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CLUSTERING AND ANOMALY DETECTION OF AIRCRAFT TRAJECTORIES FOR AIRSPACE BEHAVIOR CHARACTERIZATION

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ABSTRACT

Background: The augmenting complexity of airspace demands analytical tools that can detect significant patterns of aircraft movement, without resorting to high-dimensional flight data. Even though there has been a boost in the trajectory-based analysis, there are still no integrated frameworks of pattern identification and anomaly detection with minimal positional information. **Aim:** This study aimed to characterize airspace behavior by clustering aircraft trajectories into distinct movement regimes and detecting anomalous trajectories using a minimal-feature, data-driven approach. **Methodology:** A quantitative secondary-data design was adopted using time-stamped aircraft trajectory records. After preprocessing and trajectory construction, key kinematic and geometric features were derived, including total distance, mean speed, duration, displacement, and path efficiency. K-means clustering was applied to identify dominant behavioral regimes, while Isolation Forest was used to detect anomalous trajectories. **Results:** The analysis produced 13,376 valid trajectories from 2,317 aircraft. Four distinct trajectory clusters were identified, showing clear differences in speed, distance, efficiency, and duration. A dominant cluster represented high-speed, long-distance, and highly efficient movement, whereas another captured low-speed, low-efficiency, and irregular trajectories. Anomaly detection identified 669 anomalous trajectories (5% of the dataset), characterized by low displacement, reduced efficiency, longer duration, and lower speeds, indicating fragmented or inefficient movement patterns. **Conclusion:** These findings demonstrate that meaningful airspace behavior can be extracted from minimal positional data when clustering and anomaly detection are integrated within a unified analytical framework, supporting scalable applications in airspace monitoring and trajectory-based analysis.

Keywords: aircraft trajectories; airspace behavior; trajectory clustering; anomaly detection; path efficiency

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1. Introduction

The ever-increasing air travel in the world has led to a highly complicated and congested airspace that has created huge burdens to the already existing air traffic management systems. As the flight density increases and new operational paradigms such as urban air mobility are introduced, methods that are able to efficiently capture and analyze aircraft movement behavior are in greater demand. These conventional monitoring systems, which are based on the established control systems, might not adequately deal with the dynamic and diverse quality of the contemporary air traffic systems (Shrestha et al., 2021). At the same time, to develop aviation sustainably, it will be necessary to optimize the operation of traffic flows and infrastructure elasticity to reduce ineffective activities and provide stable work (An et al., 2019). The information on aircraft trajectories has taken center stage in solving these problems. Trajectories are spatiotemporal representations of aircraft motion, which represent navigation choices, operational, and interrelationships with other traffic and environmental factors. Therefore, trajectory-based analysis is a useful tool in comprehending the traffic patterns and assessing the airspace usage. As recent literature has shown, data-driven methods are effective in identifying structural patterns in the set of trajectory data, especially when dealing with the complexity of the airspace and the description of behavior (Li et al., 2021).

The increasing access to trajectory information has spurred the creation of analytical models to enhance operational efficiency and airspace coordination. TBO has been identified as a major enabling factor to optimize the routing plans and assist more predictable ATCs (Costas & de Oliveira, 2024). With the help of the trajectory information, a higher level of abstraction of the aircraft movement is possible, which allows recognizing the recurrent patterns and operating regimes. Simultaneously, machine learning methods have been implemented on the trajectory data, used to assist in the behavior recognition and classification. All of these techniques allow identifying unique movement patterns directly based on the spatiotemporal sequences and allow a better understanding of how aircraft function (Zhang et al., 2024). In the same vein, trajectory prediction using learning-based models has been shown to have the potential of data-driven methods in capturing intricate movement dynamics and facilitating decision-making processes in aviation systems (Bastas et al., 2020). In spite of these developments, a lot of current studies are still dedicated to particular tasks, like prediction or classification, and most of them are based on high-dimensional datasets that encompass detailed flight parameters. This restricts the use of such methods in cases where there is very little positional data.

Although the amount of trajectory data is growing, the current methods of analysis heavily rely on enhanced datasets with specific flight parameters, including altitude, speed, and vehicle-specific features.

Although this kind of information helps in improving the precision of the analysis, it is not always available in all operational situations. Furthermore, a significant part of existing studies focuses on the prediction of the trajectory or the reconstruction of a route, and only relatively little effort is devoted to the systematic description of the flight behavior with minimal data input. This subjects a serious constraint to the ability to differentiate structured and irregular movement patterns based solely on positional and temporal data. Direct impacts of operational constraints, control inputs and external disturbances typically create variations in aircraft trajectories, leading to deviations, asymmetries, and nonlinear aircraft paths that affect overall flight performance (Romanova, 2019). Moreover, the introduction of novel airspace users, such as unmanned aircraft systems, also presents an additional variability and complexity, and thus the need to adopt analytical models that can support a wide range of trajectory behaviors (Pongsakornsathien et al., 2020).

