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Evaluating the Impact of ADS-B Data Cleaning on Algorithm Performance

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Abstract
Automatic Dependent Surveillance-Broadcast (ADS-B) data have become a key resource for research on trajectory prediction, conflict detection, and air traffic management. However, due to inherent limitations in data acquisition and transmission, ADS-B datasets often contain missing points, irregular sampling, and anomalies. To ensure usability, researchers typically perform data cleaning and preprocessing before analysis. While these operations improve consistency and completeness, they inevitably alter the original data characteristics, potentially causing deviations between algorithm outputs and actual operational patterns. Existing studies tend to focus on specific cleaning methods, but lack systematic and quantitative evaluations of how different cleaning strategies impact downstream applications. To address this gap, this paper proposes an indicator-driven, structured evaluation framework. The framework integrates a multi-level data quality metric system, datasets with varying levels of cleaning, and comparative experiments under a unified prediction and analysis setup to examine how data cleaning influences algorithm performance. Experimental results demonstrate that differences in cleaning strategies can substantially affect prediction accuracy and reliability, highlighting the importance of balancing data cleaning and fidelity. This study provides a systematic approach for evaluating ADS-B data quality and establishes a more robust data foundation for trajectory prediction, safety assessment, and air traffic management applications.

Keywords: ADS-B Data; Data Cleaning; Data Quality; Algorithm Performance

Abbreviations: JOAS: Journal of Open Aviation Science, ATM: Air Traffic Management

1. Introduction

Automatic Dependent Surveillance–Broadcast (ADS-B) has become a crucial data source for air traffic management, supporting a wide range of applications. Typical studies include trajectory prediction [1, 2], flight phase identification [3], trajectory clustering and modeling [4], safety analysis [5] (e.g., conflict detection and collision risk assessment), and airport operations optimization [6] (e.g., runway occupancy and taxiing analysis). ADS-B has also become a key enabler for environmental studies such as fuel consumption estimation, contrail detection, and large-scale emissions assessment.

Despite these advances, ADS-B data quality remains a significant concern. Missing points, irregular sampling, and anomalies complicate processing and may bias analysis. To improve usability, researchers apply cleaning methods such as interpolation, smoothing, outlier removal, and resampling. However, these methods can also distort the statistical and physical characteristics of trajectories. For example, interpolation can mask subtle variations and increase prediction errors, while outlier removal may discard rare but genuine safety-critical events. These examples illustrate the conditional and sometimes counterproductive impact of cleaning on algorithm performance. Yet, existing studies rarely provide systematic and quantitative analysis of how different strategies influence downstream results.

To address this gap, this study systematically evaluates the relationship between data cleaning and algorithmic performance in ADS-B analytics. Chapter 2 reviews eight major application domains of ADS-B data to contextualize its analytical value. Chapter 3 summarizes common data cleaning techniques and proposes a generalized preprocessing pipeline integrating detection, interpolation, and smoothing. Chapter 4 presents an autoencoder-based case study that quantifies the impact of different noise types (Gaussian, drift, and spikes) on trajectory reconstruction performance, followed by a discussion of the observed impacts and implications. Finally, Chapter 5 concludes the study and outlines directions for future research. Together, these analyses aim to provide a clearer understanding of how data quality shapes learning-based ADS-B algorithms and to inform the design of more robust data processing strategies.

2. State of the Art

This chapter provides a systematic review of ADS-B technology and its current applications in aviation research. It begins with a review of the development and technical evolution of the ADS-B system, highlighting its role and advantages within modern air traffic management. Subsequently, based on a systematic literature review, the use of ADS-B data across different research domains is summarized and categorized, outlining the main directions and emerging trends. This overview lays the theoretical and practical foundation for the subsequent chapters on data cleaning and algorithm performance evaluation.

2.1 ADS-B History

In the early stages of civil aviation, air traffic controllers primarily relied on Primary Surveillance Radar (PSR) and Secondary Surveillance Radar (SSR) to monitor aircraft. However, with improvements in aircraft performance and the expansion of long-haul air routes, the limitations of PSR and SSR—such as restricted coverage, insufficient information accuracy, and delayed updates—gradually became apparent. These limitations not only increased the navigational difficulty for long-distance flights but also posed safety risks. For instance, in 1983, Korean Air Flight 007 deviated from its intended route due to insufficient radar coverage, navigation system malfunctions, and communication failures [7], ultimately entering Soviet airspace and being shot down, resulting in a major aviation accident.

To address these challenges, the aviation industry gradually developed the Automatic Dependent Surveillance–Broadcast (ADS-B) system over several decades. ADS-B leverages the Global Navigation Satellite System (GNSS) and onboard sensors, integrating information such as barometric altitude, inertial navigation, and airspeed measurements to generate aircraft state parameters. These parameters, including identification codes, position, altitude, velocity, and flight intent, are periodically broadcast via onboard ADS-B equipment [8]. Compared with traditional radar, ADS-B offers higher accuracy, shorter update intervals, broader coverage, and lower infrastructure and maintenance costs. It significantly enhances situational awareness for both pilots and air traffic controllers while reducing the burden on ground surveillance infrastructure.

The development of ADS-B can be traced back to the 1970s. In 1992, the Radio Technical Commission for Aeronautics (RTCA) first proposed ADS-related technical specifications in DO-212 [9], identifying it as a candidate technology for future air traffic surveillance. The DO-242 standard [10] issued in 1998 further established the technical framework and performance requirements for ADS-B systems. Between 1996 and 2006, the Federal Aviation Administration (FAA) conducted the CAPSTONE project in Alaska [11], demonstrating the potential of ADS-B to improve operational safety and efficiency in remote airspace. In 2003, the 11th Air Navigation Conference of the International Civil Aviation Organization (ICAO) formally recognized ADS-B as a critical surveillance technology for future air traffic management and promoted its standardization and adoption [12].

Since 2010, ADS-B has gradually entered large-scale global deployment. Various countries have promoted its adoption through regulations. The FAA requires all aircraft operating in controlled airspace to be equipped with ADS-B Out [13]; Europe has similarly mandated ADS-B under the SESAR framework [14], expecting to increase European airspace capacity by 80–100% by 2040. Australia [15] and Singapore have also implemented ADS-B mandates. In China, a national policy issued in 2015 [16] required the installation of ADS-B equipment on commercial aircraft. Meanwhile, satellite-based ADS-B [17] has enabled real-time and high-precision surveillance over approximately 70% of global airspace, and open platforms such as the OpenSky Network [18] provide large-scale ADS-B data resources for academic research.

