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# Applications and Technologies of Big Data in the Aerospace Domain

**Evgenia Adamopoulou * and Emmanouil Daskalakis**

Institute of Communication and Computer Systems, National Technical University of Athens, 15773 Athens, Greece; edaskalakis@cn.ntua.gr
* Correspondence: eadam@cn.ntua.gr; Tel.: +30-210-772-2145

**Abstract:** Over the last few years, Big Data applications have attracted ever-increasing attention in several scientific and business domains. Biomedicine, transportation, entertainment, and aerospace are only a few examples of sectors which are increasingly dependent on applications, where knowledge is extracted from huge volumes of heterogeneous data. The main goal of this paper was to conduct an academic literature review of prominent publications revolving around the application of BD in aerospace. A total of 67 publications were analyzed, highlighting the sources, uses, and benefits of BD. For categorizing the publications, a novel 6-fold approach was introduced including applications in aviation technology and aviation management, UAV-enabled applications, applications in military aviation, health/environment-related applications, and applications in space technology. Aiming to provide the reader with a clear overview of the existing solutions, a total of 15 subcategories were also utilized. The results indicated numerous benefits deriving from the application of BD in aerospace. These benefits referred to the aerospace domain itself as well as to many other sectors including healthcare, environment, humanitarian operations, network communications, etc. Various data sources and different Machine Learning models were utilized in the analyzed publications and the use of BD-based techniques enabled us to extract useful correlations and gain useful insights from large volumes of data.

**Keywords:** big data; big data analytics; aviation technology; aviation management; unmanned aerial vehicles; aerospace

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## 1. Introduction

The term Big Data (BD) refers to massive datasets deriving from multiple sources such as people, sensors, or machines [1]. BD Analytics has gained a lot of popularity lately in both business and academic domains (e.g., biomedicine, manufacturing, aviation, entertainment, and transportation) and can reveal previously unknown patterns and correlations in data [2]. Traditional definitions of BD refer to its key features as "3Vs", namely Volume, Velocity, and Variety. There are also many other models (e.g., "4V", "5V", and "8V" models) encompassing Veracity, Value, Viability, Validity, Volatility or other BD features [3–5].

The ever-increasing demand for the acquisition, analysis, and storage of large volumes of data has rendered BD an indispensable part of modern transportation systems [6]. The aerospace industry is related to the research, manufacturing, design, operation and maintenance of aircrafts, spacecrafts, Unmanned Aerial Vehicles (UAVs), missiles, space launch vehicles, etc. [7,8]. Aerospace can greatly benefit from BD-based methodologies in various ways [9] such as:

- Optimizing air traffic and reducing congestion;
- Reducing maintenance-related costs;
- Minimization of flight delays;
- Improving aircraft/spacecraft design;

- Supporting space missions;
- Improving operational efficiency;
- Advanced monitoring of aircrafts/spacecrafts;
- Advanced processing of spaceborne/airborne data;
- Increasing safety.

In an average Boeing 737, the two engines can generate up to 40 Terabytes per hour. This data can provide useful insights for air traffic controllers/dispatchers, maintenance staff as well as business stakeholders [9].

The current literature review had a threefold goal:

- To provide the reader with a clear overview of how solutions utilizing BD in aerospace can provide important benefits in several domains.
- To introduce a 6-fold categorization of the applications, aiming to make the paper more comprehensible as well as to potentially inspire and facilitate similar future research works.
- To fill the existing research gap, including in the literature review applications not only in aviation but in space technology as well.

The 6-fold categorization we introduced can be found in the following section. The first two categories were relevant to aviation technology and management. Even though UAVs are relevant to aviation technology, a different category was used, due to the different nature of these applications. The fourth category revolved around applications in the field of military aviation. The fifth category was based on the vital importance of health-related and environment-related BD-enabled solutions. The final category comprised applications relevant to Space Technology. To the best of our knowledge, at the time of writing, no literature review exists in the current scientific literature for applications of BD in both the aviation and space technology domains and there is also no other publication making use of our aforementioned categorization. Relevant review publications focused on aviation alone (e.g., the work of Burmester et al. [10]). Other review papers focused on a specific domain of the aerospace industry, e.g., the work of Chinchanikar and Shaikh [11] focusing on the use of BD analytics for additive manufacturing in aerospace applications, and the work of Skaher et al. on the use of BD and Artificial Intelligence (AI) in pilot training [12]. Oh [13] focused only on human factor considerations of applying BD in the aerospace industry. Broadening this scope and including solutions related to space technology can be very beneficial for gaining a better understanding of the usefulness of BD as well as for inspiring future research works in this field. The categorization was based on the main focus points that each publication had, and we would also like to highlight that the presence of one publication in a certain category does not exclude the possibility of this solution being relevant to other categories as well. The categorization should not be considered as strict or exhaustive, but rather as a helpful tool for better understanding the benefits of using BD and BD analytics in aerospace. In the context of the analysis of each individual publication, we focused on pointing out the main benefits BD offered as well as on presenting if the application has been tested experimentally or has been applied in real-world settings.

The remainder of the current paper is organized as follows: In Section 2, we present the steps followed in the current literature review and the categorization and subcategorization that we introduced for the analyzed publications. In Section 3, an analysis of the publications was included, based on the aforementioned categorization. Finally, in Chapter 4, we discuss the results of our analysis, draw conclusions, and describe future research directions.

## 2. Steps of the Literature Review

The 18 steps followed in the context of the current literature review can be found in Figure 1 below.

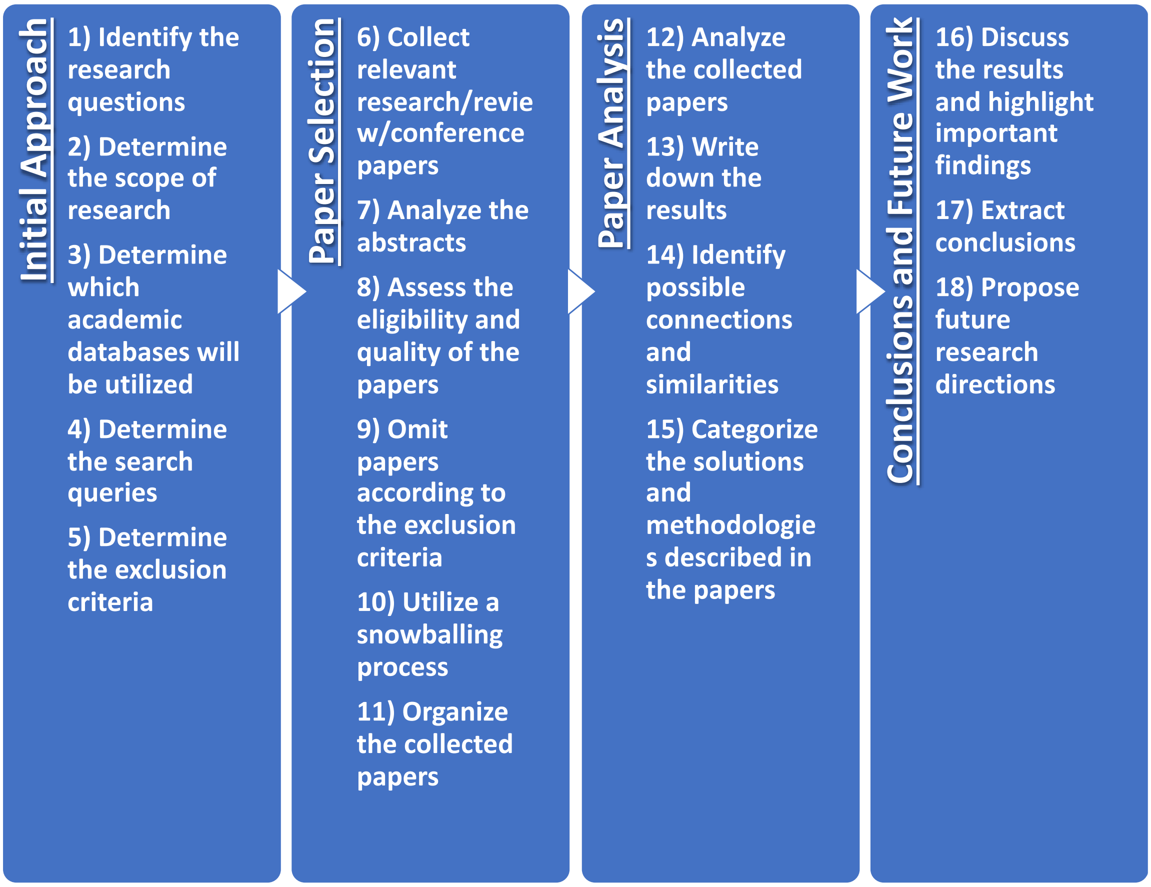


**Figure 1.** Steps Followed in the Current Literature Review.

Initially, we identified the research questions (Step 1) and the scope of our research (Step 2). The main research questions were:

- How can BD/BD analytics be applied in aerospace applications?
- What are the benefits of applying BD/BD analytics in aerospace applications?
- In which particular fields is the use aerospace BD useful/beneficial?