One of the major shortcomings of the existing study is that there are no coherent structures that can be used at the same time to identify patterns in the trajectory and detect anomalies with a minimum number of data inputs. The clustering methods are usually used to cluster similar trajectories, and the anomaly detection methods are usually used independently to detect deviations. This separation, however, limits the capability to study both normal and abnormal flight behaviors in a consistent analytical framework. As a measure of movement structure and deviation, trajectory efficiency, which is the ratio between the distance travelled and the total travel distance, is understudied. Such measures can be incorporated to give more insights into the aspects of trajectories and how they work.

This work is a proposal of a data-oriented model to cluster and identify anomalies in aircraft trajectories with the objective of describing airspace behavior. Using the positional and temporal information only, the study computes features at the trajectory level that capture the important characteristics of aircraft motion, such as speed, displacement, and efficiency. Subsequently, the unsupervised learning methods are used to detect the different regimes of trajectories and detect the unusual patterns. This method shows that substantial information about aircraft behavior and airspace use can be obtained using representations with little information, which are used to assist trajectory analysis in aeronautical systems.

2. Literature Review

The growing access to aircraft trajectory data has created a paradigm shift away from trajectory-centred analysis in aerospace systems. Trajectories are ceasing to be considered simply a record of motion and are now structured representations that can provide system-level understanding and control. Trajectory-based frameworks have been created to study dynamical systems in terms of trajectories, allowing to extract patterns governing the system without physically modelling (Berberich & Allgöwer, 2020). This view is consistent with more general trends in data-driven aerospace engineering, where machine learning tools are being deployed to rethink classical analytical procedures and enhance system behavior (Brunton et al., 2021). Trajectory-based analysis has also become significant in the operational environment, especially in conflict detection and airspace surveillance. The use of machine learning to develop conflict detection solutions in three-dimensional airspace has proven the possibility of using trajectory data in enhancing situational awareness and decision support within air traffic systems (Wang et al., 2020). These changes reveal the increased importance of trajectory analytics in both theoretical and practical aeronautical studies.

The trajectory statistics are valuable in order to simplify the flight operations and enhance the efficacy of the airspace. To maximize fuel burn, environmental impact and safety of operations, mathematical models are created to assist in decision-making. Such plans will assist in enhancing the efficiency of the routes to the air and stay within the scope of the requirements of airspace and performance (Gardi et al., 2023). The concept of airspace utilization, which is closely related to the trajectory-based optimization, requires efficient routing and traffic allocation that can help reduce congestion and enhance the system throughput. The possibility of tracing patterns gives a precious idea of the behavior of aircraft in the airspace environment, to identify inefficiencies and optimization opportunities. It has brought about more interest in approaches that can provide descriptions of the form of trajectory and how it can be determined whether it is adequate in supporting the objectives of operations.

Clustering techniques have been popularly used to determine trends in aircraft track data and to classify flight behavior. The methods are able to classify similar paths, and this can be applied to find out common routes, regimes of operation and traffic structures. Such an application is the use of trajectory clustering to categorize air traffic flows and distinguish between different types of flight operations, based on movement patterns (Bolić et al., 2022). Despite their effectiveness, clustering methods have problems of feature selection, scaling and sensitivity to variation of data. The vast majority of them require a set of features of high dimensions, which may limit their use in cases when only limited data are available. Also, pattern identification is frequently the objective of clustering methods, but unusual data or anomalies are not clearly addressed, which makes it necessary to complement with alternative analysis methods.

One of the areas of research that has become significant in the field of aviation is anomaly detection, which concerns the process of detecting anomaly trajectories that are not expected. The earlier strategies used statistical means to identify outliers, and more recent research has discussed machine learning techniques to enhance their detection accuracy and strength. An in-depth analysis of the anomaly detection techniques in aviation reveals the variety of solutions and the obstacles in the definition and detection of anomalies in a complex airspace setting (Basora et al., 2019). Recent studies have used machine learning models to find anomalies in aircraft paths, which shows that data-driven methods are effective at finding abnormal movement patterns (Keerthana & Varma, 2025). Nevertheless, the anomaly detection can be viewed as an independent activity, independent of the trajectory pattern analysis. This division restricts the capacity to interpret aberrations within the framework of larger behavioral frameworks, and therefore, there is a necessity for coupled structures that integrate clustering and anomaly recognition.