2.2 ADS-B Data current usages

This section presents an overview of the current use of ADS-B data in the research domain, identifying and organizing clusters of algorithms and application areas. In this study, the collected literature is categorized into eight major domains, spanning from trajectory modeling and operational management to environmental sustainability and cybersecurity. These analyses provide a structured overview of the evolving research landscape surrounding ADS-B applications in aviation.

2.2.1 Paper Selection

This section describes the process of identifying, screening, and organizing research publications related to the application of ADS-B data. To ensure both representativeness and research quality, we focused on journals and conferences with high academic impact in the fields of air traffic management (ATM) and digital aviation. The primary sources include the *Digital Avionics Systems Conference (DASC)*, *SESAR Joint Undertaking Annual Conference*, *Air Traffic Management Seminar (ATM Seminar)*, *International Conference on Research in Air Transportation (ICRAT)*, *Transportation Research Part C: Emerging Technologies*, *IEEE Transactions on Intelligent Transportation Systems*, and the *Journal of Air Transport Management (JATM)*. Literature retrieval was mainly conducted through academic databases such as IEEE Xplore, ScienceDirect, and Elsevier Scopus, as well as publicly available proceedings from the aforementioned conferences.

Considering that large-scale implementation and operational use of ADS-B systems began worldwide around 2012, this year was set as the starting point for the large-scale research phase of ADS-B data. Therefore, this study selected English-language publications issued between 2012 and December 2024 as the objects of analysis. We manually collected research that explicitly utilized real ADS-B flight data from the selected journals and conferences, excluding studies that relied solely on simulated or synthetic datasets.

The detailed screening process was as follows:

- **Initial Screening:** Titles and abstracts were reviewed to confirm the study's relevance to the aviation domain, such as airspace optimization, trajectory prediction, or conflict detection and avoidance (DAA).
- **Keyword Filtering:** Only papers containing the term "ADS-B" in the title, abstract, or keywords were retained.
- **Data Authenticity Criterion:** Studies were required to clearly indicate the use of real ADS-B datasets. Papers using only simulated or artificially generated trajectories were excluded.
- **Duplication and Accessibility Review:** Duplicate publications and inaccessible preprints were

removed to ensure the reproducibility and verifiability of the results.

After multiple rounds of screening and manual verification, a total of 145 papers were collected, covering representative applications of ADS-B data across diverse research domains. The distribution of the selected studies by source is illustrated in Figure 1.

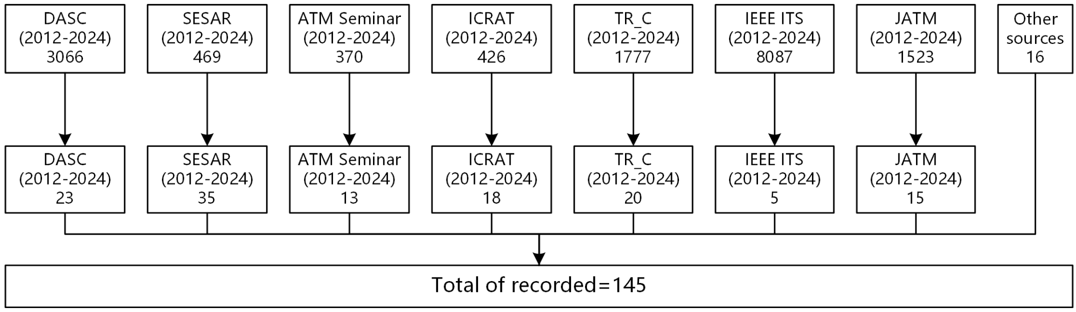


Figure 1. Paper collection flow

2.2.2 Paper Clustering and Categorization

The screened publications provided a solid data foundation for the categorization and trend analysis of ADS-B applications in this study. To systematically organize the characteristics and focal points of different research directions, we employed a mixed quantitative–qualitative approach for feature extraction and clustering of the collected literature.

Using Excel spreadsheets and reference management tools, the following key features were extracted from each selected conference and journal:

- Publication year;
- Source conference or journal;
- Paper title and author keywords;
- Application scenario;
- Research focus or analytical perspective;
- Methods and algorithmic approaches (e.g., machine learning, optimization models, statistical analysis, simulation frameworks);
- Description of the ADS-B dataset used (e.g., public data repositories, airport-specific data, or crowdsourced datasets).

In the preliminary organization stage, the literature was grouped into four broad directions: trajectory prediction, air traffic management, aircraft performance estimation, and environmental sustainability. However, a subsequent systematic comparison and semantic analysis of all research features revealed significant overlaps and hierarchical relationships among different themes.

Therefore, this study adopted a combination of thematic synthesis and semantic grouping to reclassify the literature. This process comprehensively considered the research objectives, data utilization patterns, and the functional role of ADS-B within each study, aiming to establish a classification framework that systematically reflects the overall landscape of ADS-B research.

Finally, ADS-B–related studies were categorized into eight major domains: Trajectory Modeling and Prediction, Operational Optimization and Management, Operational Safety and Surveillance, Aircraft Performance and Efficiency, Data Engineering and Enhancement, Environment and Sustainability, Security and Cybersecurity, Methodology, Simulation, and Policy. This classification framework provides the structural foundation for the domain-specific analysis presented in the following sections.

As shown in Table 1, the classification results derived from thematic induction and semantic grouping are presented, covering typical application domains of ADS-B data across eight research categories and their representative algorithms. In the following sections, each category is further elaborated in terms of its research scope and representative studies.