We utilized the SCOPUS academic database for scientific publications as well as the Google Scholar search engine to find relevant papers (Step 3). In total, 32 of the analyzed papers were published by IEEE, Springer, and the Association for Computing Machinery (ACM).

The search queries we utilized (Step 4) contained the following keywords or combinations of them: big data aviation, big data aerospace, big data avionics, big data aircraft manufacturing, big data military aircrafts, big data galaxy, spaceborne big data, satellite big data, big data aircraft emissions, big data environment, and big data health.

The exclusion criteria we utilized (Step 5) were as follows:

- The publication was not directly related to BD.
- The publication was not directly related to the aerospace domain.
- The publication did not clearly state how BD was utilized or how BD was useful in a particular application.
- The manuscript contained many typos.
- The manuscript was incomprehensible and/or was not well structured.
- The paper was published before 2014.

Initially, we read and reviewed 104 publications and ebook chapters (Step 6), analyzed the abstracts (Step 7) and assessed the quality and relevance of each source (Step 8). Out of the 104 publications initially reviewed, we excluded 37 publications based on the aforementioned criteria (Step 9) and analyzed a total of 67 scientific publications/ebook chapters. We preferred publications which were recent (of 2018 or afterwards), well-structured and provided a clear insight of how BD is utilized in the aerospace domain. A total of 62 publications were published between 2018 and 2023, 4 publications were published between 2016 and 2017 and there was one publication from 2014. We also utilized a snowballing process (Step 10). More specifically, some of the publications cited in the publications we analyzed were also analyzed. After organizing the collected papers (Step 11), we wrote down the results of the analysis (Step 12, Step 13) and we identified connections and similarities (Step 14). The identification of these connections was quite useful for forming the categorization of the publications of the current literature review (Step 15). We classified the analyzed publications into six main categories, namely:

1. Big Data in Aviation Technology;
2. Big Data in Aviation Management;
3. Big Data and UAVs;
4. Big Data in Military Aviation;
5. Aviation Big Data related to Environmental and Health Aspects;
6. Big Data in Space Technology.

Subcategories were used for each of the aforementioned categories in order to provide the reader with a clearer understanding of the usefulness of BD applied in diverse domains related to the aerospace industry. The 6 categories and 15 subcategorization we utilized together with the specific applications we analyzed can be found in Table 1. A summary of the applications can be found at the end of Chapter 3.

**Table 1.** Application of Big Data in Aerospace.

| Category | Subcategory | Publications |
|---|---|---|
| Big Data in Aviation Technology | Aircraft Design/Manufacturing | [14–18] |
| | Monitoring of Flight/Aircraft/Safety Parameters | [19–26] |
| | Health Monitoring Systems | [27–32] |
| Big Data in Aviation Management | Air Traffic Management and Trajectory Planning | [33–37] |
| | Delay Prediction and Resource Allocation | [38–41] |
| | Maintenance Optimization | [42,43] |
| | Collecting Customer Insights/Increasing Customer Satisfaction | [44–47] |
| Big Data and UAVs | Solutions for the Industry | [48,49] |
| | Solutions for Infrastructures | [50–54] |
| Big Data in Military Aviation | Supporting Military Operations | [55–57] |
| | Increasing Air Force Safety | [58–60] |
| Aviation Big Data related to Environmental and Health Aspects | Aviation Big Data related to Health Aspects | [61–64] |
| | Aviation Big Data related to Environmental Aspects | [65–68] |
| Big Data in Space Technology | Supporting Space Missions | [69–73] |
| | Solutions Utilizing Spaceborne Big Data | [74–82] |

In the final chapter of this paper, we discuss the results and highlight important findings (Step 16), extract conclusions (Step 17) and propose future research directions (Step 18).

## 3. Application of Big Data in Aerospace

### 3.1. Big Data in Aviation Technology

The first category of analyzed publications in the context of this review revolved around how BD can benefit aircraft design and manufacturing processes, how it is used for effectively monitoring flight/aircraft/safety parameters, as well as how it can improve aircraft health monitoring systems.

#### 3.1.1. Aircraft Design/Manufacturing

Aircraft manufacturing encompasses complex designs and processes which are directly related to BD collected in different stages of manufacturing. Wang et al. [14] proposed a novel architecture for industrial BD processing which was capable of batch data processing, low latency control, hierarchical industrial BD management, stream data processing, etc. This architecture integrated edge computing, which helped in reducing data transmission/decreasing latency, and a feedback loop, which was particularly useful in aviation manufacturing processes such as workshop monitoring and machine tool control. Experimental testing of the proposed architecture was performed by means of a digital aviation manufacturing workshop simulation. The experiments indicated real-time BD processing capabilities, high effectiveness, and high suitability for the aviation manufacturing domain. In [15] Crespino et al. described a novel framework for detecting machine faults in aviation manufacturing, aiming to ensure that the product quality is not compromised. The so-called Model-based Big Data Analytics as-a-Service (MBDAaaS) framework was comprised of three main stages. In the first stage, a json file was produced which contained specifications for the declarative model as regards the main objectives and indicators. The second stage encompassed the definition of the procedural model which described how the analytics would be executed/parallelized based on the requirements of the first stage. Finally, the third stage produced the deployment model which mapped each operation/tool to the corresponding services. This framework was tested on an aviation machine fault prediction use case, proving its applicability in the BD pipeline of aviation manufacturing companies.

Industrial BDintegration and sharing (IBDIS) is of vital importance for the efficiency of BD analysis in manufacturing systems. Wang et al. [16] proposed a framework for IBDIS based on fog computing, where integration and sharing were split into different subtasks carried out by fog clients. This framework ensured high security for raw data, respected data privacy, and helped in importantly decreasing the network traffic. The authors highlighted the effectiveness of the proposed framework in aircraft manufacturing and presented a specific case study in an aircraft manufacturing group located in China. In this, BD from two different companies of the manufacturing groups should be shared and integrated. These data were relevant to the manufacturing of a plane positioner and included both data regarding the position of certain key points on the wing as well as data relevant to the execution time of each particular manufacturing step.

The combination of BD and the Digital Twin (DT) as described by diverse scientific publications can be of particular interest for aviation manufacturing. Singh et al. [17] proposed a novel information management framework for Aircraft Manufacturing based on the DT, which helped in addressing BD-related challenges. The framework was comprised of four main layers, namely the physical layer, the data acquisition layer, the model layer, and the data model layer. These layers were continuously interacting with each other and were also updated regularly, thus facilitating the handling of large volumes of data throughout the DT lifecycle. The effectiveness of this framework was presented by the authors through a case study involving the aircraft wing fatigue crack growth and propagation in an aircraft manufacturing company. In another publication based on DT, Liang et al. [18] proposed a methodology for field displacement perception for component DTs, which can be implemented in precision manufacturing scenarios, such as those of aircraft manufacturing. The methodology combined the matrix completion theory with online displacement monitoring. The generated displacement model was based on the observed points as well as on the simulation BD. The method was experimentally tested, achieving high efficiency and high precision, yielding a max error smaller than 0.094 mm and a median error smaller than 0.054 mm in an average timeframe smaller than 0.48 s.

