-standing of intricate aviation physics. In contrast, this research introduces a hybrid approach that employes the power of deep learning and data-driven techniques by combining trajectory clustering and Bidirectional Long Short-Term Memory (BiLSTM) modeling, offering a more straightforward yet highly accurate alternative. The proposed model and method serve as a proof of concept, demonstrating their potential to accurately predict other relevant flight characteristics or parameters in practical applications.

2. Related Work

Some related works have been reviewed and summarizes as follows. Bianco and Bielli [2] introduce a method that incorporates 20 automated procedures into future air traffic control systems to enhance safety, capacity, and efficiency. The method explores functions like flow control, strategic flight control, and terminal area sequencing, alongside optimization models and solution algorithms. The paper also identifies research gaps and trends, outlining a hierarchical framework for decomposing air traffic control systems based on planning horizons and control functions. [3] proposes a machine learning approach for trajectory prediction without explicit aircraft modeling. It leverages historical data to train a model (e.g., Generalized Linear Model) for supervised learning regression. The authors then utilize the model to predict key trajectory aspects, such as vertical climb speed and traffic flow, ultimately focusing on optimizing aircraft spacing for Continuous Descent Operations (CDO). Basora et.al [4] presents an improved clustering method (HDBSCAN) for analyzing air traffic flow patterns. HDBSCAN efficiently handles varying density clusters and requires minimal parameter tuning. The study utilizes Euclidean distance and Symmetrized Segment-Path Distance to cluster over 9,000 flights, revealing distinct traffic patterns.

A tool for optimizing flight trajectories in Japan is proposed in [5]. This tool replicates onboard Flight Management System calculations and prioritizes fuel efficiency by optimizing cost indices, flight paths, and initial mass configurations. The goal is to improve air traffic efficiency through accurate trajectory prediction and advanced arrival time calculations. [6] proposed an LSTM-ELM hybrid method for air traffic delay prediction. This three-phase approach involves data preprocessing, a dual-sided LSTM for backpropagation with beta weight estimation, and ELM training. While effective for 15 and 30-minute delay prediction, the method's post-training modeling limits versatility. The authors recommend exploring online learning techniques like Reinforcement Learning for potentially better results. In [Wu, 2022], the authors address trajectory prediction challenges due to aircraft maneuver uncertainty. They propose a deep learning approach that combines clustering and spatiotemporal feature extraction (K-Medoids, CNN-BiLSTM with joint attention) using publicly available, large-scale ADS-B data. This method achieves superior prediction accuracy compared to traditional models (BP, LSTM, CNN-LSTM).

While prior research has primarily focused on trajectory prediction, this work employs a machine learning approach using Bidirectional Long Short-Term Memory (BiLSTM) networks. To enhance prediction accuracy, we incorporate preprocessing step involving trajectory clustering to increase trajectory prediction. The flight parameters employed in this research are consistent with those presented in [6].

3. Methodology

This study aims to construct a deep learning model for predicting flight trajectories. Flight Data Monitoring (FDM) data of turbofan engine aircraft was obtained from NASA's DASHlink repository [NASA, DASHlink]. The data were converted to a usable format, and preprocessed for data quality and consistency. The dataset was subsequently filtered to encompass only Duluth to Minneapolis flights for spatiotemporal analysis by using time, latitude, and longitude parameters. For trajectory prediction, additional parameters such as altitude, heading, and groundspeed were incorporated.

Data preprocessing included cleaning, sorting, sampling rate adjustment, dimensionality reduction, and normalization.

Flight data was clustered into distinct flight patterns using K-means clustering, with cluster numbers optimized through a combination of Elbow method, Silhouette score, and a heuristic approach. The resulting clusters were used to train six Bidirectional Long Short-Term Memory (BiLSTM) models, each capturing specific flight characteristics. The impact of clustering on trajectory prediction accuracy was assessed through a comparison with a model trained on unclustered data. Finally, the performance of the trained models in predicting flight trajectories was evaluated using multiple metrics. Figure 1 provides a visual representation of the methodology.