Table 1. Summary of ADS-B Application Categories, Main Methods, and Data Roles

Category	Main Methods	Role of ADS-B Data
Trajectory Modeling and Prediction	Clustering (DBSCAN, K-means) LSTM/Transformer prediction Autoencoder feature extraction DTW PCA Hybrid physical–data models	**Core data source**
Operational Optimization and Management	MILP Simulated annealing Heuristic algorithms KPI-based performance metrics Historical traffic analysis	**Real-time/historical traffic input**
Operational Safety and Surveillance	DAA geometric models Anomaly detection (thresholds, clustering, autoencoc Monte Carlo risk evaluation	**Flight monitoring and safety baseline**
Aircraft Performance and Efficiency	Dynamic equation inversion Maximum likelihood estimation Bayesian inference Particle filtering Regression and neural networks	**Model calibration data source**
Data Engineering and Enhancement	Kalman filtering Map-matching Multisource fusion Data indexing Generative models (TimeGAN)	**Primary processing object**
Environment and Sustainability	Trajectory-based emission estimation Remote sensing data fusion Optimal control route planning	**Environmental assessment input**
Security and Cybersecurity	Intrusion detection (ML classifiers) Protocol vulnerability testing SDR signal analysis	**Research target**
Methodology, Simulation, and Policy	Open-source simulation platform development Data standardization Policy and privacy analysis	**Research infrastructure and policy object**

Trajectory Modeling and Prediction. This domain focuses on modeling historical and real-time aircraft trajectories and predicting their future states. The core tasks include 4D prediction, estimated time of arrival (ETA) calculation, trajectory pattern clustering and quantification of prediction uncertainty. As the core data source, ADS-B provides continuous, high-precision measurements of aircraft position, velocity, and altitude, forming the foundation for trajectory modeling and prediction. The data quality directly affects model accuracy and reliability. Gui et al. [19] proposed a semantic trajectory representation for arrival flight clustering to support airspace design, flow management, and ETA estimation; Wang et al. [20] applied PCA-based dimensionality reduction and DBSCAN clustering for preprocessing, followed by a Multi-Cell Neural Network (MCNN) for short-term trajectory prediction in terminal maneuvering areas (TMA); and Wang et al. [21] integrated clustering-based preprocessing with hybrid MCNN models to improve ETA prediction accuracy.

Operational Optimization and Management. This domain focuses on improving the overall efficiency of airspace and airport operations, encompassing air traffic flow management, surface operations (taxiing and sequencing), terminal maneuvering area coordination, and airspace structure optimization. ADS-B data play a central role by providing continuous and fine-grained historical and real-time traffic information, serving as a reliable input for optimization models and decision-support systems. It enables accurate operational performance evaluation and data-driven strategy optimization. Research in this area often applies Linear Programming, Simulated Annealing, and heuristic algorithms to address sequencing, scheduling, and routing problems. Other studies employ queuing models and Key Performance Indicators (KPIs) for operational assessment or mine historical ADS-B data to identify bottlenecks such as taxiway congestion and sector capacity limits. Basora et al. [22] combined DBSCAN clustering with Random Forest regression for sector occupancy prediction, and Delahaye et al. [23] used hierarchical clustering with Transformer models for flow pattern detection and capacity management.

Operational Safety and Surveillance. This research domain aims to enhance aviation safety and situational awareness through data-driven analysis. It covers conflict detection and resolution (DAA / ACAS), abnormal event detection (e.g., go-arounds, unstable approaches), assessment of collision risk and airspace complexity, and performance evaluation of surveillance systems. As an independent surveillance source, ADS-B data provide continuous and high-precision trajectory and state information, enabling real-time monitoring of aircraft behavior, detection of potential conflicts and anomalies, and quantitative assessment of operational safety. Bonifazi et al. [24] identified unstable approaches and go-arounds using ADS-B data, employing rule-based methods and Gaussian Mixture Models (GMM) for anomaly detection and integrating runway and weather information for improved accuracy. Rorie et al. [25] conducted the first real-world evaluation of the ACAS Xr airborne collision avoidance system. Zhang et al. [26] investigated conflict-free routing strategies and compared multiple optimization algorithms, while Bao et al. [27] proposed a multi-airport terminal area risk prediction framework to assess inter-airport conflict probabilities.

Aircraft Performance and Efficiency. This research area focuses on deriving aircraft performance parameters from flight data to calibrate or complement existing models such as BADA, and to evaluate energy efficiency across aircraft types and flight phases. Key parameters include aircraft mass, drag polar, thrust settings, fuel consumption, and speed profiles. In this context, ADS-B data provide essential flight state information—such as ground speed, vertical rate, and heading—enabling large-scale, fleet-level performance analysis even in the absence of detailed design data. This supports more accurate and data-driven model calibration and validation. Sun et al. [28] developed a probabilistic framework to estimate aerodynamic parameters from operational data; Schultz et al. [29] integrated FDR and ADS-B data to model fuel consumption and operational efficiency using machine learning methods; and Alligier et al. [30] predicted aircraft mass and speed intent during climb to enhance physics-based trajectory prediction.

Data Engineering and Enhancement. This category focuses on improving the quality and usability of raw ADS-B data, which form the foundation for subsequent analytical and modeling applications. Key tasks include data cleaning and anomaly detection, missing-value imputation, multi-source data fusion, data compression and indexing, and synthetic data generation. In this domain, ADS-B data themselves are the core subject of engineering—aimed at producing cleaner, more complete, and more interoperable datasets that support trajectory prediction, operational analysis, and safety evaluation. Tabassum et al. [31] conducted long-term statistical analysis to identify anomalies and assess the impact of systematic errors on trajectory accuracy. Wandelt et al. [32] introduced an efficient compression and indexing framework to enable scalable querying and analytics of large-scale ADS-B records. Spinielli et al. [33] developed a reproducible reference trajectory dataset by integrating multiple surveillance sources for performance assessment under the EUROCONTROL PRU initiative.

Environment and Sustainability. This research area focuses on quantifying the environmental impact of aviation operations and exploring sustainable optimization strategies, including greenhouse gas and pollutant emission assessment, contrail formation detection and avoidance, and noise evaluation. Owing to its wide coverage and high temporal resolution, ADS-B data serve as a crucial source for environmental modeling and validation. For instance, Roosenbrand et al. [6] proposed a method to estimate contrail altitudes using shadows in Landsat satellite imagery, with ADS-B data employed as ground truth for validation. Sun et al. [34] integrated satellite-based and ground-based ADS-B data with wind field information to improve emission estimation and compared actual flight trajectories with optimal routes to quantify excess emissions.

Security and Cybersecurity. This domain focuses on identifying and mitigating cybersecurity threats targeting the ADS-B system itself, such as False Data Injection Attacks (FDIA), signal spoofing, and message tampering, to ensure the integrity and reliability of surveillance information. In this field, the ADS-B protocol, signal, and data link are the direct subjects of vulnerability analysis and protection technology research. For example, Cretin et al.[35] proposed a Domain-Specific Language (DSL)-based testing framework to evaluate the resilience of Air Traffic Control (ATC) systems against FDIA, while Khan et al. [36] employed machine learning techniques for ADS-B intrusion detection.