#### 3.1.2. Monitoring of Flight/Aircraft/Safety Parameters

Air turbulence is likely to cause a major concern to aviation companies, since it can lead to the discomfort of passengers, injuries, as well as aircraft structural damage or even accidents in extreme cases. Air turbulence can be measured by utilizing measurements of the Vertical Overload, the Eddy Dissipation Rate (EDR), or the Derived Equivalent Gust Velocity (DEVG). Huang et al. [19] proposed a new methodology to estimate EDR based on Quick Access Recorder (QAR) BD. The authors tested their methodology on QAR BD collected by Boeing and Airbus aircrafts in China from 2016 to 2018. The EDR measurements using the aforementioned methodology were visualized spatially and could be obtained with a reasonable time cost. The methodology was compared to traditional air turbulence measurement methodologies and was proven to provide a reasonable indicator when calculating the air turbulence risks during a flight, while also being less sensitive than the traditional methodologies in cases of measurements deriving from different aircrafts. QAR BD was also utilized in other scientific publications which can be found below. In [20], Wang et al. made use of QAR BD from the Civil Aviation Administration Of China (CAAC) to identify potential problems deriving from the take-off pitch angle. A very small take-off pitch angle of an aircraft may result in the aircraft overrunning the runway and may also reduce its capability of avoiding obstacles at a low altitude. The authors utilized QAR BD from 54 different airlines and made a comparison between the industry-wide data and the data of each individual airline. The data analyzed included the take-off pitch angle, the correlative speed at rotation as well as the liftoff speed. In a use case outlined by the authors, the take-off pitch angle of the A321 aircraft of a specific airline was found to be too small. Right after that, the airline was informed about the problem and immediately took the necessary steps to avoid potential future events of a very low take-off pitch angle. In [21], Xie et al. utilized QAR BD from Chinese airlines during 2018 for detecting unstable approach events. The authors performed spatio-temporal pattern analysis as well as exploratory correlation analysis. The Pearson correlation coefficient was calculated to explore the correlation of unstable approach events and other factors such as the wind grade, bad weather conditions, and altitude. The experimental results indicated different spatio-temporal distribution characteristics of Airbus and Boeing aircrafts in cases of unstable approach events as well as a clear correlation existing between bad weather conditions, wind grade, altitude, and unstable approach cases.

The mandatory use of the Traffic Alert and Collision Avoidance System (TCAS) is of paramount importance for the safe and effective management of air traffic. Such systems have significantly reduced the risk of mid-air collisions. Schafer et al. [22] analyzed TCAS BD in order to extract useful insights about the usage characteristics and the efficiency of such systems. Around 250 billion aircraft transponder messages collected from over 125,000 aircrafts from the OpenSky network were analyzed. The authors noted that 89.5% of aircraft equipped with Automatic Dependent Surveillance–Broadcast (ADS–B) had an operational TCAS. The authors also observed that alerts by TCAS were frequent in parallel approaches of aircraft, in conflicts between standard arrival and departure procedures, as well as in cases of top-of-climb and beginning-of-descent of aircrafts. Olive et al. [23], also used BD from the OpenSky network in their work. More specifically, the authors utilized BD from the OpenSky network regarding aircrafts broadcasting the "7700" emergency code related to general emergencies over a period of two years and combined this data with crowdsourced sources such as social networks. The main goal of this combination was to extract a semi-labelled dataset containing trajectories as well as to train Machine Learning (ML) models which will be able to provide explanations about potential emergencies based on trajectory data, when no other data are available.

An important parameter for evaluating an aircraft's performance is the engine thrust. In [24], Deiler compared three different models for determining thrust with limited ap riori information about the characteristics of a flight's performance, utilizing BD from a database with operational flights of Airbus A320 neo aircraft. More specifically, a linear, a local-linear, and a nonlinear model were compared in representing an engine's thrust. The non-linear model was found to be the most accurate of the three and it was extended by means of temperature correction, resulting in a robust and accurate model with reduced requirements for computational resources as compared to other state-of-the art methodologies.

The analysis of different aircraft measurements and parameters can provide insights which are very important for aviation safety. Wooder et al. [25] utilized a surface fitting method and BD from the FlightGear simulation software in order to extract possible correlations among different variables and parameters. The proposed method helped to identify correlations even between variables which initially seemed irrelevant to each other. Testing of the proposed methodology indicated that it is a capable solution and can successfully identify relations in processes which focus on aircraft fault detection. In their publication, Li et al. [26] also proposed a variable selection algorithm which was aimed at effectively mining variables which are highly correlated to an aircraft's safety. The algorithm can be useful in cases of aviation BD containing a very large number of variables (e.g., 3000 or more). Simulation results indicated satisfactory efficiency and high capability in dimensionality reduction.

#### 3.1.3. Health Monitoring Systems

The utilization of aircraft operation data and past events for improving the operation and the availability of aircraft through effective health monitoring systems is crucial for aviation. Jiao et al. [27] demonstrated a Prognostic Health Management (PHM) system which made use of an aviation BD mining platform. The platform was based on the Hadoop cloud architecture and used BD deriving from the whole lifecycle of an avionics system. The platform also analyzed the correlations among different tasks/system states and provided early warnings for potential faults. Forest et al. [28] proposed an end-to-end scalable pipeline for analytics based on aviation BD and tailored for aircraft health monitoring. Through this, users could extract features from flight operation BD stored on a cluster, and the pipeline also included clustering and dimensionality reduction algorithms as well as had visualization capabilities. The implemented health monitoring application could be easily used even by inexperienced users. The following two publications referred to different BD-based architectures for aviation health monitoring systems. Xie et al. [29] presented an architecture for helicopter health management systems. The architecture was comprised of three main modules, namely the helicopter health management module, the helicopter fault monitoring and diagnosis module, as well as the helicopter fault knowledge map. The authors analyzed the correlations among the different components mentioned above, as well as described the main sources of BD such as the flight parameter recorder data logging control box, the engine vibration sensor, the drive shaft vibration sensor and many others. Zhaobing et al. [30] described an architecture for a health management system for civil aircrafts. It was comprised of four layers, namely the base layer, the data layer, the business logic layer, and the decision output layer. The operation BD that the architecture utilized consisted of the air–ground data link, the ground data link, and the operational data. The authors also examined the use of the proposed architecture in a typical fault case of the aircraft's air conditioning, noting that the architecture could predict the fault in a timely manner.

The smart diagnosis of faults drastically improves aviation safety and helps in reducing downtime, operating costs, and expensive repairs. Luo et al. [31] proposed an architecture which helped in the early detection of errors or problems in an aircraft's electronic parts from the navigation, instrumentation, communication, and automatic control systems. Towards this direction, BD was used to generate Long Short-Term Memory (LSTM), Support Vector Machine (SVM), Random Process, and Unscented Particle Filter (UPF) models. Data preprocessing was included in this architecture and is also a vital part, as in avionics data, data loss, noise interference, and abnormal measurements are common phenomena. This architecture was tested on a maintenance scenario, proving its capabilities in fault detection and remaining lifetime prediction. Ning et al. [32] proposed an LSTM autoencoder model for detecting errors as well as for the classification of faults/problems. The model was tested on BD from a commercial fleet and was found very effective and capable of detecting the health state of an aircraft as well as of detecting diverse faults (e.g., in pressure control valves, in 390F sensors, or in 450F sensors) with high accuracy.

### *3.2. Big Data in Aviation Management*

The second category of analyzed publications included BD-enabled applications related to air traffic management, trajectory planning, prediction of delays, effective resource allocation, maintenance optimization as well as applications for increasing customer satisfaction and collecting customer insights.