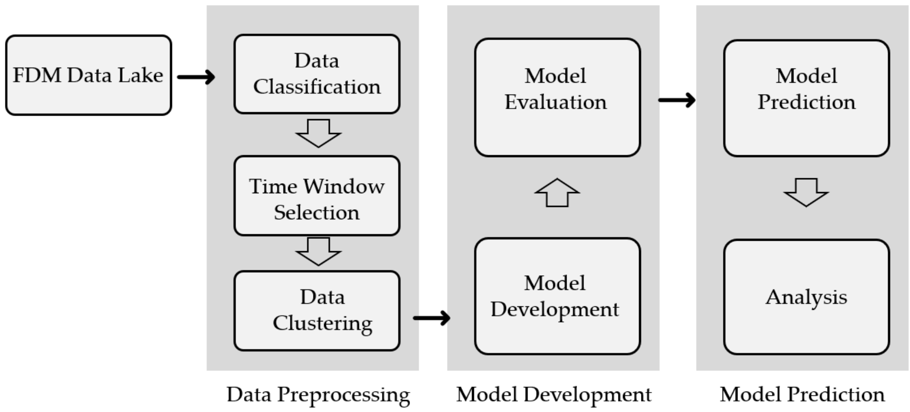


Figure 1. Research Methodology

4. Feature Selection and K-Means Clustering

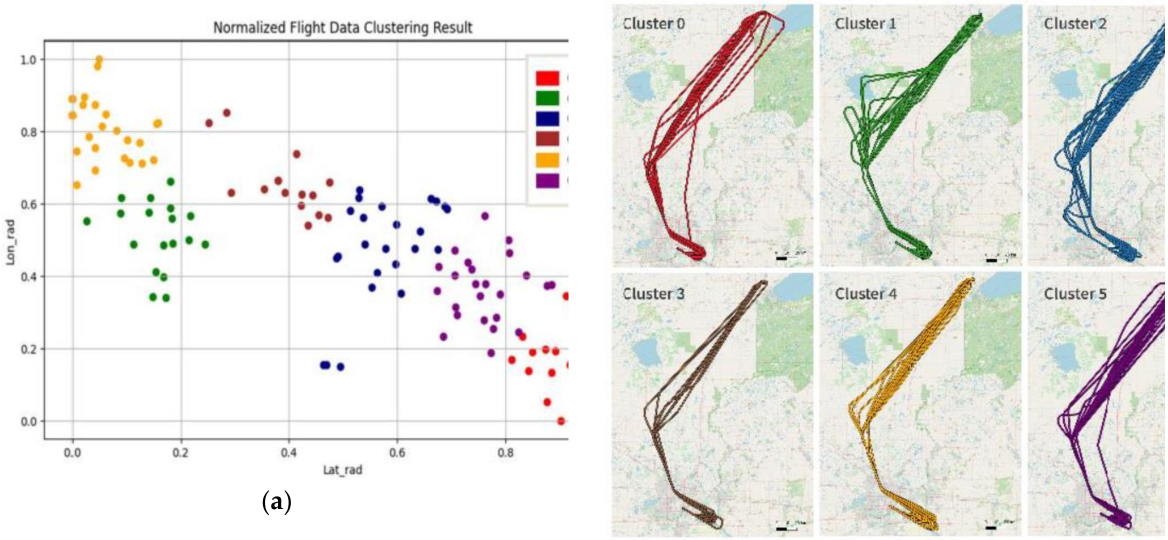
FDM data contains hundreds of flight parameters such as altitude, ground speed, latitude, longitude, etc. For the data at hand, the number of parameters stored in each file is 182 with different sampling rate. However, not all parameters are required for the current case. In order to select which parameters most relevant to the trajectory model prediction, feature selection procedure is need to be conducted. This step is a pivotal aspect in every machine learning problem including the case at hand. There are several methods to select feature most relevant to the output of the model, for example using correlation analysis or physic relation-based selection and some other methods. For the case at hand, manual selection is chosen which directly related to the spatiotemporal information. The parameters employed to train the model include time, latitude, longitude, altitude, groundspeed, and heading angle.

Once the parameters selected, the flight data are further processed to cluster based on their similar patterns. The algorithm employed for this purpose is the K-Means algorithm. This algorithm operates by iteratively assigning data points to the nearest cluster centroid dan recalculating the centroid location based on the newly formed clusters. The centroid of points $(x_1, y_1), (x_2, y_2), (x_3, y_3), \cdots (x_n, y_n)$ is calculated based on Equation (1).

$$\left(\frac{x_1 + x_2 \cdots x_n}{n}, \frac{y_1 + y_2 \cdots y_n}{n}\right) \tag{1}$$

K-Means algorithm is an unsupervised algorithm that still requires us to determine the number of clusters (or K value) that we want to group our data into. This can be done with techniques such as elbow method and silhouette score method. The research employs both method to determine the K value.

