S.NO	JOURNAL PAPER NAME	AUTHORS NAME	SOURCE	READINGS
1	EXPLORE DATA ANALYSIS ON AVIATION DATA SET	SABA FIRDOUS,HASEEBA FATHIYA,LIPSA SADATH	IEEE	This paper mentions that airline Industries are witnessing a transition that drives decisionmaking using data and analytics. There is a growth in the amount of data generated by various industries, which can be analyzed, interpreted, and processed by businesses to be beneficial for the company. Enterprises that use big data efficiently have a perceivable advantage over their competitors; their performance gap keeps growing as more pertinent data is produced. Big Data analytics can be used in the airline industry to improve the performance of aviation operations [2]. Data collected from customer profiles, social behavior, etc. can be efficiently used by airlines to provide personalized services to customers. They can also be used to analyze passenger flow, cost reduction and to enhance revenue. On normalized informational indexes, for example, flight following information or climate, traditional information mining strategies are effective. Aviation informational collections surpass work area registering capacities. Huge information investigation offers the adaptability, extensibility, and question usefulness of the flight business through cloud-based information base design. Next comes the analytics. Flight datasets require manual information cutting, which requires some investment. These issues can be tackled by applying large 541 2021 International Conference on Computational Intelligence and Knowledge Economy (ICCIKE) | 978-1-6654-2921-4/20/$31.00 ©2021 IEEE | DOI:

				10.1109/ICCIKE51210.2021.9410686 Authorized licensed use limited to: University of Prince Edward Island. Downloaded on June 03,2021 at 17:55:20 UTC from IEEE Xplore. Restrictions apply. information scientific procedures, information warehousing and programming answers for quick reaction information mining. Cloud computing is the utilization of assets that are dispersed as an administration over the Internet.
2	FLIGHT DELAY FORECASTING AND ANALYSIS OF DIRECT AND INDIRECT FACTORS	FUJUN WANG,JUN BI,DONGFAN XIE,XIAOMEI ZHAO	IEEE	This paper mentions that airline industries With increasingly tight flight schedules, the prediction of aviation resources is developing rapidly. The differences in the current research are mainly in the prediction methods and the input factors considered. Prediction methods are either based on statistics (Stats) or based on machine learning (ML) or deep learning (DL). The influencing factors considered are mainly divided into direct and indirect factors. As mentioned earlier, the direct influencing factors are those that have nothing to do with the time series, which will not be accumulated. However, the indirect factors are related to the time series, these factors will accumulate over time, and finally affect the delay of a flight. Much literature addresses the statistical analysis. Tu et al. used a genetic algorithm to fit delay data and study long- and shortterm flight departure trends [4]. The model included seasonal influences, daily trends, and random trends, enabling users to grasp general delay characteristics. Hsiao and Hansen considered the influence of arrival queues, passenger flow, weather and other factors on flight delays [5]. Through econometric analysis of the contribution rates of various factors to delays, the model explained 72–

				73% of the variation in the average delay. Hao et al. used econometric and simulation models to calculate and decompose delays, considering direct factors such as quarter-hourly data on throughput, demand, and arrival rates [6]. Rodriguez-Sanza et al. [7] used a Bayesian network and timeseries features to model randomness and time variation of flight delays. However, the prediction results consisted of statistical guidance rather than a tactical operation
3	BIG DATA ANALYTICS IN AIRLINES	Hamida Abd El Samie Mohamed, Mahmoud Ramadan Al-Azab	IEEE	This paper mentions that in airline industry Big data is considered a driving force that can enhance economic growth, prosperity and solve societal problems (Mayer-Schönberger and Cukier, 2013; Verhoef, et al., 2016). Big data comprises an array of modern analytical technologies and business possibilities (Mikalef et al., 2018). These new systems handle a wide range of data, from sensor data to Web and social media data that enhances business agility by fostering automated real-time actions and immediate decision making (Mikalef et al., 2018). Moreover, big data is a cultural and technological phenomenon that stands on the interaction of (1) Technology: maximizing computation power to gather, analyze, link, and compare large datasets. (2) Analysis: to identify patterns in order to make economic, social, technical, and legal claims. (3) Mythology: large datasets offer a higher form of intelligence and knowledge that can provide insights that were previously unfeasible (Boyd and Crawford, 2012). Big data represents the information assets characterized by such a high volume, velocity and variety to require specific technology and analytical methods for its transformation into value (De