Methodology, Simulation, and Policy. This category provides foundational tools, frameworks, and policy support for aviation research. It includes the development of open-source simulation platforms, advocacy of reproducible research practices, establishment of data standards, and discussion of regulatory and privacy issues related to ADS-B deployment. In this context, ADS-B serves both as input data for constructing realistic scenarios in simulation environments and as a focal topic in advancing data-sharing policies, privacy protection, and industry standards. For example, Mehlitz et al. [37] proposed the RACE framework for comprehensive airspace data analysis, while Bolic et al. [38] systematically elaborated on the European ATM Open Science Alliance and its Open Performance Data Initiative (OPDI), which aim to foster transparency and open research in the ATM domain.

To provide a clearer overview of the application fields of ADS-B data, we conducted a quantitative analysis of field attribution for 145 valid papers from journals including DASC and SESAR, based on the eight aforementioned classification categories. The results are presented in Figure 2. It should be noted that some papers cover multiple fields (e.g., Data Engineering + Aircraft Performance Calculation) and are assigned to multiple application fields in accordance with the rule of "counting each involved field separately". Consequently, the total number of papers counted in the pie chart is greater than the actually counted 145 valid samples.

From the overall distribution, papers related to Operational Optimization and Management represent the most prominent field in ADS-B data research, accounting for 30.6%. This is followed by Operational Safety and Surveillance (23.6%) and Trajectory Modeling and Prediction (18.5%). These three fields collectively account for over 70% of the total, forming the mainstream directions of ADS-B data applications. This reflects a high alignment between ADS-B data-related research and the core application scenarios of ADS-B: Operational Optimization and Management directly addresses the efficiency needs of air traffic management (ATM) systems, such as "improving airspace utilization and reducing flight delays"; meanwhile, Operational Safety and Surveillance, as well as Trajectory Modeling and Prediction, leverage the "real-time positioning and dynamic tracking" capabilities of ADS-B to serve the safety requirements of "flight conflict early warning and rapid identification of abnormal states".

In contrast, the proportions of papers in the fields of Security and Cybersecurity (2.5%), Environment and Sustainability (5.1%), and Methodology, Simulation and Policy (5.1%) are relatively low, collectively accounting for less than 15%. These fields represent the directions with relatively smaller proportions in current ADS-B data application research.

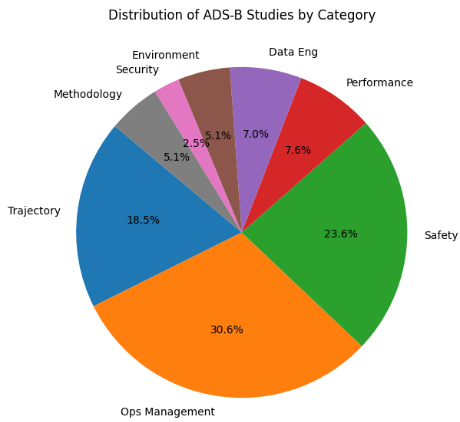


Figure 2. Distribution of studies across 8 ADS-B application domains

3. Summary of ADS-B Cleaning Methods, work flow

3.1 Data Quality Issues in ADS-B Surveillance

Real-world ADS-B data often contain a considerable amount of noise and anomalous errors. Several studies have conducted in-depth analyses of these issues. For instance, Tabassum et al. [39] systematically demonstrates various types of anomalies found in ADS-B messages, while [40] and [41] provide detailed examinations of noise sources and error mechanisms within crowdsourced datasets. These studies collectively indicate that ADS-B data quality is heavily influenced by factors such as hardware performance, signal environment, and network structure, resulting in inconsistencies and unreliability across raw observations.

In general, the quality issues of ADS-B data can be categorized into four dimensions:

(1) **Completeness**: ADS-B data often suffer from message loss, missing fields, and update interruptions, leading to temporal or spatial discontinuities in flight trajectories. Such problems are mainly caused by variations in receiver performance, signal attenuation, and the instability of crowdsourced networks, resulting in insufficient data coverage.

(2) **Consistency**: Some data exhibit internal contradictions in temporal, spatial, or physical attributes, such as out-of-order timestamps, abrupt altitude jumps, or unrealistic speed values. These issues typically arise from clock drift, decoding errors, or improper data aggregation from multiple sources, undermining the logical coherence of trajectories.

(3) **Accuracy**: Systematic deviations may exist between the reported ADS-B values and the actual flight states—for example, discrepancies between barometric and geometric altitude or significant errors in reported positions and speeds. The main causes include quantization errors, receiver precision limitations, and environmental interference.

(4) **Reliability**: ADS-B datasets may contain random noise, falsified messages, or artifacts introduced by multi-source fusion, all of which degrade the credibility and usability of the information. Such reliability issues are particularly prominent in open, crowdsourced data collection environments, increasing uncertainty in subsequent analyses and modeling.

In summary, various types of errors may occur throughout the collection, transmission, and aggregation of ADS-B data. Without proper treatment, these problems can severely affect the performance of downstream algorithms and compromise the reliability of analytical results. Therefore, systematic data cleaning and quality control are essential prerequisites to ensure the usability and accuracy of ADS-B data for further research and algorithmic applications.

3.2 Data cleaning methods

3.2.1 Task-Oriented Filtering

Filtering ADS-B data is typically the initial step in data cleaning. Depending on the research objectives and application scenarios, most studies perform preliminary filtering of raw ADS-B data before analysis to ensure that the data used are relevant and representative. Common filtering strategies can be broadly categorized into range-based filtering and attribute-based filtering.

(1) Range-Based Filtering

This approach primarily selects ADS-B data based on temporal or spatial ranges. Temporal filtering can limit the data to specific seasons, dates, or time periods to match the study timeframe. Spatial filtering focuses on particular routes, airspaces, or airport operations. Additionally, trajectories within specific geographic boundaries (e.g., latitude/longitude ranges or airspace altitude layers) may be extracted to construct local operational networks or airspace models.

(2) Attribute-Based Filtering

Beyond temporal and spatial constraints, researchers may remove trajectories that are irrelevant or do not meet task-specific criteria. This type of filtering is often based on flight rules, operational states, aircraft types, or flight phases. For example, Dhief et al. [42] excluded flights operating under Visual Flight Rules (VFR) in a go-around behavior study. Similarly, Liu et al. [**LIU2024104652id**] filtered trajectories under consistent weather conditions in their study on taxiing optimization at Shenzhen Bao'an Airport to reduce the influence of weather variations and runway configurations.