#### 3.2.1. Air Traffic Management and Trajectory Planning

Effective Air Traffic Flow Management is of paramount importance for modern aviation, especially given the increasing number of Unmanned Aerial Vehicles (UAVs). Gui et al. [33] proposed a model for the calculation of air traffic flow, based on BD from Automatic Dependent Surveillance-Broadcast (ADS-B) ground stations and the received ADS-B messages. Through the analysis of the constructed dataset and by mapping the information extracted to each corresponding route, the authors could predict the air traffic flow for more than 200 routes. For this, two different algorithms were tested, namely LSTM and Support Vector Regression (SVR). Experimental testing of the algorithms indicated that LSTM could provide more accurate results, even when abnormal measurements were present. Air traffic BD was also used in the publication of Madhavrao and Moosakhanian [34], where it was combined with weather BD. More specifically, the authors demonstrated a BD platform where synthetic flight trajectory data were fused with data from the Federal Aviation Administration (FAA) NextGen Weather Services. The platform used complex queries in order to determine the impact of weather and helped in the strategic planning of airlines and air traffic managers. In the experimental testing of the platform, different usage scenarios related to aviation were tested and the platform could estimate the weather impact in a timely manner, also applying diverse business rules. Petrou et al. [35] demonstrated a BD framework for accurately predicting long-term streaming trajectory data with low latency. Surveillance BD was utilized which was enriched with heterogeneous data from various sources. The architecture consisted of the stream processing layer (including a trajectory synopses generator, a semantic integrator, and a future location prediction), a batch processing layer (including a data manager and trajectory clusterer), a visual analytics module, and an interactive visualization module. A stream of surveillance data combined with archival data from different sources were provided as inputs, while the output of the architecture encompassed the stream of trajectory predictions.

BD related to the aircrafts' trajectories can also be useful for evaluating a flight's performance as well as in trajectory visualization solutions. Based on their previous work on the AIRPORTS DL framework, Garcıa-Miranda et al. [36] presented an end-user application which was capable of computing diverse metrics and performance indices, based on BD about flown trajectories. The application could calculate the metrics in a scalable way and some of the metrics displayed in the application included the peak load, the number of conflicts as well as the traffic density. The authors described a potential workflow for calculating these metrics in advance as well as providing a user-friendly dashboard to access the metrics. Zhao et al. [37] proposed a methodology for processing real-world flight BD and subsequently using this data to visualize multiple flight trajectories in different time frames. The methodology provided the capability to display multiple trajectories of the same route on Google Earth application. This enabled the comparison of different trajectories as well as the identification of potential problems/dangers based on the identified deviations. The authors underlined that their method provided benefits over other similar applications, by improving contrast as well as by overcoming the problem of displaying a single track only at a specific timeframe. Testing of the methodology was conducted based on flight data from the Airbus A321 aircraft, proving its feasibility and effectiveness.

#### 3.2.2. Delay Prediction and Resource Allocation

Flight delays can have negative impacts on customer satisfaction and lead airlines to financial losses. Therefore, flight delay prediction can be very beneficial. Jiang et al. [38] aimed to extract useful patterns in cases of flight delays so that they could achieve precise delay prediction with the aid of aviation BD and ML models. Some of the parameters the authors analyzed to see if and how they were correlated to delays were: the weather conditions, the flight date and time, the location, the airport congestion, etc. The authors then generated an SVM model, a Decision Tree model, a Random Forest (RF) model, a Convolutional Neural Network (CNN), as well as a Multilayer Perceptron model for flight delay prediction. For the experimental testing of the models, the authors utilized Airline OnTime Performance (AOTP) data as well as Quality Controlled Local Climatological Data (QCLCD) data. The CNN model was found to be the best of the five, yielding an accuracy of 89.32% in delay prediction. The publication of Gui et al. [39] also examined several factors which may lead to flight delays and used ML models to execute flight delay prediction tasks. The authors divided the main causes of delays into four main categories: flight-related (e.g., flight number, flight delay history, and pre-flight conditions), airport-related (e.g., air traffic flow and leave/arrive speed), air-route-related (e.g., peak traffic flow and real-time traffic flow) and other (e.g., what season it is, if it is a holiday, and if an unexpected event has happened). ADS-B BD together with other sources of data (e.g., weather conditions and airport information) were used to experimentally test the generated LSTM and RF models for flight delay prediction. The RF model was found to be the most accurate of the two, reaching an accuracy of 90.2%.

Efficient airspace resource management can play an important role in reducing flight delays as well as in air route optimization, proper adjustments in flight schedules, layout planning, etc. Towards this direction, Shi et al. [40] presented a residual airspace resources evaluation methodology for commercial aviation based on BD. Specifically, QAR BD was used with a specific focus on the exit of the terminal area and the key waypoints. The authors conducted successful experimental testing of the methodology in a commercial airport in China, accurately calculating the residual airspace resources. In contemporary and future Air–Ground Vehicle Networks (AGVNs) there are many challenges regarding resource allocation, secure communication and mobility management. Sun et al. [41] proposed a network architecture for AGVNs where a unified surveillance plane could be utilized to provide local as well as global BD to stations, serving a side system for the established communication links. The authors outlined how the side information can be obtained, organized, managed, and finally used in the context of a so-called Aviation Data Lake (ADL). In ADL, data analysis methodologies, ML models, and multilateration filters could be utilized for acquiring local and global information. The ADL provided many benefits in resource allocation, security, resource management, etc. The authors highlighted the viability of the approach and provided numerical results in a case study including ADL-assisted handover of low-altitude UAVs.

#### 3.2.3. Optimizing Maintenance

Scheduled and unscheduled aircraft maintenance workloads are characterized by uncertainty. Based on that, Dinis et al. [42] explored the use of Bayesian Networks as a BD predictive analytics tool. The Bayesian Networks were based on the BD from maintenance projects of a Maintenance, Repair and Overhaul (MRO) organization in Portugal. The Bayesian Network models were developed based on different hypothesis variables and were evaluated, demonstrating their applicability as well as their superiority over contemporary approaches for capacity planning. The authors also highlighted that this solution could also help in sales planning, as well as that the consideration of uncertainty in the decision-making progress in the context of this solution could contribute to more informed decisions regarding the required manpower. Daily and Peterson [43] presented an example where the GE Aviation company combined BD from different sources to improve its predictive maintenance capabilities. These sources encompassed flight data, air quality data, environmental data, etc. This allowed the company to cluster the engine data according to the operating environment. It was found that the environment in certain places (e.g., China, the middle east) could lead the turbine to heat up and could reduce the efficiency. All the above contributed to better predictive maintenance as well as to the avoidance of unnecessary maintenance.

#### 3.2.4. Collecting Customer Insights/Increasing Customer Satisfaction

BD analytics can provide useful insights about customer behaviors and customer satisfaction. In [44] Sternberg et al. examined if social BD of a certain airline could be utilized to improve certain performance metrics. In specific, BD from Turkish Airline's social media was processed, together with data from other sources such as the monthly number of passengers, the stock price, and the quarterly revenue. The authors performed text mining, used a Naïve Bayes classifier to classify text and implemented predictive and visual analytics. Through their experiments, they identified a weak relation between the business data and social BD. However, from the findings, explanations could be provided about the customer behavior and satisfaction, based on the social media data. Khalil et al. [45] presented a Linear Regression model for predicting flight-related web searches of commercial aviation customers. Flight searches are some of the most popular web searches, so the accurate prediction of such searches is very useful and BD analytics help in this prediction. The authors utilized the BD framework SparkML library and statistics. Experimental testing on the proposed model was conducted using BD from domestic airports and yielded an accuracy of about 90%. Ling and Weiguo [46] described how BD can increase aviation service quality and customer satisfaction. BD from different sources (e.g., historical data, data from mobile operators or tourist platforms) can be utilized for flight arrangement optimization (e.g., to make adaptations to routes, to adjust flight time and the prices). Furthermore, personalized travel services can be provided to customers based on their preferences and other data related to them (e.g., date of birthdays and route preferences). Three other examples for the usefulness of BD included the fast and efficient collection of customer satisfaction feedback (e.g., through microblogs or fora), efficient emergency handling increasing the sense of safety of customers, and finally the maintenance optimization resulting from BD analytics which increases the sense of safety of customers and can also lead to decreased prices.