The implementation of the K-Means algorithm along with K = 6 reveals subtle patterns in same route flight data, enhancing prediction accuracy despite interpretation challenges. The result is depicted in Fig 2.



(**a**) (**b**)

Figure 2. Clustering Result and Respected Trajectory

4. Trajectory Model Development

3.1. Trajctory Model Training

Six BiLSTM models will be trained, one for each cluster. However, to calculate the effect of clustering on the trajectory prediction model, one model will be trained using unclustered flight data. These clusters will be trained strictly using the data from their respective clusters. The model will have an 80/20 train-test split, leaving one flight data to be used for a validation test later on. The dataset used for training these models is almost raw, with only feature selection and sampling rate standardization performed to it to ensure the highest quality results.

The input layer of our model encompasses neurons that capture various features of flight trajectories, including time, latitude, longitude, altitude, groundspeed, and heading. Each neuron in the input layer corresponds to a specific parameter, enabling the network to comprehensively process the multidimensional input vectors. As for the output layer, it is designed to generate the predicted flight trajectory. Since the goal is to predict the future positions of the aircraft, the output layer consists of two neurons representing latitude and longitude. These neurons output continuous values, representing the predicted latitude and longitude coordinates for the upcoming time steps. The structure of the network is depicted in Fig. 3.

Each cluster has a unique model architecture. To prevent overfitting, we randomized training data and used L2 regularization. Models use PyTorch with 128 hidden layers, optimized through experimentation. Hyperparameters are tuned individually per cluster, considering data volume and complexity. Table 4.1 details each model's settings.

e-ISSN: 2715-6958 p-ISSN: 2721-5342

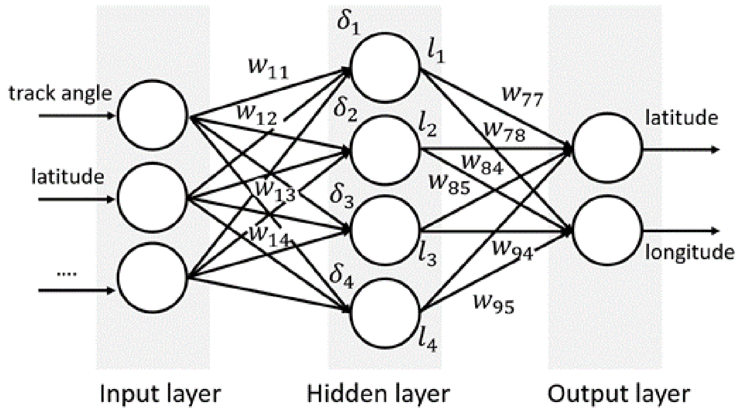


Figure 3. BiLSTM Model Structure

Table 1. Model Architecture and Hyperparameters

Model	Epochs	Hidden Layer Size	Batch Size	Sliding Window	Learning Rate
Cluster 0	50	145	150	25	0.000010
Cluster 1	50	128	200	20	0.000050
Cluster 2	50	156	82	35	0.000001
Cluster 3	50	128	200	20	0.000100
Cluster 4	30	128	256	20	0.000100
Cluster 5	50	185	128	35	0.000005
Unclustered	150	128	256	20	0.000100

3.2. Model Evaluation

Root means square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) are widely employed metrics for assessing the accuracy of predictive models, particularly in the domain of trajectory prediction. Each of the metrics is formulated as,

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(predicted_i - actual_i)^2} \quad (2)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|actual_i - predicted_i| \quad (3)$$

$$MAPE = \frac{1}{n}\sqrt{\frac{1}{n}\sum_{i=1}^{n}\frac{actual_i - predicted_i}{actual_i}} \times 100\% \quad (4)$$

These metrics are also employed in this research and their corresponding performance when applied to the data at hand are presented in Fig. 3.