3.2.2 Outlier Detection and Removal

After the initial filtering, it is usually necessary to identify and remove outliers in order to ensure the reliability of subsequent analyses. [8] review summarized and investigated common methods for outlier detection and handling. Common outlier handling methods include the removal of entire trajectories, local cleaning of individual abnormal points, and automated detection based on clustering or deep learning techniques.

The most common approach is the removal of entire trajectories. Outlier trajectories can arise from various reasons, the most frequent being incomplete data, such as trajectories with too few sampling points to accurately represent the flight process, which need to be excluded.

For trajectories that are generally valid but contain a few abnormal points, researchers typically perform local cleaning. Common types of noise include duplicate points and physically impossible "jump points." Methods such as Gaussian filtering or particle filtering are often used to smooth trajectories and correct these anomalies.

In addition, density-based clustering algorithms like DBSCAN are widely applied in outlier detection and cleaning. DBSCAN can automatically identify outliers based on point density and separate them from normal trajectories, allowing simultaneous trajectory clustering and outlier removal. Compared to traditional filtering methods, DBSCAN offers greater flexibility and automation, particularly for trajectory data with uneven spatial distribution.

Autoencoders (AE), as a deep learning approach, can also be employed for anomaly detection. AE learns typical patterns of normal trajectories during training, and abnormal trajectories or points usually exhibit larger reconstruction errors. These errors can then be used to identify and remove outliers. AE is capable of capturing nonlinear relationships in data, making it particularly suitable for high-dimensional and time-series ADS-B trajectory data, and it can be combined with filtering or clustering methods for more precise cleaning.

3.2.3 Interpolation and resampling

In ADS-B data processing and trajectory reconstruction, interpolation and resampling are two essential preprocessing techniques. Interpolation focuses on repairing missing data points and ensuring trajectory continuity, while resampling aims to unify the temporal or spatial distribution of data, thereby improving the stability of subsequent analysis and model training. Since both techniques are often applied together in practice, they are presented here in an integrated discussion.

(1)Interpolation

The objective of interpolation is to estimate missing values between known points, thereby converting discrete trajectories into continuous and smooth curves. Depending on the fitting principle, common interpolation methods can be categorized into three groups:

Linear and Polynomial Interpolation This is the most widely used class of interpolation techniques, which assumes that variations between adjacent points follow a linear or low-order polynomial relationship. These methods are computationally efficient and suitable for short time intervals or smooth motion, but their ability to capture nonlinear behavior—such as turning or climbing—is limited. Representative methods include linear interpolation [43] and polynomial interpolation.

Spline-Based Interpolation Spline methods fit piecewise polynomial functions while maintaining continuity at segment boundaries, achieving higher smoothness and stability. Typical examples include linear spline interpolation [44], cubic spline interpolation [45], and piecewise cubic Hermite interpolation (PCHIP) [46], which introduces shape-preserving constraints to prevent unrealistic oscillations. Compared with simple linear methods, spline-based interpolation offers superior smoothness and shape retention, making it widely used for flight trajectory reconstruction and long-duration signal completion.

Spatially Adaptive Interpolation This approach ensures consistent spatial resolution along the trajectory, achieving globally uniform point density while preserving geometric accuracy and spatial consistency.

(2) Resampling Methods

Resampling aims to transform irregularly spaced ADS-B data into a unified format suitable for downstream analysis and model input. According to the dimension of unification, resampling techniques can be classified into four categories:

Fixed-Time Interval Resampling This method extracts or generates data points at a fixed temporal interval, ensuring uniform time distribution along the trajectory. It is the most fundamental form of temporal standardization, with sampling intervals ranging from one second [47] to several minutes [48], depending on the temporal resolution required by the study.

Trajectory Feature-Based Resampling Instead of relying on fixed intervals, this approach resamples according to geometric characteristics such as turning points or curvature changes, thereby reducing redundancy while preserving essential trajectory features.The representative algorithms are: RDP Algorithm (Douglas–Peucker) [49]: Iteratively removes points with distances below a given threshold from the line connecting the start and end points, retaining only key inflection points. This reduces data volume while maintaining the overall geometric structure of the trajectory. Fixed Number of Inputs algorithm: Uses interpolation to map each trajectory into a fixed number of points, ensuring consistent input dimensions for deep learning models such as autoencoders [50] and Transformers [51].

Spatial or Curve-Based Resampling This category focuses on spatial uniformity or curve smoothness. Points are extracted along the trajectory at fixed spatial intervals to achieve uniform spatial density, which is particularly useful for spatial analysis tasks such as airport vicinity trajectory density mapping or taxiway path planning, where uneven temporal sampling may otherwise cause spatial distortion.

3.2.4 Smoothing

After temporal or spatial resampling, researchers often apply trajectory smoothing to further suppress noise, reduce trajectory jitter, and preserve the essential motion trend, thereby providing more reliable inputs for subsequent analysis and model construction. According to their underlying principles and computational characteristics, trajectory smoothing methods can generally be categorized into three groups:

(1) Model-based filtering methods

These methods rely on state-space or probabilistic estimation models to describe the relationship between the aircraft's true motion states and observational noise, achieving optimal trajectory estimation and smoothing. Representative algorithms include the Kalman Filter [52] and Extended Kalman Filter, which obtain optimal state estimates by minimizing the covariance of recursive estimation errors. Owing to their strong dynamic modeling capability and physical interpretability, such methods are widely used for aircraft state estimation and altitude smoothing tasks.

(2) Signal processing–based filtering methods

In this approach, the trajectory is treated as a time-series signal, and digital filters are employed to suppress undesired frequency components, thus achieving trajectory smoothing. Typical examples include the finite impulse response (FIR) low-pass filter [53], the Exponential Moving Average (EMA) algorithm [54] , and the bilateral window averaging method [55]. By convolutional or recursive operations, these methods effectively remove oscillatory noise from uniformly sampled trajectories.

(3) Curve-fitting and geometric-statistical methods

These methods approximate the entire trajectory using mathematical curves or geometric-statistical representations to achieve global-level smoothing, producing continuous and geometrically consistent trajectories. For instance, the smoothing cubic spline [56] is a variational fitting technique that balances data fidelity and smoothness through an optimized regularization parameter. The Hough voting algorithm [57], based on the global geometric consistency of trajectories, maps local trajectory features into a parameter space and serves as a common tool for geometric trajectory reconstruction.

3.2.5 ADS-B data cleaning pipeline

Overall, ADS-B data cleaning typically follows a logical progression from macroscopic filtering to microscopic refinement.