### *3.3. Big Data and UAVs*

The third category of analyzed publications deals with UAVs which are aerial vehicles, not carrying a human operator and can fly autonomously or be controlled remotely [47]. The following applications are divided into solutions for industry and solutions for different infrastructures.

#### 3.3.1. Solutions for the Industry

Source localization is extremely important in industrial monitoring as well as in other fields (e.g., search and rescue and electronic countermeasure). The use of illegal radiation can have negative effects in the operation and the communications of industrial facilities. Li et al. [48] proposed two methodologies for the simultaneous localization of different emitters which utilized BD collected by a UAV. The main goal was to improve the original two-step Direct Position Determination (DPD) methods which face non-homogeneity and are sensitive to the environment. First, the authors proposed a weight Direct Position Determination (DPD) methodology which used blindly estimated Signal-to-Noise-Ration (SNR) and then proposed an optimal weight DPD methodology. The UAVs were mounted with an antenna area which intercepted signals at specific time slots. Simulation results of the proposed methodologies showed that they outperformed traditional two-step DPD methodologies in both resolution and localization accuracy. Fernández-Caramés et al. [49] described a UAV-based solution for the automatic execution of inventory tasks and industrial item traceability tasks which could ensure data trustworthiness and thus facilitate the extraction of reliable BD analytics (e.g., analytics for supply chain efficiency). The solution utilized Blockchain technology, a distributed ledger, and smart contracts technologies. The UAV collected real-time inventory data as well as could locate items in a warehouse by making use of the Signal Strength Indicator (SSI) of Radio Frequency Identification (RFID) tags. Experimental testing of the system in a real industrial environment indicated its feasibility as well as its faster performance as compared to executing these tasks manually.

#### 3.3.2. Solutions for Infrastructures

The following three BD-based solutions were related to the electricity infrastructure and to the communication infrastructure. Image recognition is widely used in power distribution systems for various reasons such as identification of poles and wires, measurement of the icing thickness in power lines, measurement of the distance between wires and trees, etc. Hu et al. [50] proposed a methodology for detecting transmission towers based on BD and UAVs. The methodology made use of a Recurrent Convolutional Neural Networks (RCNNs) model for extracting characteristics of the towers, training the tower model as well as achieving quick image recognition and subsequently generate the power lines. For acquiring the BD required by the model, photos were used which were captured by a fixed-wing UAV. Experimental testing of the methodology showed that it could achieve fast and efficient identification of transmission towers. Although the methodology was not as accurate as the tree barrier modelling methodology that it was compared to, it could achieve similar accuracy in a much faster way, yielding an average decrease of 14.2% of the required time for the computations.

UAVs can be utilized for delivering wireless services (e.g., a 5G mobile network) to targeted areas. However, in such cases there is often a tradeoff between energy consumption of the UAV and the delivery of wireless capacity to areas which have to be explored as they are not necessarily known in advance. Towards this direction Guo [51] demonstrated a Deep-Reinforcement-Learning-based methodology which utilizes BD for the optimization of both aggregate and minimum service provisioning. The proposed solution offered stable performance, helped reduce overfitting phenomena and was also partially explainable. The methodology addressed Quality of Service (QoS) and Quality of Experience (QoE) requirements and achieved decreased energy consumption. Experimental testing of the methodology, showed that it outperformed rule-based UAVs in terms of efficiency and stability, reaching a 40% energy consumption reduction. Another similar solution was proposed by Xu et al. [52], this time for ensuring network communication and the capability to manage BD in cases of disasters. When a disaster happens, network communications may be disrupted. To tackle this, the authors proposed a solution where UAVs served as mobile edge nodes and the LoRaWAN protocol was used to connect UAVs with the control center. Two algorithms were proposed for task management and queue management. Experimental testing indicated that the solution could provide a relatively cheap and easily deployable Mobile Edge Computng service, which increased the service range as compared to an edgeless contemporary solution, while maintaining the same level of SNR and path loss. Providing mobile cellular services is quite power consuming for UAVs and often a charging infrastructure is employed including charging stations. Jung et al. [53] proposed an Energy Management System (EMS) solution which incorporated a sharing mechanism among different charging towers and aimed at minimizing the operating costs of UAV-solutions encompassing BD analytics. The solution was based on a Deep Reinforcement Learning model and experimental testing showed satisfying results in terms of optimizing energy sharing and energy consumption. The solution also contributed to minimizing the need of purchasing energy directly from the utility company. Another IoT-enabled solution which is not directly related to network infrastructures but can help in such applications comprising different base stations and BD processing was proposed by Wan et al. [54]. This solution consisted of three main layers. At the first layer, distributed sensors produced raw data. At the second layer based on mobile edge computing, UAV base stations collected the data, and performed an initial processing. Finally, at the third layer, a cloud service received the data from the previous layer and performed further processing and evaluation. The authors proposed a Lyapunov-optimization-based algorithm for online edge processing as well as Deep-Reinforcement-learning-based model for efficient path planning of the UAVs. Experimental testing of the solution indicated its feasibility, effectiveness, and capability of increasing the service coverage.

### *3.4. Big Data in Military Aviation*

The fourth category of analyzed publications included applications which can support air force military operations as well as increase the safety in military aircraft.

#### 3.4.1. Supporting Military Operations

The characterization of aircrafts is of vital importance for military aircrafts as it can help determine if an observed aircraft poses a threat or not. Zhao et al. [55] demonstrated a BD-based solution for characterizing if a specific aircraft is commercial or military based on diverse kinematic attributes. For this, the authors relied mostly on BD from ADS-B messages and Global Positioning System (GPS) technology, rather than on radar communications. The ADS-B messages included information about the ground/vertical speed, the altitude, the heading, the call sign, the exact position, etc. For achieving accurate classification of the aircrafts, a CNN model was used. Although the solution was not yet fully finalized, experimental results showed a promising capability of accurately predicting the type of an aircraft. Dästner et al. [56] demonstrated how different Machine Learning methodologies and ADS-B BD can be utilized to classify and identify military aircrafts in real-time applications. More specifically, RF, Gradient Boost Trees and Multilayer Perceptron classification techniques were used. Experimental testing indicated mediocre results, yielding a 60% classification accuracy. Based on that, the authors proposed the use of these models as complementary/additional tools for detecting military behavior.

BD can also facilitate decision making in military operations. In [57] Norman et al. described how commercially tested BD analysis methodologies could help the Joint Strike Fighter program, acquire stronger knowledge management and analysis capabilities for testing and evaluation processes. At the same time, the authors highlighted how these methodologies could also lead to faster and more efficient decision making. Some indicative examples of how BDA could support military aviation and the Joint Strike Fighter system in specific included: (i) flight classification and determination of what maneuvers a military aircraft performed; (ii) deriving unknown relations by utilizing association rules; (iii) conducting predictive maintenance of aircrafts and facilitating physical inspection. Finally, the authors noted that through BD analytics regarding 1400 flights, data analysts with no technical knowledge for aircraft failures could predict failures with a satisfying accuracy of 70%.

#### 3.4.2. Increasing Air Force Safety

Frantis [58] presented a BD-based architecture for increasing air force safety. The author underlined that there can be many different data sources such as aircraft data recorder files, military flight planning systems, logistic information systems, civil flight planning systems, ADS-B messages, weather data, military real-time data links, etc. The proposed architecture was comprised of three layers. The first layer included all the data sources and the interconnections with other systems. The second layer encompassed a BD database which had the main task of data handling/processing. Finally, the third layer included the user interface and translated the search results into a form which was understandable by the user. The third layer included an application which enabled the user to make questions and data queries, as well as processed script batch files which had already been created. In [59], Cai et al. made specific proposals for improving the Aircraft Engine

Health Management systems which the authors underlined that are applicable in fighter aircrafts as well as in large military transport aircrafts. The role of BD was highlighted and the main pillars for the improvements were (i) improved data management; (ii) advanced fusion of heterogeneous information; (iii) accurate prediction methodologies; (iv) proper system integration. Regarding the prediction methodologies in specific, BD analytics could come in handy regarding the processing of heterogeneous engine data. Expert systems, fuzzy logic as well as Neural Networks, Bayesian networks, and Hidden Markov models were some of the examples of models proposed for improving prediction tasks (e.g., fault diagnosis, predictive maintenance). Finally, regarding the integration, the importance of integrating the Health Management system with the Engine Control system and other onboard systems was noted.