Trajectory-based behavioral models need to be evaluated with suitable measures that are able to reflect the underlying structure and variability of movement patterns. In dynamic systems used in behavioral modeling, common and unusual patterns are typically evaluated, and metrics are needed that can be able to differentiate between normal behavior and abnormalities (Im et al., 2020). This involves assessment of variables like consistency, efficiency and variability in movement in the context of aircraft trajectories. Combining clustering and anomaly detection in a single analytical system can complement the analysis of the trajectory behavior by offering different views on the pattern structure and deviation. This is done through such approaches that allow a more in-depth approach to the aircraft movement and facilitate descriptive and diagnostic analysis.

The literature reviewed also showcases the developments in the field of trajectory analysis, clustering, and anomaly detection, but all of them are typically utilized separately or based on the enriched datasets. Scalable and interpretable techniques that can be applied to a limited amount of data and can model both structured and irregular behaviors are still needed. This paper fills this gap by combining clustering and anomaly detection to offer a comprehensive approach to aircraft trajectory analysis.

3. Methodology

3.1 Research Design

This research design is a quantitative data-driven research design, which will examine the aircraft trajectory behavior based on pattern extraction and anomaly detection. It is founded on the analysis of secondary data in which the already recorded aircraft positional data are converted into representations at the trajectory level and studied with the help of statistical and machine-learning methods.

3.2 Data Source

The data employed in the study is a subset of aircraft routes in terms of position measurements by surveillance. It also contains latitude and longitude values in time stamps to individual aircraft IDs which can be reconstructed to create time-varying flight paths within a specified time period. The data was gathered based on a limited amount of aircraft route data, which was meant to assist in the study within the domain of airspace research and defining motions (Gala, 2024). The data set has adequate spatial and temporal resolution to extract trajectory-level features that are pertinent to aircraft movement and operational behaviour.

3.3 Data Preprocessing and Trajectory Construction

The first stage of preprocessing included standardizing the formats of the variables, which included converting timestamps and validating coordinates. To maintain data integrity, records with invalid or missing positional values were ignored. Temporal values were transformed into a standard time scale, and it was possible to compute the time differences between observations accurately. Flights were sorted into distinct paths with batch identifiers. The observations in the trajectories were sequentially sorted by their timestamps and sequence numbers. This structure allowed the representation of each trajectory as a time-ordered sequence of spatial coordinates.

3.4 Feature Engineering

In order to make the positional data useful in quantitative analysis of aircraft movement, there was derivation of trajectory-level features of aircraft movement were derived. The great-circle distance between two successive observations in a trajectory was calculated by the use of the Haversine formula:

$$d = 2R\arcsin\left(\sqrt{\sin^2\left(\frac{\Delta\phi}{2}\right) + \cos(\phi_1)\cos(\phi_2)\sin^2\left(\frac{\Delta\lambda}{2}\right)}\right)$$

where $\phi$and λdenote latitude and longitude, respectively, and $R$is the Earth's radius.

Using this formulation, the following point-level features were calculated:

- Distance between consecutive positions
- Time difference between observations
- Speed, computed as distance over time
- Bearing, representing the direction of movement

These point-level features were subsequently aggregated at the trajectory level to derive descriptive variables, including:

- Total trajectory distance
- Mean and standard deviation of speed

- Trajectory duration
- Net displacement between start and end points

The ratio of net displacement to total distance travelled was declared a path efficiency measure, which offers a measure of the linearity of the trajectory.

3.5 Trajectory Clustering

The analysis of the trajectory-level features was performed with the help of the K-means clustering algorithm to determine specific patterns in aircraft movement. Before the clustering, features were put into standard form to make them comparable across scales.

The elbow method was used to identify the optimal number of clusters, where the within-cluster sum of squared distances is considered at different cluster levels. Out of this analysis, four clusters have been chosen in order to have balanced interpretability and model performance.

The K-means algorithm partitions the dataset into $k$clusters by minimizing the objective function:

$$J = \sum_{i=1}^{k} \sum_{x \in C_i} \| x - \mu_i \|^2$$

where C_i represents cluster i, and μ_i is the centroid of that cluster.

This clustering method can be used to identify homogeneous clusters of trajectories with similar movement properties.