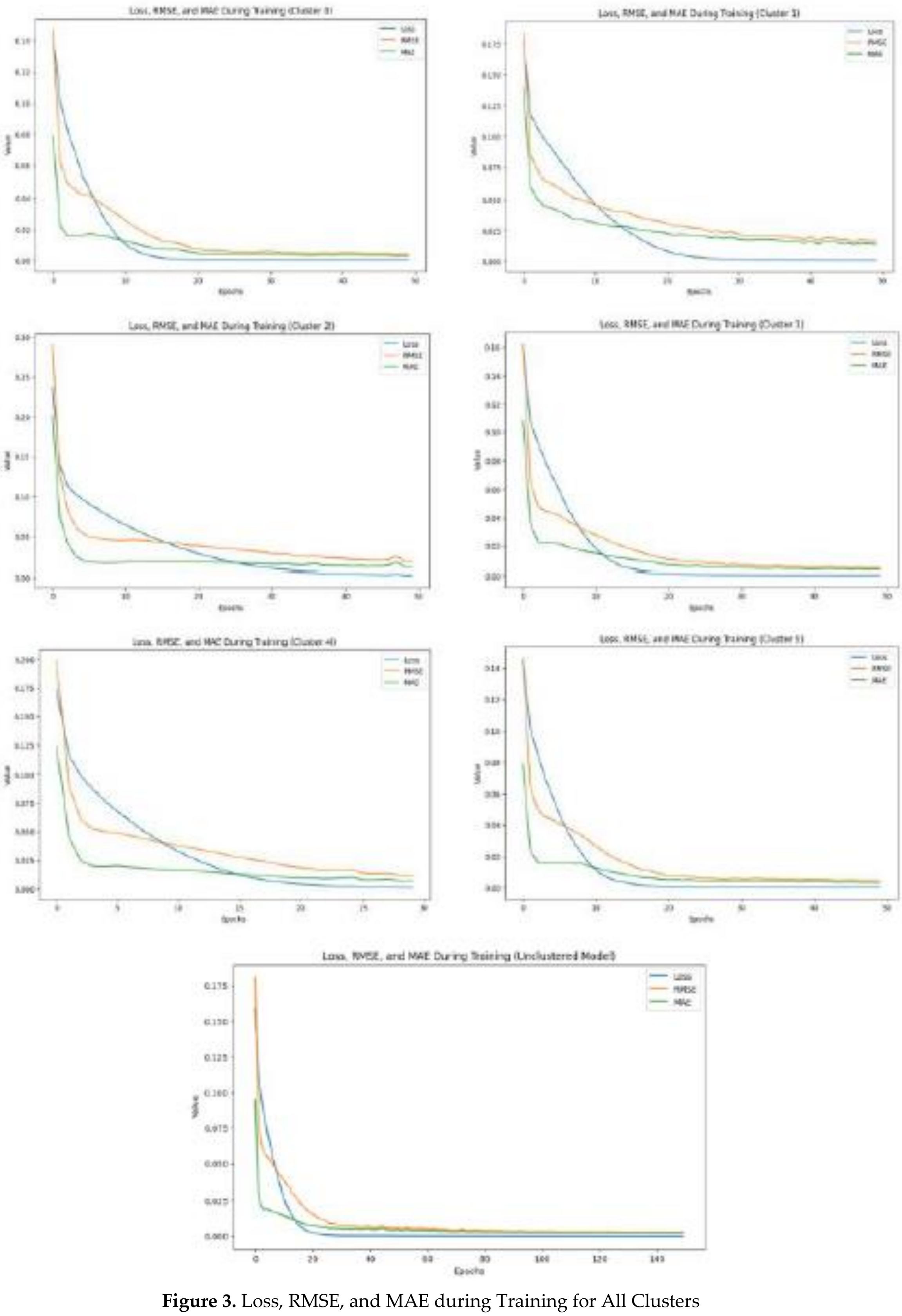


Figure 3. Loss, RMSE, and MAE during Training for All Clusters

 doi: 10.47355/AVIA.V5I2.89

e-ISSN: 2715-6958 p-ISSN: 2721-5342

4. Results and Analysis

Using the trained and complete model from each cluster, a validation test is done by selecting a predetermined point or sample from a random flight that is not used for model training from each cluster to predict the route of a flight until their destination. Across all clusters, the point selected will have roughly the same latitude at 45.78 degrees. This specific latitude is chosen because at this point the flight would have progressed enough for the model to have sufficient data to learn patterns to create accurate prediction, while still having multiple critical points where the decision making is essential to the model. Identical latitude value is also chosen to ensure the simulation's validity between different cluster models. The yellow point is the sample input point, yellow line is the resulted predicted route from our model and the gray line is the original route from the sample flight data.