				Mauro et al., 2015). In sum, it is a larger-scale and complex data that traditional data processing applications and software tools are insufficient to capture, curate, manage, and process it within a reasonable period of time (Snijders et al., 2012). Big data is commonly described by the three "Vs", volume, velocity and variety of data (Laney,2001; McAfee and Brynjolfsson, 2012). Most definitions of big data include the three main characteristics of volume (amount of data), velocity (speed of data in and out), and variety (range of data types and sources) (Song and Liu,2017). Volume refers to the sheer amount of data available for storage, processing, and analysis (Hausladen and Schosser, 2020). This includes all data sources from aircraft, airports, and institutions strongly connected to them, which could be databases of maintenance centers, weather stations, satellite networks, and the Internet (Yin and Kaynak, 2015; Kasturi et al., 2016). Velocity refers to the speed at which data are generated and processed (Lee, 2017). Variety refers to the different types and sources of data collected (Akter, 2016). In aviation, very large amount of flight data is generated and there is an essential need to analyze such data in real time (Kasturi et al., 2016). Technological advances allow firms to use various types of structured, semi-structured, and unstructured data (Lee, 2017). Structured data refers to the tabular data found in spreadsheets or relational databases (Gandomi and Haider, 2015). Text, images, audio, and video are examples of unstructured data
4	Predictive Maintenance and Performance Optimisation in Aircrafts using Data Analytics	Shakthi Weerasinghe	IEEE	This paper mentions that the airline industry have Research on adopting big data and data analytics

		,Supunmali Ahangama D		techniques for aviation has been a raising subject from 1980s. The technology was adopted concurrently with the early adaptors in similar industries particularly for the purpose of customer oriented marketing. Aviation data analytics also considers a similar motive in different aspects [11] in establishing a collaborative platform for sustainable air operations specifically oriented at overcoming operational limitations of an airline. Large scale industry equipment manufacturers, particularly engine, auto mobile etc. have applied big data technologies for optimizing operations and reliability of the products [7], [12], [13], having proposed both the concepts of “Industrial Internet” and “Industrial Internet of Things” (IIoT). In fact, these stands at the core of the aviation big data especially in the context of real-time analysis. Airbus Industries Aircraft Maintenance Analysis (AIRMAN) is a real time monitoring, and fault diagnosis tool [6], [15] developed in order to provide early detection of anomalies and enhance effective resolution in a timely manner reducing aircraft downtime. Although, the system provides the indications of handling large scale real-time data in an efficient manner, the predictability of faults are not discussed. However, based on the contemporary notion of Prognosis & Health Management (PHM) the predictive forecasting model - “Predictivity”, launched in 2013 established a forecasting model to operate on real-time data [7], as a result of which allowed engines to operate with lower Labs studies on wireless transmission based fault-tolerant system on real-time data of Anti-icing systems [12] is a commendable work on establishing the viability of using

				real-time parameter-data analysis for in-flight and ground based decision support. In a similar isolated attempt, research in predictive analytics based on Automatic Dependent Surveillance – Broadcast (ADS-B) feeds [17] have also suggested potential use cases for performance optimization as a function of flight plan and trajectory concerning effects of weather on the performance in terms of aerodynamic and engines. Therefore, indirect applicability of data analytics for the purpose of enhancing efficiency has been overseen although for having concerns on the rapid and high dynamism of environmental factors which is one of the factors that could be considered in a true 'integrated' environment for analysis.
5	PREDICTIVE ANALYTICS WITH AVIATION BIG DATA	Samet Ayhan, Johnathan Comitz and David Gerberick	IEEE	This paper mentions Big data means data that cannot be handled and processed in a traditional manner. It will be so large as to not fit on a single hard drive,as a result,it will be processed on a number of cores [8]. There are number of articles and books on big data, analytics, data warehousing and OLAP technology and related research issues. While some of these research focus on physical and conceptual design, others target maintenance issues and stream processing. However, to the best of our knowledge, there is no work done similar to ours in the aviation domain where operational real-time or near real-time surveillance data is turned into a warehouse enabling critical decision making and predictive analytics in the literature. Research matters pertaining to data warehousing and OLAP technology can be found in various resources [9-13]. A significant amount of research in the database community has been dedicated to the physical and logical

				design of data warehous In traditional DBMSs, it was assumed that the DBMS is a passive repository storing a large collection of data elements and that humans initiate queries and transactions on this repository. Abadi et al. [18] called this a human-active, DBMS-passive (HADP) model. They called the opposite a DBMS-active, human-passive (DAHP) model due to fact that, the role of the DBMS in the case of monitoring applications is to alert humans when abnormal activity is detected. According to them, monitoring applications are very difficult to implement in traditional DBMSs. First, the basic computation model is wrong: DBMSs have a HADP model while monitoring applications often require a DAHP model. The ASDI data feed is a continuous stream of messages delivered over a TCP/IP network socket from an upstream ASDI vendor. A data distribution server was created to receive one stream from Embry-Riddle Aeronautical University (ERAU), record the ASDI data, and make it available locally. The ASDI data feed produced by ETMS is a stream of data packets containing Zlib compressed XML documents of ASDI messages with a binary header. ASDI messages can be flight plan related data, oceanic reports, or Host track reports. Each NAS center identifies a flight plan by its own three character alphanumeric Computer Identification (CID) code. The ASDI stream contains messages for a flight from each