3.6 Anomaly Detection

An Isolation Forest model was used to identify the presence of tracks that are outliers. This approach is especially appropriate to the unsupervised detection of anomalies, as it isolates observations in recursive partitioning of the feature space. The model gives a score of anomaly to every single trajectory, and the outliers take fewer partitions to be separated. The proportion of anomalies was set to 5% to define the expected level of contamination in the data. The anomalous trajectories were compared to normal ones to determine the difference in important movement features, such as speed, distance, duration, and path efficiency.

4. Results

4.1 Dataset Characteristics and Descriptive Statistics

The processed data is in the form of trajectory-level data based on the raw positional measurements. Following preprocessing and feature engineering, 13,376 valid trajectories were acquired, which are 2,317 different aircraft during one month in July 2019. The summary of the dataset features is shown in Table 1. The mean length of the trajectories is about 1,440 seconds (24 minutes), and the mean distance of the trajectories is 220.32 km, which means that the dataset is mainly composed of short- to medium-range flight segments. The mean speed of 548.72 km/h is in line with the normal cruise and transitional flight regimes in controlled airspace.

The data shows that it is large enough and has enough variability to extract patterns at the trajectory level and analyze behaviors.

4.2 Trajectory Pattern Identification through Clustering

K-means clustering was applied to trajectory-level features in order to determine the prevailing patterns of flight behavior. The elbow procedure suggested that additional reduction of inertia was smaller than in the previous four clusters, and therefore, four clusters (k = 4) were chosen as interpretable and stable.

Table 2 is a summary of the cluster-wise feature characteristics. The findings show that there is a distinct separation between groups of trajectories in various aspects, such as speed, distance, duration and path efficiency.

Cluster 1 is the dominant in nature, with high-speed, long-range, and highly efficient paths, which suggest consistent and near-linear flight paths in line with en-route operations. Cluster 2, on the other hand, has low speeds, long duration, and much lower path efficiency, implying irregular or non-linear motions like holding patterns or path fragmentation. Clusters 0 and 3 are intermediate regimes, with Cluster 0 having relatively structured but slower trajectories, and Cluster 3 having moderate-speed trajectories with greater variability. In order to further authenticate the distinction between the trajectory groups, a feature-space visualization was done. As Figure 1 illustrates, the clusters are separable in terms of the speed-distance gradient, meaning that the clustering essentially represents the different operational regimes. The linear trend seen among clusters is caused by the natural correlation between the length of the trajectory and the mean speed of the trajectory, and variations in the trend are caused by inefficient or non-uniform movements.

4.3 Trajectory Efficiency and Spatial Behavior Analysis

In order to investigate the spatial properties of aircraft movement further, the correlation between displacement and path efficiency was studied. These give an idea of the proportion of the routes that aircraft follow directly, as opposed to the distance of the route covered. Figure 2 shows that there is a sharp division between high and low efficiency tracks. High-displacement paths are typically linked with an efficiency value near to unity, which means that the movement is close to linear. On the other hand, the low displacement trajectories are characterized by much lower efficiency, which is a circuitous or fractured movement behavior.

The results of this distinction support the clustering findings, especially pointing to the behaviour of Cluster 2, which is in low-placement, low-efficiency space. These paths are suggestive of irregularities of operation or local movement patterns as opposed to structured point-to-point travel.

4.4 Anomalous Trajectory Identification

Anomaly detection was also done on an Isolation Forest model at the same level of features on the trajectory. The model detected 669 abnormal trajectories, which are about 5% of the data, which is in line with the pre-determined level of contamination. Table 3 shows the comparative features of normal and anomalous trajectories.

Anomalous routes are distinguished by significantly smaller displacement and path efficiency, longer time and slower speed. This shows that the abnormal behavior is mainly linked to inefficient and non-linear movement patterns, and not high-speed or long-distance flights, which are extreme. These results indicate that anomaly detection is successfully learning those trajectories that are not typical operational behavior, especially those that are local, looped or interrupted motion. Figure 3 demonstrates that anomalous trajectories are very distinctly discontinued compared to normal trajectories in the feature space, with a clustering of regions relating to both low displacement and low path efficiency.

The findings indicate that much useful information can be obtained regarding aircraft movement behavior in the airspace being studied using only minimal positional information, and that meaningful trajectory patterns and anomalies can be identified.