As illustrated in Figure 3, the cleaning process generally consists of the following steps:

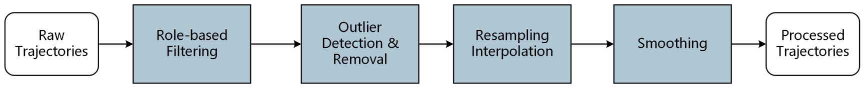


Figure 3. Pipeline of ADS-B data cleaning

First, the raw ADS-B data are filtered by temporal, spatial, and flight-related attributes according to the research objectives, in order to extract a subset that meets the analysis requirements. Next, preliminary denoising is performed, including duplicate removal, elimination of trajectories with excessive missing data, and correction of abrupt anomalies, thereby improving data completeness and consistency. On this basis, interpolation and resampling are applied to fill missing values and to unify the temporal or spatial resolution, providing a structured foundation for subsequent algorithmic processing. Finally, trajectory smoothing is carried out to further suppress residual noise and random jitter, extracting the core motion trends that reflect the true flight dynamics.

In recent years, several open-source tools have provided comprehensive support for implementing the above data-cleaning procedures. Among them, the Traffic Library [58] has been widely adopted. It offers ready-to-use implementations for each stage of the workflow, greatly simplifying the pre-processing of ADS-B data. Researchers can transform raw data into high-quality trajectories without developing low-level algorithms manually, which significantly lowers the technical barrier to aviation data processing and allows greater focus on downstream analytical tasks.

It should be noted that the above workflow is derived from a systematic review and comparative analysis of the collected papers. However, the survey reveals significant inconsistencies in how data-cleaning procedures are described across studies. Some works mention only general terms such as “filtering” or “pre-processing” without detailing the specific methods or parameter configurations. This lack of transparency and consistency undermines the reproducibility and comparability of research outcomes and may also affect the reliability of conclusions regarding algorithmic performance.

3.3 Analysis of Data Cleaning Operations

The previously discussed data cleaning procedures can enhance the completeness, consistency, accuracy, and reliability of ADS-B data. However, their impact on downstream algorithms is complex and multifaceted.

Outlier Removal: Eliminating outliers helps filter noise and improve data purity, yet misjudgments may remove legitimate maneuvers (e.g., temporary avoidance), thereby reducing the accuracy of flight pattern modeling. Excessive removal of marginal data can also reduce the sample size and weaken the representativeness of rare conditions such as adverse weather or remote airspace. Moreover, among the two methods introduced earlier, DBSCAN is sensitive to uneven trajectory densities and may misclassify sparse but normal points as anomalies. The Autoencoder (AE), on the other hand, relies on sufficient and high-quality normal data for training; any bias in the training set may shift the anomaly detection threshold, causing normal trajectories to be incorrectly flagged as outliers and introducing additional judgment errors.

Interpolation and Resampling: These techniques are commonly used to fill missing points and unify temporal resolution, thereby improving the continuity and comparability of trajectories. However, excessive or improper interpolation may smooth out genuine micro-maneuvers (e.g., speed adjustments), while resampling, as a data transformation process, may introduce artificial variations in speed and acceleration. Such alterations can distort the instantaneous motion parameters of aircraft, making it difficult for models that depend on short-term motion states (e.g., LSTM-based trajectory prediction) to capture key dynamics, thus increasing prediction errors. In addition, interpolation may blur instantaneous proximity between aircraft, reducing the sensitivity of conflict detection and risk identification.

Smoothing: Kalman or low-pass filters effectively suppress high-frequency jitter in positional data, producing smoother trajectories and facilitating the calculation of derived features such as heading and curvature. Nevertheless, smoothing can weaken sharp trajectory characteristics, such as the precise onset and recovery points of turns, which may negatively affect maneuver-based anomaly detection (e.g., go-around identification) and flight phase classification models.

Overall, ADS-B data cleaning is a crucial step in improving data integrity and reliability. However, as the above limitations indicate, over-cleaning may remove essential flight characteristics, while insufficient cleaning may fail to meet the quality requirements for algorithmic processing. Both extremes can adversely affect downstream analysis and model performance.

Therefore, in practical applications, researchers need to balance data fidelity and usability when designing preprocessing pipelines. In the following chapters, the influence of different cleaning strategies on algorithm performance will be quantitatively evaluated through experiments.

4. use case: investigation of the noise impact on Auto Encoder algorithm

4.1 Objective

This section presents a complete case study that constructs artificial noise experiments to quantitatively evaluate the effects of three typical noise types-Gaussian noise, drift, and spikes—on the trajectory reconstruction performance of an auto-encoder (AE) model. The results further help to identify key priorities and directions for the data cleaning stage.

The experiment employs an ADS-B dataset collected at Zurich Airport, covering trajectory data recorded from 04:57:13 (UTC) on October 1, 2019 to 18:57:37 (UTC) on November 30, 2019, as shown in Figure 4. The dataset contains approximately 2.8 million ADS-B messages, representing the complete trajectories of about 14,000 flights. Each record includes fields such as timestamp, altitude, longitude, latitude, ground speed, heading, callsign, and ICAO24 code, with longitude ranging from 7.5702 to 9.5276 and latitude from 46.8019 to 48.1302.

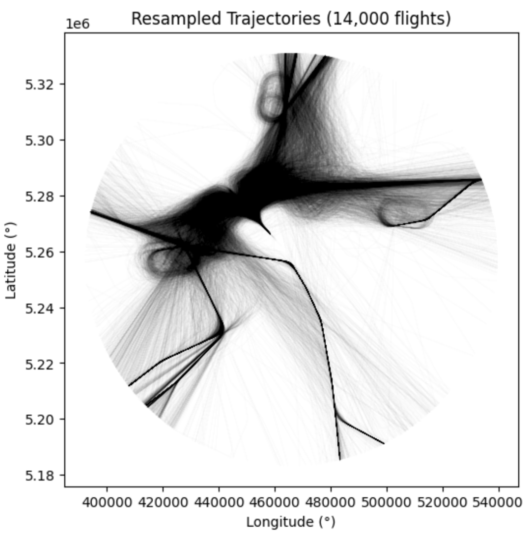


Figure 4. Visualization of the whole dataset

For model training, the data were preprocessed as follows: trajectories were resampled so that each one contained 100 coordinate points, ensuring a uniform input dimension; and normalization was applied to preserve the spatial proportion of coordinates.

4.2 Auto-encoder Model

In terms of algorithm selection, this study builds a simple yet stable AE model. The AE learns the latent space representation of flight trajectories by performing unsupervised feature compression and reconstruction, enabling it to reproduce the input trajectory data.