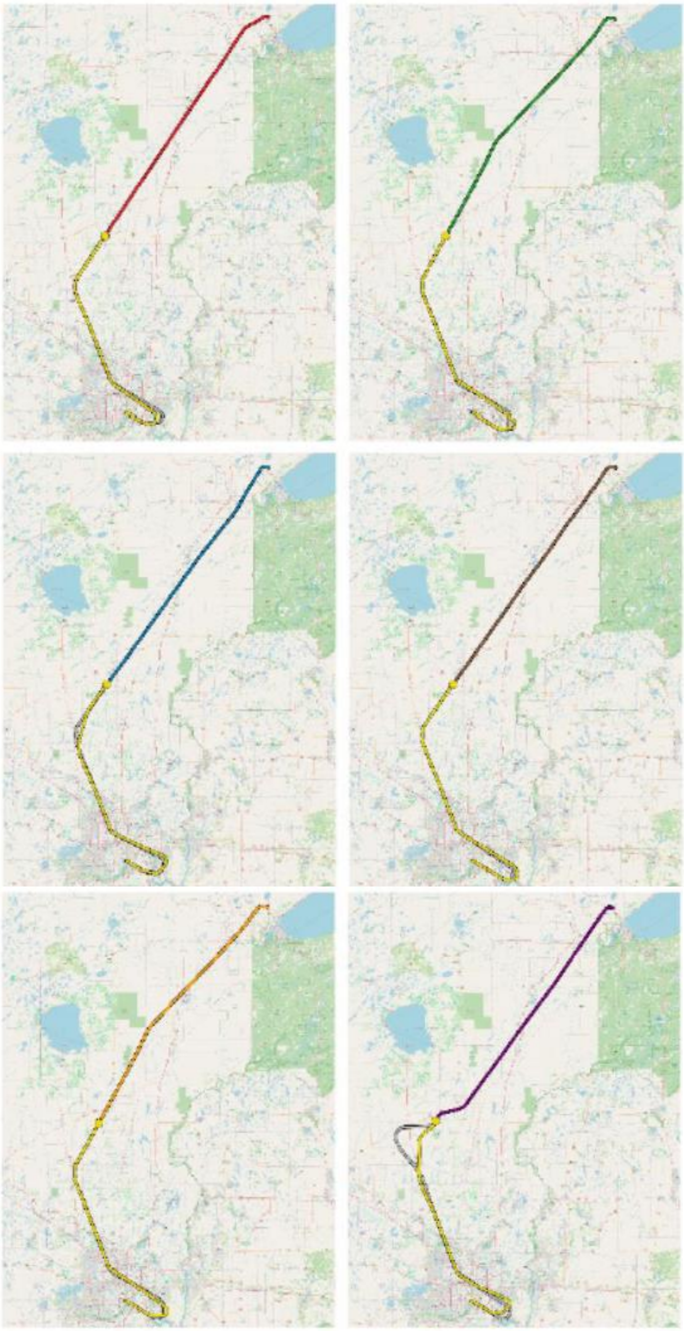


Figure 5. Predicted Route for All Clusters

Table 2. Evaluation Indicator of Each Cluster

ID	Evaluation Indicators					
	Latitude			Longitude		
	MAE	RMSE	MAPE	MAE	RMSE	MAPE
C0	0.00011	0.000225	0.014%	0.000159	0.00035	0.0098%
C1	0.00074	0.001308	0.094%	0.000529	0.00088	0.0325%
C2	0.00022	0.000366	0.028%	0.000317	0.00054	0.0195%
C3	0.00001	0.000048	0.002%	0.000075	0.00017	0.0046%
C4	0.00004	0.00009	0.005%	0.000180	0.00033	0.0111%
C5	0.00154	0.002473	0.195%	0.001604	0.00247	0.0985%

Table 3. Unclastered Model Evaluation

ID	Evaluation Indicators					
	Latitude			Longitude		
	MAE	RMSE	MAPE	MAE	RMSE	MAPE
W/ Clustering	0.000106	0.000219	0.0136%	0.000229	0.000482	0.0141%
No Clustering	0.000122	0.000248	0.0214%	0.000253	0.000588	0.0225%

We will use the model that is trained using unclustered data and perform the same validation test as the models with the clustered data. The orange line is the unclustered model result, the yellow line is the clustered model result, and the gray line is the original flight data.