5. Discussion

The findings show that aircraft trajectories may be systematically stratified by positional and temporal information only into a set of behavioral regimes. The results of clustering prove that the behavior of the trajectory is organized around the most important movement features like speed, distance, and path efficiency, and is not randomly distributed. The existence of a large high-efficiency cluster implies that a significant share of aircraft traffic has predictable, directional routes that are related to structured navigation and predetermined routes. Whereas the discovery of a low-efficiency cluster draws attention to the paths with unsteady movement patterns. Such paths have less displacement compared to the total travelling distance, along with longer times and slower speeds, with non-linear or disjunct movement. It can be related to local operations, holding patterns or non-standard routing structure. The noticeable separation of such regimes suggests that the parameter of path efficiency is a powerful parameter determining the structure of trajectories and provides a goal-oriented basis to distinguish directed and irregular flight behavior.

The outcomes of the anomaly detection confirm this interpretation, as they demonstrated the trajectories that do not follow the dominant movement structure. These aberrant tracks are not characterized by extreme values, but abnormalities in the motion patterns, such as low efficiency, long period and decreased displacement. This means that aircraft trajectory abnormalities can be more adequately explained as an interruption of movement coherence as opposed to mere statistical outliers. The correlation of clustering and anomaly detection enhances the analytical framework even further. Clustering gives the current condition of organization of trajectory behavior and detects anomalies in non-organized trajectories. That low-efficiency clusters are related to aberrant paths suggests that the abnormal patterns of movement are detectable by all forms of analysis. With such a combination, it is possible to describe the normal behavior and diagnose abnormalities, which provides a full understanding of the aircraft's motion dynamics.

The patterns of observed trajectories are also in line with the literature and previous research that shows that aircraft movement can also be divided into different regimes of operation by using the trajectory-based analysis. It has been demonstrated that clustering methods can be useful to differentiate between structured and more variable movement patterns, especially in real-time air traffic scenarios (Deng et al., 2022). The current results further this viewpoint by demonstrating that this type of segmentation can still be done with small sets of features. The findings of the anomaly detection are consistent with the previous studies describing abnormal trajectories as the deviation of the common movement patterns. Past studies have underscored the fact that abnormalities are typically linked to ineffective or perturbed movement patterns as opposed to solitary numerical limits, which aligns with the low-efficiency and low-displacement attributes found in this study (Basora et al., 2019; Jasra et al., 2025). This substantiates the meaning that anomaly detection is to be based on structural deviations in the trajectory behavior.

The combination of clustering and anomaly detection is indicative of strategies proposed in more recent literature that emphasize the significance of examining anomalies in the framework of underlying trajectory features. Analyses based on clustering have shown that anomalies are easier to interpret when compared to grouped trajectory structures, as opposed to being unrelated (Corrado et al., 2021). Likewise, the results of the abnormal trajectory detection study in operational airspace have shown that the cluster-wise method enhances the reliability and interpretability of detection (Wang et al., 2025). The focus on trajectory structure and representation also aligns with the general trends in data-driven aerospace analytics. The recent studies also highlight the significance of learning concise and meaningful representations of trajectory data to characterize the behavior in an effective way (Liu et al., 2025). Moreover, the behavioral metrics to define movement consistency are consistent with new directions, which support structural consistency as a significant measure of system behavior (Chen and Pan, 2022). The discovery of the stable regimes of trajectories and regular anomaly patterns is associated with the previous studies on the reliability of trajectory modeling. To interpret the trajectory data reliably, the models need to be able to always capture both normal and abnormal behaviors in diverse conditions, which is justified by the organized findings in the present study (Hashemi et al., 2020). These results also align with previous studies on the characterization of trajectories in the vicinity of terminal air space, where control-action-based modeling has been demonstrated to be effective in capturing both structured and non-structured patterns of aircraft movement, especially when operating in complex operational conditions (Chakrabarti & Vela, 2023).

The results have significant implications for airspace analysis and aeronautical research. To begin with, they show that there are meaningful patterns of trajectory that can be obtained using minimal positional measurements, eliminating the need to use high-dimensional or proprietary data. This enhances scalability and application of the trajectory analysis to other working environments. Second, the clustering and anomaly detection mixture provides a convenient framework to acquire knowledge about the normal and abnormal aircraft behavior. Such an approach can complement airspace monitoring systems as it enables the detection of existing movement patterns and, simultaneously, allows recognizing deviations that may require operational attention. Third, the movement structure may be determined with the help of the simplest measure of trajectory efficiency as an analytical measure that is the easiest to use. The metric can be useful in using the route analysis, efficiency analysis and irregular movement pattern detection, which can contribute to the improvement of the trajectory-based decision-making process.