In [60], Morgan et al. described the important role of BD in military campaign simulation and subsequently in better decision making in defense as well as in increasing safety for air force pilots. The so-called Synthetic Theater Operations Research Model (STORM) for campaign simulation included air and space warfare among other warfare types (i.e., land, maritime, amphibious). BD in such tools could help detect consistent threads as well as causal threads. The authors also described a relevant suite which had several postprocessing and visualization capabilities. Large-scale air attack simulation, exploration of combat maneuvers and weapons testing, analyzing measurements from sensors which detect aircrafts, status of critical aviation resources, determination of aircraft loss were just some examples of the aspects covered in the simulation tool.

### *3.5. Aviation Big Data Related to Environmental and Health Aspects*

Aviation BD can also benefit applications related to environmental (e.g., measuring pollutants) and health aspects (e.g., controlling the spread of diseases).

#### 3.5.1. Aviation Big Data Related to Health Aspects

BD can facilitate the fight against major health incidents, such as the recent pandemic of COVID-19. Lin and Hou [61] described how AI and different sources of BD helped in combatting the COVID-19 pandemic in east Asia. BD from aviation, railway, and ground transportation systems, from customs or immigration databases, from pandemic-specific COVID-19 or healthcare databases, from social media, from card transaction databases, from security cameras, from wearable tracking devices or car GPSs are just some examples of BD sources that helped in flattening the curve of the pandemic. Examples of the AI tools utilizing BD described in the aforementioned publication were about facilitating targeted lockdowns, classification of patients, early diagnosis, facilitating communications, providing notifications for the pandemic, self-health reporting, etc. Gallego and Font [62] proposed a methodology which could early detect the reactivation of the tourist markets, which had been influenced by the COVID-19 pandemic. The main goal of this methodology was to support Destination Management Organizations managers in taking informed policy decisions as well as in minimizing the negative effects of COVID-19 in tourism. Making use of operational transactional BD (i.e., air passenger searches, website visits, bookings, selections) the proposed methodology helped to better understand the market behavior and to stimulate demand.

BD can be very useful for combatting epidemics and pandemics including but not limited to COVID-19. Jia et al. [63] demonstrated a multidimensional framework describing the contribution of BD in such situations. The frameworks spanned the prevention, control, and repair related to major health incidents. In specific, IoT data collection platforms, BD from mobile devices, from social media and even from big gene banks could be utilized for the early detection of an epidemic/pandemic. Regarding the response mechanisms, BD for the predictive analysis of virus dynamic models as well as BD for supporting decision making systems and reporting systems could be very useful. Research regarding the development of vaccines or medicines for a disease could also make use of BD (e.g., for genetic data analysis or for real-time data analysis from patients based on IoT). Using

BD could also help in tracking infected persons or persons that came in contact with infected individuals as well as in determining the source of a specific infection. Finally, the authors also provided examples of the potential of using BD for eliminating fear, for policy adjustments as well as for analysis of an epidemic's/pandemic's impact from a political, social, or economic point of view. Rocklöv et al. [64] demonstrated how BD was used to contribute to monitoring the introduction and spread of the Chikungunya in Europe during 2017. The authors utilized aviation BD for areas with active transmission of the specific virus in order to estimate the risk of virus importation from other areas. Then, they used BD from Twitter posts to estimate mobility patterns of users as well as to estimate the risk of short-range dispersion. Finally, BD was used to estimate the seasonal vectorial capacity of the one of the species of mosquitoes which was responsible for the dispersion of the disease (i.e., Aedes albopictus species). The authors extracted indicators for identifying the virus dispersion and made estimations of the suitability of local climate for a potential virus outbreak.

#### 3.5.2. Aviation Big Data Related to Environmental Aspects

BD can be extremely helpful in the field of pollutant and emission measurement. In [65] Lu et al. utilized BD from a civil airport in China in order to calculate the Landing and Takeoff (LTO) emissions of different pollutants. Utilizing hourly LTO data of 302 days of 2015 about the specific airport, the authors calculated the annual emissions of sulfur dioxide ($SO_2$), nitrogen oxides ($NO_x$), Volatile Organic Compounds (VOCs), carbon monoxide (CO), particles with a diameter of 10 μm ($PM_{10}$), and particles with a diameter of 2.5 μm ($PM_{2.5}$). A Monte Carlo methodology was also used to conduct uncertainty analysis of the results. The uncertainty varied from 7% to 10% in different pollutants. The overall BD-based methodology outperformed other traditional methodologies in terms of accuracy. Environmental BD can play an important role also in the maintenance of aircrafts and the reduction in their emissions. Martínez-Prieto et al. [66] proposed a data model which aimed to increase the flight efficiency, reduce fuel consumption and pollutant emissions as well as to ensure customer satisfaction. The authors combined BD from diverse providers as well as reconstructed flight trajectories. The main goal of this model was to convert ADS-B messages of different sources into clean and easy-to-use information, taking advantage of surveillance information, flight information and air traffic control data. An information processing pipeline was also developed in the context of this model which helped to clean, transform, and enrich the data from the ADS-B messages. The effectiveness of the model was also proved through a two-week evaluation with data deriving from three different providers. Zhao et al. [67] presented their design of a system for monitoring urban air quality, based on UAV technologies and BD. The authors described the hardware design and provided details about the storage module, the processor, the transmission module with GPRS connectivity, the UAV, the air quality sensor, and the anti-interference system. This solution included measurements of the dust particle concentration, the CO concentration, the temperature, and the humidity. The electromagnetic anti-interference system helped in ensuring reliability even under harsh conditions. Experimental testing of the solution proved its capability of successfully measuring different air quality parameters as well as of providing adequate anti-interference.

BD analytics can play an important role in wildfire prevention and management. Athanasis et al. [68] demonstrated a solution which aimed at improving the surveillance for wildfire prevention and management, through the near real-time analysis of BD deriving from UAVs. A BD cluster was utilized by the authors and a MapReduce algorithm was implemented to identify images from burning forests. The solution was tested in the Greek island Lesvos during 2018 and it was found to importantly improve the required time to analyze the images received by the UAVs, thus contributing to a timelier and more reliable management of the authorities regarding the emergency response crews. The authors also highlighted that the execution time of the BD analysis was not affected by the area covered by the images.

### 3.6. Big Data in Space Technology

The sixth category of the publications presented in this literature review included BD application related to the support of space missions and solutions utilizing spaceborne BD.

#### 3.6.1. Supporting Space Missions

Dong et al. [69] proposed an BD-enabled architecture for supporting launches at rocket launch sites. The architecture was comprised of many different elements including, space mission planning, mission management, command support, visualization of launch mission status, analysis and fusion of launch vehicle operating data, detection of faults and errors, equipment diagnostics and performance evaluation, decision support, allocation of resources, monitoring of dangerous chemicals, emergency response system, training simulation, software management, knowledge management, etc. The BD utilized in this architecture came from two main categories, the launch mission data (e.g., monitoring of the flight phase, weather data, organization, and command data) and the daily operating data (e.g., equipment management data, simulation data, and monitoring data of launch facilities).

Ensuring that astronauts remain healthy is of vital importance for the performance and the success of space missions. Prysyazhnyuk and McGregor [70] proposed a novel BD analytics visualization methodology which aimed at improving clinical decision systems in space. This spatio-temporal visualization methodology provided an accurate description of the astronaut's body functions and trajectory of health state and could also help in the detection of anomalies and potential pathologies. The visualization technique was capable of depicting task and time specific dynamics and its feasibility was tested during terrestrial simulation experiments. Aiming to expand the capabilities of the health analytics platform called Artemis, Yeung and McGregor [71] presented a solution based on BD analytics which helped in the determination of the health state taking into consideration the countermeasure activities in microgravity performed by astronauts. Such activities are performed in order to help them better physically and psychologically adapt to the space environment. The tool functioned as a feedback component within Artemis and through BD analytics, a better overview of the overall astronaut's health could be provided which incorporated the effects of the countermeasure activities performed. A case study was also provided by the authors, to highlight the usefulness of their tool in optimizing life support systems in space.