The autoencoder consists of two symmetric subnetworks: an encoder and a decoder. The encoder takes a 200-dimensional preprocessed trajectory vector as input and compresses it through three layers with 128, 64, and 32 neurons, respectively. The last layer outputs a 32-dimensional latent representation, which captures the embedded features of the trajectory in a lower-dimensional space. The decoder mirrors the encoder's structure, expanding through layers of 32, 64, and 128 neurons, and finally reconstructing the trajectory back to a 200-dimensional output vector.

The model's reconstruction error is optimized using the Mean Squared Error (MSE) loss function, defined as:

$$\mathcal{L}_{\text{rec}} = \frac{1}{N} \sum_{i=1}^{N} |0 x_i - \hat{x}_i|0^2$$

, where x_i denotes the input trajectory vector, $\hat{x}_i$ is the reconstructed output of the model, and N is the number of samples. This loss function reflects the *information fidelity* of the reconstruction process. When the model is well-trained and effectively learns the trajectory behavior features, the reconstructed output $\hat{x}$ closely follows the overall trend of x, with only minor deviations in local details.

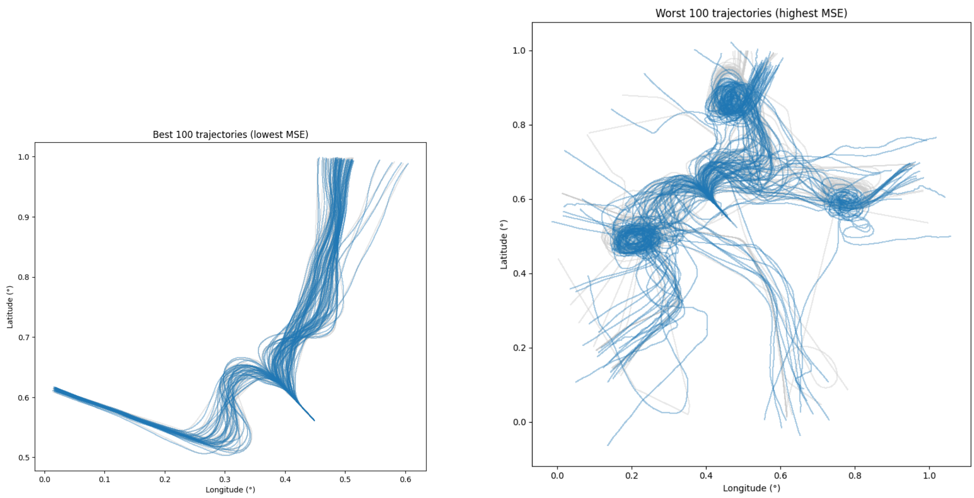
The dataset is split into training and validation sets in an 8:2 ratio, and the AE is trained in an unsupervised manner under the same normalization conditions. During training, both training and validation losses are continuously monitored to evaluate convergence and prevent overfitting. After approximately 200 epochs, the losses stabilize and converge to MSE ≈ 0.002, indicating that the model successfully learns the main spatial structure of flight trajectories and demonstrates strong reconstruction capability.

4.3 Baseline Generation

In this process, a trained AE model is used to identify the trajectories most similar to clean data, which are then selected as the baseline for subsequent experiments. Specifically, the model reconstructs all normalized trajectory samples and computes the reconstruction error for each trajectory. The most representative subset of trajectories with the lowest reconstruction errors is selected as the baseline dataset.

This means that if a trajectory can be reconstructed by the model with an extremely low error, its morphological features are highly representative and regular within the training data distribution, reflecting the typical trajectory patterns learned by the model. Such trajectories are considered the most "reconstructable" samples in the dataset—that is, the ones closest to clean data.

As shown in Figure 5a, the baseline trajectories exhibit high smoothness and spatial consistency, conforming to the physical laws of real flight paths. In contrast, high-error samples, showed in Figure 5b, often contain data anomalies or noisy points. Therefore, by leveraging the AE model's reconstruction error as a selection criterion, it becomes possible to automatically identify high-quality trajectory data without manual thresholds or interpolation procedures. This method helps avoid errors or inappropriate parameter settings that can arise during manual preprocessing, thereby producing a statistically sound and model-adaptive baseline dataset. In total, 100 high-quality trajectories were selected as the baseline dataset for the experiment.



(a) The best 100 trajectories

(b) The worst 100 trajectories

Figure 5. Visualization of reconstructed trajectories

4.4 Noise Injection

To systematically analyze the impact of different noise types on AE reconstruction performance, three typical artificial noise sources were injected into the baseline trajectories: Gaussian noise, drift noise, and spike noise. These correspond to the most common sources of error in ADS-B data and collectively simulate disturbances that occur during data acquisition, transmission, and decoding. The experiment procedure is shown in Figure 6.

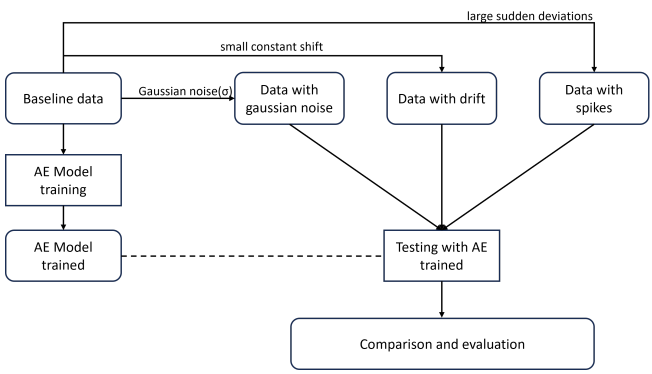


Figure 6. experiment procedure

Gaussian noise simulates random measurement errors affecting ADS-B signals during reception or localization—such as GNSS range errors, multipath propagation, or receiver thermal noise—resulting in small position fluctuations. It is implemented by adding Gaussian perturbations to each coordinate dimension of the baseline trajectories.

Drift noise represents time-dependent cumulative deviations caused by positioning or clock synchronization errors, commonly manifested as gradual longitude or latitude shifts over time. This type of error may originate from GNSS reference drift, sensor calibration bias, or timestamp misalignment. It is simulated by superimposing a small linear offset proportional to time on the trajectory coordinates.

Spike noise corresponds to sporadic outliers or sudden jumps in ADS-B messages, such as decoding errors, packet loss, or transient interference leading to abrupt changes in altitude or speed. In the experiment, random subsets of points were selected from each trajectory and perturbed with sudden amplitude changes of random magnitude.