There are various limitations to this research. It can only be analyzed with positional and time data; it is impossible to incorporate the contextual data, such as altitude, weather, type of aircraft and airspace limitations. Therefore, the identified patterns of trajectories are operational states that are not fully contextualized, but generalized behavioral regimes. Use of one clustering algorithm and one method of anomaly detection might influence the results. Other unsupervised learning techniques can produce alternative sets of trajectories or anomaly sets, and ought to be explored in the future. Future research can take the current research a step further by considering more data sources, and the framework can be tested in different airspace systems. The relationship between contextual variables and the analysis of the relationship between different analytical methods would strengthen and enhance the strength and generalizability of the trajectory-based behavior models.

6. Conclusion

With little information on trajectories, meaningful characterization of airspace behavior is possible when patterns are studied within the framework of an integrated analysis. The results indicated that aircraft paths can be divided into various behavioral regimes depending on the variations in speed, distance, displacement, duration, and path efficiency. Specifically, the analysis identified consistent and efficient flight trajectories and low-efficiency and irregular trajectories, as well as anomaly detection identified further isolated trajectories that did not follow prevailing behavioral patterns. Clustering and anomaly detection alone were able to give a consistent understanding of the normal and unusual aircraft movement, which showed that irregularity is better explained by the structure of trajectories rather than by specific numerical extremes. These findings validate the usefulness of path efficiency as a convenient measure of movement coherence and justify its applicability to the analysis of trajectories in airspace. The framework was created based on positional and temporal data only, yet still gave interpretable, operationally relevant results. This means that there is a high scale-up potential for airspace surveillance, behavioral screening, and trajectory-based decision-making. More details of the technique, contextual variables, and other unsupervised techniques could be elaborated to make the technique more robust and generalized.

Tables

Table 1. Overview of the secondary aircraft trajectory dataset used in the study.

Metric	Value
Total trajectories	13,376
Total aircraft	2,317
Time range (start)	2019-07-01 02:02:30+00:00
Time range (end)	2019-07-31 22:53:45+00:00
Mean trajectory duration (sec)	1440.45
Mean trajectory distance (km)	220.32

Mean speed (km/h)	548.72

Table 2. Cluster-wise summary of trajectory characteristics based on distance, speed, duration, displacement, and path efficiency.

Cluster	Total Distance (km)	Mean Speed (km/h)	Speed Std (km/h)	Duration (sec)	Displacement (km)	Path Efficiency	Num Trajectories
0	81.65	202.84	30.36	1425.35	70.16	0.85	1,520
1	280.48	701.23	124.28	1387.71	254.39	0.91	6,255
2	71.49	168.11	52.93	1823.97	19.07	0.27	1,020
3	217.32	540.00	196.94	1432.07	157.56	0.72	4,581

Table 3. Comparative summary of normal and anomalous trajectories identified through anomaly detection.

Category	Total Distance (km)	Mean Speed (km/h)	Speed Std (km/h)	Duration (sec)	Displacement (km)	Path Efficiency	Num Trajectories
Normal	227.04	566.43	135.91	1410.00	190.35	0.81	12,707
Anomalous	92.70	212.38	78.67	2018.72	30.33	0.28	669

Figures

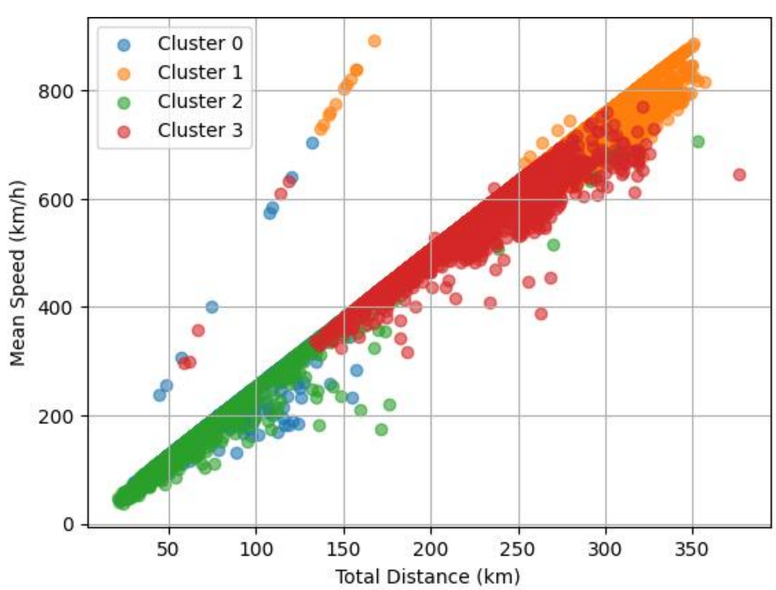

Figure 1. Trajectory clusters visualized in distance-speed feature space.