The useful life of on-orbit satellites can be affected by several factors such as the remaining life of batteries, the condition of the solar array, the reaction wheels, etc. Huang et al. [72] proposed a Bayesian framework for estimating the remaining useful lifetime of operating satellites, based on BD. The particular framework depended on historical telemetry BD from other satellites as well as on certain parameters regarding the performance degradation of critical components. The feasibility of the framework was demonstrated through an example where the framework was used to determine the remaining lifetime of a satellite, based on data for the array wing power losses and for the Li-Ion battery degradation.

#### 3.6.2. Solution Utilizing Spaceborne Big Data

The Besançon Galaxy Model (BGM) [73] is a popular tool performing statistical analysis for the Galactic structure and evolution. Aiming to expand the capabilities of this model, Mor et al. [74] demonstrated a theoretical framework called BGM FASt which facilitates the study of the Milky Way based on Bayesian methodologies. This framework could utilize BD such those of the aforementioned Gaea space mission and it also executed multi-parameter inference. Experimental testing of the framework showed a dramatic decrease in the time required for execution (about 10,000 times lower) as compared to the standard BGM model, while providing very similar results with it. The framework could also infer stellar mass density, star formation history and the initial mass function at the same time.

In [75], Kiemle et al. referred to the earth observation BD (e.g., images, multispectral data) from satellites, managed by the German Aerospace Center as well as to the Data

Information Management System (DIMS). The German Satellite Data Archive has been a vital part of many earth observation missions. The DIMS can handle massive volume of data and is comprised of different components which are relevant to processing management, product/order management, online product publishing/delivery, handling online user information, handling data access as well as monitoring, reporting, and control.

Synthetic Aperture Radar (SAR) BD from satellites can be utilized in the study of ocean wave observations. Huang and Li [76] used spaceborne Wave Mode (WM) BD over a period of ten years for extracting parameters related to the ocean, namely the Significant Wave Height (SWH) and the Mean Wave Period (MWP). The already known parametric model was used for the calculations and statistical analysis of the results was also conducted. The calculations were in agreement with the in situ buoy data with a correlation coefficient of 89% of SWH and 83% for MWP. Spaceborne SAR data can also be used for detecting oil spills on the sea. Zeng and Wang [77] proposed a Deep Convolutional Neural Network (DCNN) for detecting oil spills, utilizing SAR data from satellites. The authors conducted experiments utilizing 20.000 SAR patches and compared the model's performance with other Machine Learning classifiers (VGG-16 and AAMLP). The proposed model outperformed both models in terms of accuracy, recall, and precision metrics, reaching 94.01% accuracy, 83.51% recall and 85.70% precision. The authors also underlined the high distinguishability of the features learned by the proposed model, which contributed to its very satisfying performance.

Disasters can seriously affect the proper functioning of the communication infrastructure and obstruct humanitarian relief operations. Nagendra et al. [78] demonstrated how satellite BD analytics could benefit such operations in cases of disasters. A case study was presented regarding a BD analytics platform which supported humanitarian operations during the floods which occurred in the Indian state Kerala. This platform facilitated logistical planning as well as the execution of security missions. The data sources which were utilized included satellite images, geospatial data, weather data, etc.

BD can also be used in image decompression applications as well as for creating libraries for programming languages. Nuñez et al. [79] proposed a tool for the decompression of images of the under-development space telescope PLATO, which will survey different stars. In the publication, compression was initially carried out for the BD processed by the telescope. The images were cropped and then compressed utilizing a lossless algorithm. Soon after that, the compressed data were sent as telemetry to the ground service module in the form of data packets. The authors' tool collected and classified these data packets and utilizing metadata and other scientific data they reconstructed the cropped and compressed images. Breddels and Veljanoski [80] presented the so-called vaex library for the Python programming language which can be particularly useful in the processing of massive astronomical catalogues as well as for other datasets. The library was comprised of different packages for visualization, client–server communication, mapped storage as well as one package specifically for astronomy. This astronomy-oriented package enabled transformations and selections as well as memory mapped storage. The authors incorporated streaming algorithms and enabled the processing of datasets which are larger than what the hardware specifications of a computer would normally allow. One use case described by the authors and highlighting the usefulness of the library, is handling photometry, astrometry, and spectrometry data deriving from the Gaea space mission. A BD-based methodology utilizing data from the same space mission was proposed by Castro-Ginard et al. [81]. Specifically, the authors' methodology had the main goal of detecting open clusters (a kind of star cluster, sharing some characteristics and having about the same age). For this, an unsupervised clustering algorithm and a supervised Artificial Neural Network (ANN) were utilized. The search of open clusters using this methodology yielded a 45% increase in known open clusters.

Settling insurance claims of farmers in case of natural disasters suffers from type-I (rejection of claims of eligible farmers) and type-II errors (approval of claims of ineligible farmers). Aiming to minimize these two errors, Negendra et al. [82] demonstrated how satellite BD analytics can help in minimizing such errors. Satellite multispectral imagery BD was used to estimate crop area, yield, and area of the vegetation as well as to detect anomalies and invalid points in the data used for the calculation of the yield. The feasibility of the approach was validated through the presentation of a case study in India.

A summary of the analyzed applications described in this chapter is provided in Table 2 below.

**Table 2.** Summary of the analyzed applications in the context of the current paper.

| Subcategory | Specific Application |
|---|---|
| Aircraft Design/Manufacturing | Architecture for industrial BD processing in aviation manufacturing [14], framework for fault prediction in aviation manufacturing [15], fog-computing-based framework for BD integration and sharing applicable in aircraft manufacturing [16], DT-based information management framework in aircraft manufacturing [17], and field perception method for component DT in aircraft manufacturing [18] |
| Monitoring of Flight/Aircraft/Safety Parameters | EDR estimation methodology based on QAR BD [19], identification of problems affecting flight quality based on QAR BD [20], detection of unstable aircraft approach events based on QAR BD [21], estimating usage characteristics and the efficiency of the TCAS of aircrafts [22], BD-based analysis of in-flight emergencies [23], determination of thrust based on BD [24], aircraft fault detection based on FlightGear simulation BD [25], and variable selection algorithm for mining variables highly correlated to an aircraft's safety [26] |
| Health Monitoring Systems | PHM based on aviation BD mining [27], scalable pipeline for aircraft health monitoring [28], BD-based architecture for helicopter health management systems [29], BD-based architecture for health management of civil aircrafts [30], architecture for the early detection of errors in an aircraft's electronic parts [31], and detection of faults and problems in commercial fleet [32] |
| Air Traffic Management and Trajectory Planning | Air traffic flow analysis based on ADS-B BD [33], using air traffic and weather BD for improving strategic planning of airlines [34], trajectory prediction based on surveillance and other BD [35], using flown trajectories BD to calculate flight performance indices [36], and visualization of multiple trajectories, utilizing flight BD [37] |
| Delay Prediction and Resource Allocation | Flight delay prediction using multiple ML algorithms [38], flight delay prediction based on ADS-B and other BD [39], BD-based residual airspace resource evaluation methodology [40], and BD-enabled network architecture for AGVNs [41] |
| Maintenance Optimization | Optimized maintenance and resource allocation based on BD analytics [42] and improving predictive maintenance by utilizing BD from heterogeneous sources [43] |
| Collecting Customer Insights/Increasing Customer Satisfaction | BD-based analysis of customer engagement of a commercial airline [44], linear regression model for predicting flight-related web searches [45], and increasing customer satisfaction and improving aviation service quality by utilizing BD from different sources [46] |
| Solutions for the Industry | Improving source localization in industrial facilities by using UAV BD [48] and BD analytics for supply chain efficiency based on UAV BD [49] |
| Solutions for Infrastructures | Detection of electrical transmission towers based on BD from UAVs [50], BD-based methodology for optimizing 5G service provisioning from UAVs [51], optimized BD management leading to better disaster management [52], EMS based on BD analytics for minimizing operating costs of UAVs [53], and BD data management optimization in applications with UAV base stations [54] |
| Supporting Military Operations | BD analysis for characterizing if an aircraft is commercial or military [55], using ADS-B BD for real time classification of aircrafts [56], and improving knowledge management and analysis for testing and evaluation processes of the Joint Strike Fighter program using BD analysis [57] |
| Increasing Air Force Safety | BD-based architecture for improving military flight safety [58], improving military aircrafts' health management systems by utilizing heterogeneous BD [59], and role of BD in improving military campaign simulation capabilities [60] |
| Aviation Big Data related to Health Aspects | Flattening the curve of COVID-19 by using BD analysis from diverse sources [61], BD-based methodology for the early detection of the reactivation of tourist markets [62], multidimensional framework illustrating the importance of BD in fighting major health incidents [63], and utilization of BD for controlling the introduction and spread of the Chikungunya virus [64] |