Each of the three noise types was configured with multiple intensity levels to observe how varying magnitudes of error affect model performance. As illustrated in Figure 7, Gaussian noise causes overall jitter while preserving trajectory shape; drift noise induces gradual spatial displacement over time; and spike noise introduces localized abrupt deviations.

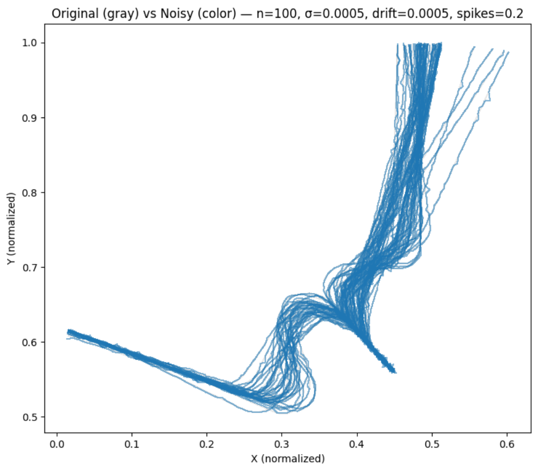


Figure 7. Trajectories with added noise

The resulting noisy trajectories thus possess controlled and interpretable noise characteristics, closely corresponding to realistic ADS-B error patterns and providing a solid foundation for robustness analysis of the AE model.

4.5 Metrics and Results

To quantitatively evaluate the AE model's reconstruction robustness, the Root Mean Squared Error (RMSE) was adopted as the primary evaluation metric, measuring the overall deviation between the reconstructed and the true noisy trajectories:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \hat{x}_i)^2}$$

where x_i is the model input, $\hat{x}_i$ is the reconstructed output, and N is the number of samples. A smaller RMSE indicates that the model's reconstruction is closer to the true trajectory, implying stronger robustness.

For each noise type, experiments were conducted under multiple noise intensity parameters, and the RMSE distribution for each condition was recorded. All tests were performed using the same AE model configuration to ensure that performance variations stem solely from noise perturbations. To enhance statistical reliability, each experiment was repeated 10 times, and the results were averaged.

As shown in Figure 8, the results indicate that:

In the Gaussian noise group, increasing the noise level (σ) leads to a clear rise in RMSE and greater variance, suggesting high sensitivity to random high-frequency perturbations.

In the drift noise group, RMSE increases slightly with stronger drift, but the overall growth remains slow, indicating that the AE model can capture the global trajectory trend and tolerate gradual cumulative deviations.

In the spike noise group, RMSE shows the smallest fluctuations and remains nearly stable, rising only slightly when the spike probability is high, implying that occasional outliers have limited effect on overall reconstruction.

In summary, the AE model is most sensitive to Gaussian-type random noise, while showing greater tolerance to drift and spike noise. This suggests that, during the ADS-B data cleaning stage, attention should focus on smoothing and reducing high-frequency noise (e.g., localization jitter or measurement fluctuation). In contrast, short-term anomalies or mild drifts can often be mitigated by the model itself. Therefore, noise suppression strategies should emphasize smoothing filters and interpolation optimization, rather than excessive removal of local outliers, in order to preserve the structural integrity of trajectories.

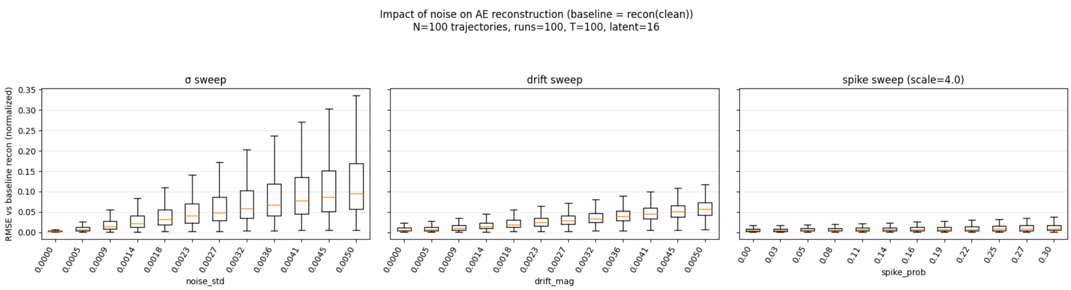


Figure 8. boxline of result

4.6 Discussion

The choice of the AE as the analytical model was mainly motivated by its simple architecture, unsupervised learning capability, and strong performance in trajectory reconstruction tasks. However, it is important to note that the AE serves only as an illustrative example to reveal the relationship between noise and algorithmic performance. The impact of noise strongly depends on the model's structure and learning mechanism—models such as LSTM, CNN, or Kalman filters may demonstrate markedly different levels of robustness. Future research will therefore extend the comparative analysis to various model architectures to derive more generalizable conclusions.

Similarly, regarding evaluation metrics, while RMSE effectively measures reconstruction accuracy, additional indicators such as temporal consistency, structural similarity, and feature preservation rate may be introduced in future work to better assess performance in trajectory prediction, classification, or anomaly detection tasks.

Moreover, since the AE model requires a fixed input dimension, this study did not further investigate the effect of missing-value errors on reconstruction performance, which is typically addressed by interpolation or resampling techniques during data cleaning. Future studies can incorporate different data imputation strategies within this framework for comparative analysis.

In conclusion, the experiments and analyses in this chapter validate the AE model's reconstruction behavior under various noise conditions, providing empirical evidence for understanding how data quality influences algorithmic performance. Future research will build upon this work by expanding the range of model types, evaluation metrics, and noise modeling complexity, ultimately establishing a comprehensive and interpretable evaluation framework for assessing the impact of ADS-B data cleaning on downstream algorithmic performance.

5. Conclusion

In this paper, we reviewed key application domains of ADS-B data, from trajectory modeling and prediction to methodology, simulation and policy. We outlined the major cleaning procedures, including outlier removal, interpolation, resampling, and smoothing. Using an autoencoder-based case study, we quantitatively assessed how different noise types (Gaussian, drift, and spikes) affect trajectory reconstruction, which indicates, for AE-based reconstruction models, noise suppression in the data cleaning stage should prioritize smoothing or interpolation optimization rather than excessive removal of local outliers, in order to preserve the overall trajectory structure. Future research will further extend the evaluation to multiple algorithm types and performance metrics, aiming to establish a more systematic framework for analyzing the impact of data quality on downstream result.

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