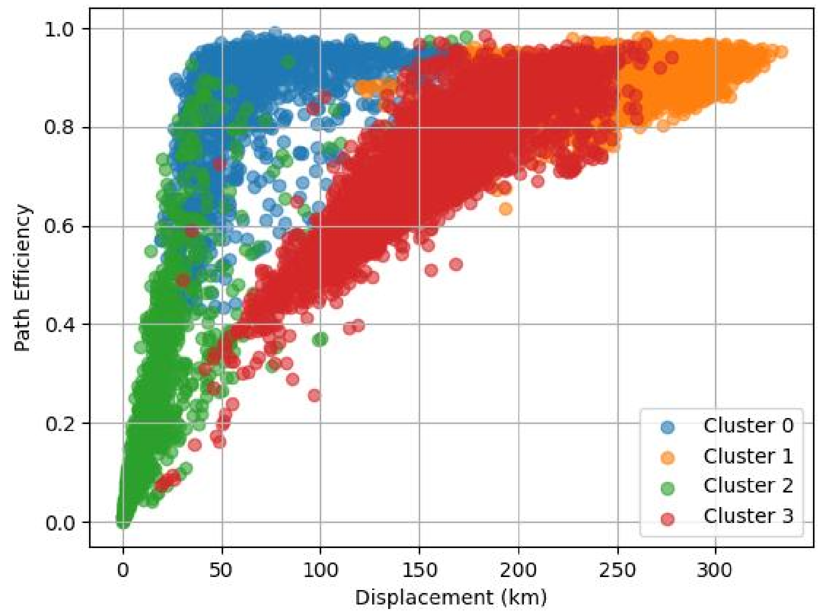

Figure 2. Trajectory clusters visualized in displacement-efficiency space.

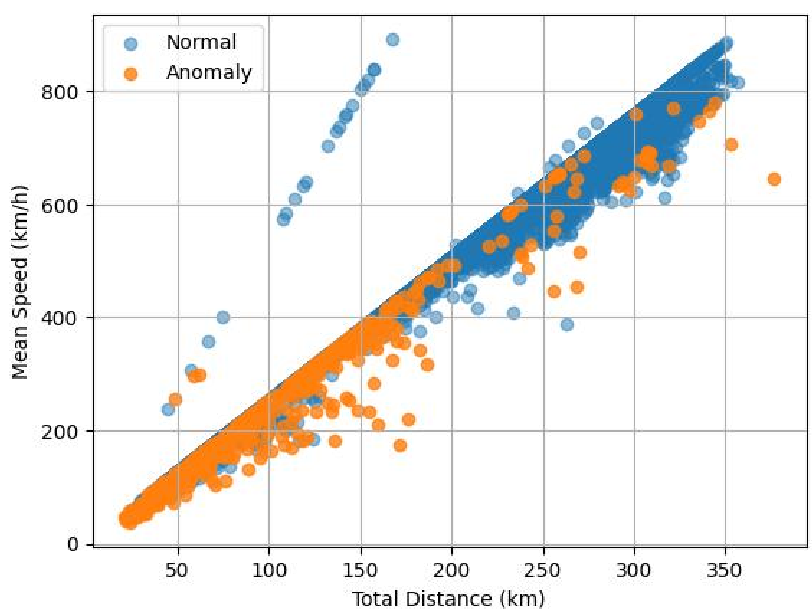

Figure 3. Separation of normal and anomalous trajectories in feature space.

REFERENCES

1. An, H., King, N., & Hwang, S. O. (2019). Issues and solutions in air-traffic infrastructure and flow management for sustainable aviation growth: A literature review. *World Review of Intermodal Transportation Research*, *8*(4), 293-319.

2. Basora, L., Olive, X., & Dubot, T. (2019). Recent advances in anomaly detection methods applied to aviation. *Aerospace*, *6*(11), 117.