**Table 2.** *Cont.*

| Subcategory | Specific Application |
| --- | --- |
| Aviation Big Data related to Environmental Aspects | Using BD to calculate the emissions of different pollutants during landing and takeoff [65], BD model for reducing fuel consumption and pollutant emissions of aircrafts [66], monitoring urban air quality based on BD and UAVs [67], and UAV BD analysis for improving surveillance for wildfire prevention and management [68] |
| Supporting Space Missions | BD-enabled architecture for supporting launches at rocket launch sites [69], BD analytics visualization methodology for improving clinical decision systems in space [70], BD analytics for space medicine decision support [71], and BD-based Bayesian framework for estimating the remaining lifetime of operating satellites [72] |
| Solutions Utilizing Spaceborne Big Data | BD-based theoretical framework for facilitating the study of the Milky Way [74], BD management for improving earth observation [75], BD for ocean wave observation [76], oil spill detection from spaceborne SAR BD [77], satellite BD for supporting humanitarian relief operations [78], image decompression tool for BD deriving from a telescope [79], Python library for processing astronomical catalogues and spaceborne BD [80], utilizing BD for detecting open clusters [81], and optimization of settling insurance claims of farmers based on satellite BD [82] |

## 4. Discussion of the Results/Conclusions

The present literature review surveyed a wide range of publications related to the use of BD in aerospace. A total of 67 publications were analyzed, and a 6-fold main categorization was formed, followed by a subsequent subcategorization for the analyzed publications, covering important aerospace aspects. A total of 15 subcategories were utilized. The main aim of this categorization was to provide the reader with a clear overview of how BD can be applied in aerospace and what benefits it can provide.

In the first category (i.e., Big Data in Aviation Technology), we saw many BD-enabled applications that greatly facilitated aircraft design and manufacturing processes, and helped in the detection of manufacturing errors as well as in increasing efficiency. BD from a multitude of heterogeneous sources enabled us to extract useful parameters and indicators related to the safety, efficiency, and engine health of aircrafts and could importantly reduce potential unstable approaches and accidents. BD also contributed to extracting correlations among seemingly irrelevant variables.

In the second category (i.e., Big Data in Aviation Management), BD-based applications were described which helped in effective air flow management, in creating and visualizing aircraft trajectories, in reducing flight delays, in determining the causes of flight delays, in having a more effective resource allocation, in optimizing maintenance procedures and reducing maintenance costs, in gaining insights for aviation based on social media BD as well as in collecting feedback from customers and in increasing customer satisfaction.

Due to the nature of UAV-based applications, the benefits of BD in such applications were examined in a separate category (i.e., 3. Big Data and UAVs). The usefulness of BD in different UAV-based publications was highlighted in many examples, e.g., in executing inventory tasks or facilitating manufacturing processes in industrial environments, in effectively identifying poles and wires in power distribution systems, in providing network communications in distant places or in cases of disasters, in reducing UAV charging costs, as well as in improving their service coverage.

Regarding the fourth category (i.e., Big Data in Military Aviation), BD was utilized in applications for the characterization of if an aircraft is military or not, for facilitating decision making in air force operations, in simulating military campaigns, for improving the maintenance procedures of military aircrafts and for increasing the safety of military aircrafts' pilots.

Moving on to the fifth category (i.e., Aviation Big Data related to Environmental and Health Aspects), publications mainly revolved around tackling major health incidents, reducing the spread of diseases, measuring air quality, reducing aircraft emissions, as well as in preventing and managing natural disasters.

Finally, in the sixth category (Big Data in Space Technology) which contained 13 publications, we saw how BD-enabled applications, can support rocket launches, support clinical decision systems in space, estimate the remaining lifetime of satellites, help in earth and space observation, contribute to advanced analysis of spaceborne data as well as support humanitarian operations or resolve insurance claims based on satellite data.

In the publications we analyzed, heterogeneous data sources were used (e.g., QAR data, ADS–B messages, data from the OpenSky network, GPS data, engine data, healthcare data, data from the social media, satellite image data, and weather data) and diverse ML models have been implemented (e.g., SVM, LSTM, Bayesian Networks, RF, CNN, Multilayer Perceptron, and Linear Regression). Examples of BD sources and ML models found in the analyzed papers as well as the main categories of the categorization we introduced are summarized in Figure 2 below.

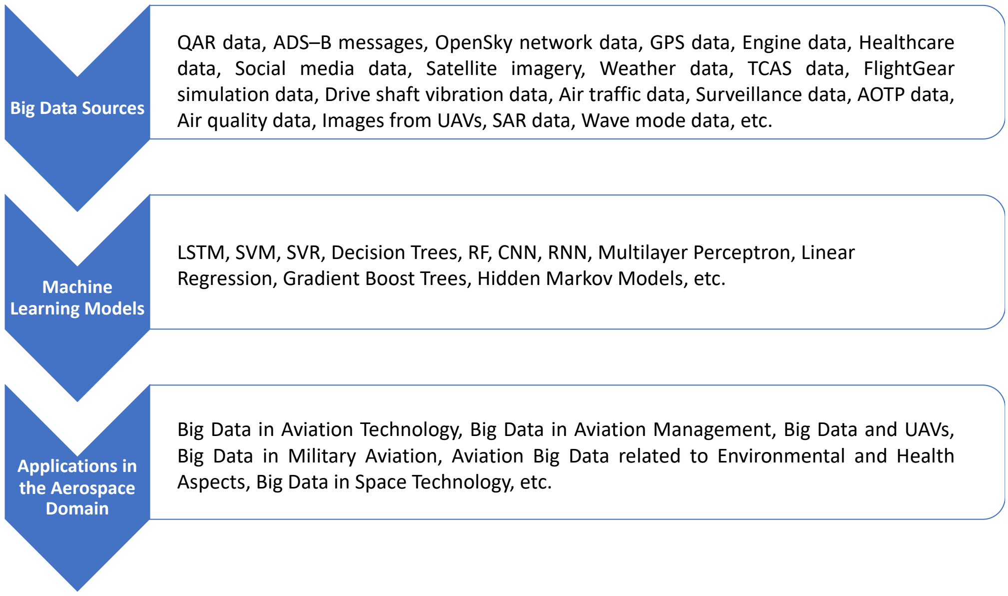


**Figure 2.** Examples of BD sources and ML models used in the analyzed papers.

In conclusion, approaches based on BD and BD analytics have gained momentum over the last few years and can play a vital role in different fields of the aerospace sector. As future research directions, we propose literature review approaches based on all or some of the categories stated in the current review. A review focusing on the application of BD in Space Technology only, or another review using a categorization based on the ML models used in BD-enabled aerospace applications would also be interesting. Finally, we would also suggest a literature review on the challenges posed by the utilization of BD and BD analytics in the aerospace domain.

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