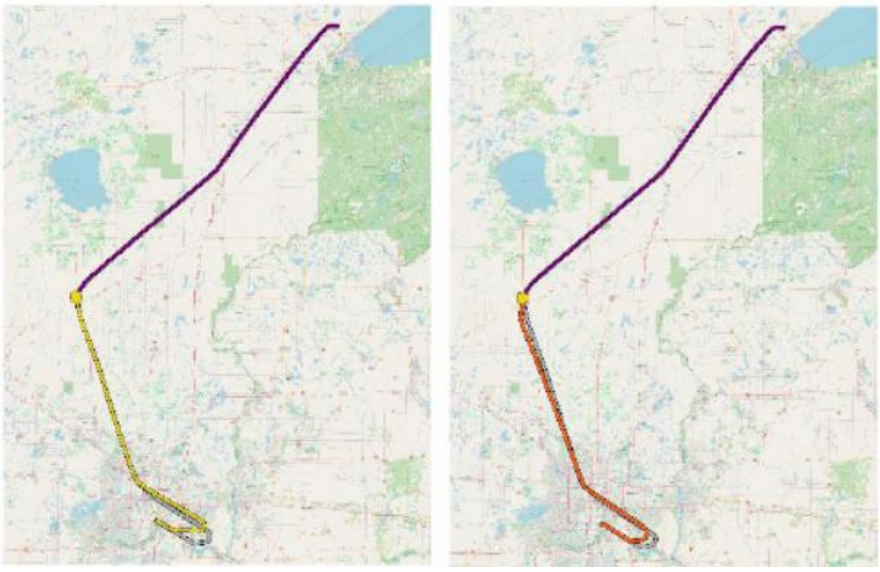


Figure 6. Clustered vs Unclustered Result

The model successfully predicted flight trajectories with minimal errors across six clusters. Predictions were accurate during en-route phases but showed differences in approach phases due to route complexity. Cluster 5 and 2 models strug-gled with detecting holding phases. Clustered models improved prediction accuracy by 15% for latitude and 10.5% for longitude compared to the unclustered model. Despite a smaller dataset, clustered training led to better pattern learning and predictions. The model also successfully captures the specific patterns and trends that exist within some cluster, though not all.

5. Conclusions

A trajectory prediction model that is capable of accurately predicting aircraft trajectory was successfully developed using a hybrid method based on K-means clustering and BiLSTM. In this research, we identify six distinct trajectory clusters for the data at hand. For each cluster, a unique trajectory prediction model was trained and developed. These individual trajectory prediction models demonstrated the ability to predict flight paths with minimal errors. The accuracy of each predicted trajectory was measured using RMSE, MAE, and MAPE. Clustering process proves to positively influence the trajectory prediction model and is capable of producing more accurate predictions. The process increases prediction accuracy by 15% on latitude, and 10.5% on longitude.

Acknowledgments
The authors would like to acknowledge the financial support provided by Institut Teknologi Bandung (ITB) through the P2MI 2024 funding scheme. Their funding enabled the execution of this research project.

References

1. IATA. (2023, August) Air passenger market analysis. Air Passenger Market Analysis. [Online]. Available: https://www.iata.org/en/iata-repository/publications/economic-reports/air-passenger-market-analysis---june-2023/
2. L. Bianco and M. Bielli, "Air traffic management: Optimization models and algorithms," Journal of Advanced Transportation, vol. 26, no. 2, 1992.
3. A. de Leege, M. van Paassen, and M. Mulder, "A machine learning approach to trajectory prediction," in AIAA Guidance, Navigation, and Control (GNC) Conference, 2013.
4. L. Basora and J. Morio, "A trajectory clustering framework to analyze air traffic flows," November 2017. [Online]. Available: https://www.sesarju.eu/
5. A. Harada, N. Takeichi, and K. Oka, "An optimal trajectory-based trajectory prediction method for automated traffic flow management," in AIAA Scitech 2019 Forum, 2019.
6. M. Y. Aghdam, S. R. Kamel, S. J. Chabok, and M. Khairabadi, "Optimization of air traffic management efficiency based on deep learning enriched by the long short-term memory (LSTM) and extreme learning machine (ELM)," 2020.
7. Y. Wu, H. Yu, J. Du, B. Liu, and W. Yu, "An aircraft trajectory prediction method based on trajectory clustering and a spatiotemporal feature network," Electronics, vol. 11, no. 21, 2022.
8. Jacobs E and Sherman A 1939 Airfoil Section Characteristics as Affected by Variations of The Reynolds Number NASA Report 586Author 1, A.B.; Author 2, C.D. Title of the article. *Abbreviated Journal Name* **Year**, *Volume*, page range.