3. Bastas, A., Kravaris, T., & Vouros, G. A. (2020). Data driven aircraft trajectory prediction with deep imitation learning. *arXiv preprint arXiv:2005.07960*.
4. Berberich, J., & Allgöwer, F. (2020, May). A trajectory-based framework for data-driven system analysis and control. In *2020 European Control Conference (ECC)* (pp. 1365-1370). IEEE.
5. Bolić, T., Castelli, L., De Lorenzo, A., & Vascotto, F. (2022). Trajectory clustering for air traffic categorisation. *Aerospace*, *9*(5), 227.
6. Brunton, S. L., Nathan Kutz, J., Manohar, K., Aravkin, A. Y., Morgansen, K., Klemisch, J., ... & McDonald, D. (2021). Data-driven aerospace engineering: reframing the industry with machine learning. *Aiaa Journal*, *59*(8), 2820-2847.
7. Chakrabarti, S., & Vela, A. E. (2023). Modeling and characterizing aircraft trajectories near airports using extracted control actions. *Journal of Aerospace Information Systems*, *20*(2), 81-101.
8. Chen, J., & Pan, S. (2022). Learning representations via a robust behavioral metric for deep reinforcement learning. *Advances in Neural Information Processing Systems*, *35*, 36654-36666.
9. Corrado, S. J., Puranik, T. G., Fischer, O. P., & Mavris, D. N. (2021). A clustering-based quantitative analysis of the interdependent relationship between spatial and energy anomalies in ADS-B trajectory data. *Transportation Research Part C: Emerging Technologies*, *131*, 103331.
10. Costas, P., & de Oliveira, I. R. (2024). Advancing Operational Efficiency: Airspace Users' Perspective on Trajectory-Based Operations. *arXiv preprint arXiv:2412.08783*.
11. Deng, C., Choi, H. C., Park, H., & Hwang, I. (2022). Trajectory pattern identification and classification for real-time air traffic applications in Area Navigation terminal airspace. *Transportation Research Part C: Emerging Technologies*, *142*, 103765.
12. Gala, V. (2024). Subset of Opensky Dataset for aircraft trajectories [Data set]. Fraunhofer FOKUS, Berlin, Germany. https://doi.org/10.5281/zenodo.12751775
13. Gardi, A., Lim, Y., & Sabatini, R. (2023). Optimisation of Flight Trajectories and Airspace. *Sustainable Aviation Technology and Operations: Research and Innovation Perspectives*, 165.
14. Hashemi, S. M., Botez, R. M., & Grigorie, T. L. (2020). New reliability studies of data-driven aircraft trajectory prediction. *Aerospace*, *7*(10), 145.
15. Im, D. J., Kwak, I., & Branson, K. (2020). Evaluation metrics for behaviour modeling. *arXiv preprint arXiv:2007.12298*.
16. Jasra, S. K., Valentino, G., Muscat, A., & Camilleri, R. (2025). A comparative study of unsupervised machine learning methods for anomaly detection in flight data: Case studies from real-world flight operations. *Aerospace*, *12*(2), 151.
17. Keerthana, K., & Varma, N. V. (2025). Anomaly Detection in Aircraft Trajectories using Machine Learning. *Authorea Preprints*.
18. Li, B., Du, W., Zhang, Y., Chen, J., Tang, K., & Cao, X. (2021). A deep unsupervised learning approach for airspace complexity evaluation. *IEEE Transactions on Intelligent Transportation Systems*, *23*(8), 11739-11751.
19. Liu, S., Li, W., Yao, D., & Bi, J. (2025, April). Effective and efficient representation learning for flight trajectories. In *Proceedings of the AAAI Conference on Artificial Intelligence* (Vol. 39, No. 12, pp. 12211-12219).

20. Pongsakornsathien, N., Bijjahalli, S., Gardi, A., Symons, A., Xi, Y., Sabatini, R., & Kistan, T. (2020). A performance-based airspace model for unmanned aircraft systems traffic management. *Aerospace*, *7*(11), 154.

21. Romanova, I. K. (2019, November). Study of the influence of deformations and asymmetry on aircraft movement parameters. In *AIP conference proceedings* (Vol. 2171, No. 1, p. 130001). AIP Publishing LLC.

22. Shrestha, R., Oh, I., & Kim, S. (2021). A survey on operation concept, advancements, and challenging issues of urban air traffic management. *Frontiers in Future Transportation*, *2*, 626935.

23. Wang, R., Li, F., Xu, X., Wang, Y., Ma, Q., & Li, L. (2025, April). Abnormal trajectory identification in terminal area based on cluster analysis of flight trajectory data. In *2025 5th International Conference on Big Data Engineering and Education (BDEE)* (pp. 7-11). IEEE.

24. Wang, Z., Liang, M., & Delahaye, D. (2020, February). Data-driven conflict detection enhancement in 3d airspace with machine learning. In *2020 International Conference on Artificial Intelligence and Data Analytics for Air Transportation (AIDA-AT)* (pp. 1-9). IEEE.

25. Zhang, M., Zhang, L., & Liu, T. (2024). Aircraft Behavior Recognition on Trajectory Data with a Multimodal Approach. *Electronics*, *13*(2), 367.