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BEHAVIORAL EVIDENCE OF PUBLIC AIRCRAFT WITH HISTORICAL DATA: THE CASE OF BOEING 737 MAX 8 PK-LQP

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This paper studies a significant amount of residual evidence characterized by the historical flight trajectory of PK-LQP (B737 MAX 8), which underwent an accident. Subsequently, this method is employed to generate novel safety-relevant knowledge based on existing flight data. At the beginning of this study, the method is applied by developing the hypothesis with the support of all data collected from online and offline reports, ADS-B data from flightradar24, and a statistical approach. This preliminary study employs Python as an essential program for the purpose of data collation and analysis. The results show that in the data offered by KNKT (The Indonesian National Transportation Safety Committee-Indonesia), the aircraft (PK-LQP) demonstrated unusual behaviour in comparison with the typical climbing phase that is produced by the dataset valid B737 MAX 8 (the ground truth data). The results also confirmed the hypothesis proposed in this study.

Keywords: accident, evidence, historical flight trajectory, hypothesis

1 INTRODUCTION

Accidents that involve air transportation can have multiple contributing causes, such as maintenance that does not follow the procedures provided by the manufacturer, human error, adverse weather, or technological faults. These factors can all play a role in causing an accident. Therefore, one of the criteria that must be maintained and enhanced to sustain the expansion and development of this industry is the safety of air transportation. The safety associated with an aircraft represents a significant concern that requires the industry to be extremely sensitive [1]. To this end, several regulations have been produced to be followed by manufacturers as well as other concerned sectors during the development of a commercial flight [2]. The field of technology has been considered the primary source of knowledge that underpins the development of aircraft technology, which recently has been offering further safety by reducing the potential for human errors (pilot) [3] through the implementation of semi-autonomous or autonomous modes (autopilot); this has been expected to reduce accidents caused by pilots who operate the aircraft [4].

Accidents or incidents of aircraft may trigger the development of relevant mitigation strategies [5]. Lately, businesses that deal with aircraft have adopted a proactive approach to safety by adopting mechanisms that can recognize hazards before the occurrence of potential mishaps [6]. Presently, there are no applications within aircraft maintenance that consider an analysis of the historical data of the flight. This study is one part of the road-map research in the novel development of a safety application based on the behavior of the aircraft.

2017 has been considered the golden year of aircraft sales for manufacturers. During this year, the B737 MAX 8 aircraft was launched with a festive reception from the airline industry wherein the sales until March 2019 had a 5012-units flight order, while only a 387-units flight order has been sent to the customer [7]. However, this golden age came two an end when two major accidents rocked the aviation industry, resulting in a major decline in aircraft sales. The first of the two accidents occurred at the end of 2018 (flight 610) [8], while the other occurred in early 2019 (Ethiopian Airlines flight 302) – both the aircrafts failed during phase climbing [9].

According to the CAST/ICAO Common Taxonomy Team (CICTT), there are six general phases of a commercial flight - taxi, take-off, climbing, cruise, descent, and landing [10]. Based on the research conducted by Boeing Company, the Accidents Commercial aircraft from 1950 to 2004, nearly 17% of the aircraft suffered an accident during the take-off and climbing positions [11]. Based on this information, the focus of this study is on the very same positions. The take-off position occurs when the aircraft has an altitude of 35 feet above runway elevation; after this, it transitions into the climbing position, wherein it continues to climb until it is 1,000 feet above ground or follows the Visual Flight Rules (VFR) pattern, whichever precedes [1].

This study is designed to evaluate the hypothesis that flight parameters (features) received by automatic dependent surveillance-broadcast (ADS-B) will perform flight behavior. This hypothesis is a prediction that is concerned with the accident of PK-LQP. Furthermore, the study also presents ongoing analyses regarding the search for anomalies in air traffic information from the PK-LQP aircraft to provide a state-of-the-art review of pilot behavior studies categorized by trajectory data types. The case study employed in this study utilizes the historical data of flight 610 (PK-LQP), as provided by Flightradar24. The data from the accident is then compared with the dataset provided by the OpenSky database [12]. Past trajectory data from aircraft are commonly used to predict anomaly behavior [13][14].

The section continues as follows: section 2, which is research methods, describes how to develop the hypothesis, Strategy to prepare readiness information, aircraft parameters, and anomaly behavior. Section 3 is the result and discussion section that analyses the outcomes and discusses research findings, while the conclusions summarize the findings.

2 RESEARCH METHODS

The first step of the research method in this study was to develop a hypothesis that assumes that all phenomena occur with evidence [15]. This evidence or information is highly significant in disclosing evidence of movements left behind by the B737 MAX 8 aircraft. Therefore, evidence is very crucial to observation. Meanwhile, the observation of evidence that precedes the hypothesis, may be regarded part of the scientific process in the limited sense [16]. In other words, a hypothesis is an observation based on a cause and effect relationship. Therefore, the hypothesis needs to be developed before making observations on the data evidence. A hypothesis is an observation based on a cause and effect relationship. This approach follows the scientific method [17] for developing the hypothesis which involves the following steps: Description of aspects or sources, formulation of the developing topic, finding expert-reported causes, establishing a hypothesis, designing a study framework, analyzing research evidence, drawing conclusions, and conveying outcomes. Fig. 1 shows how the hypothesis was developed.

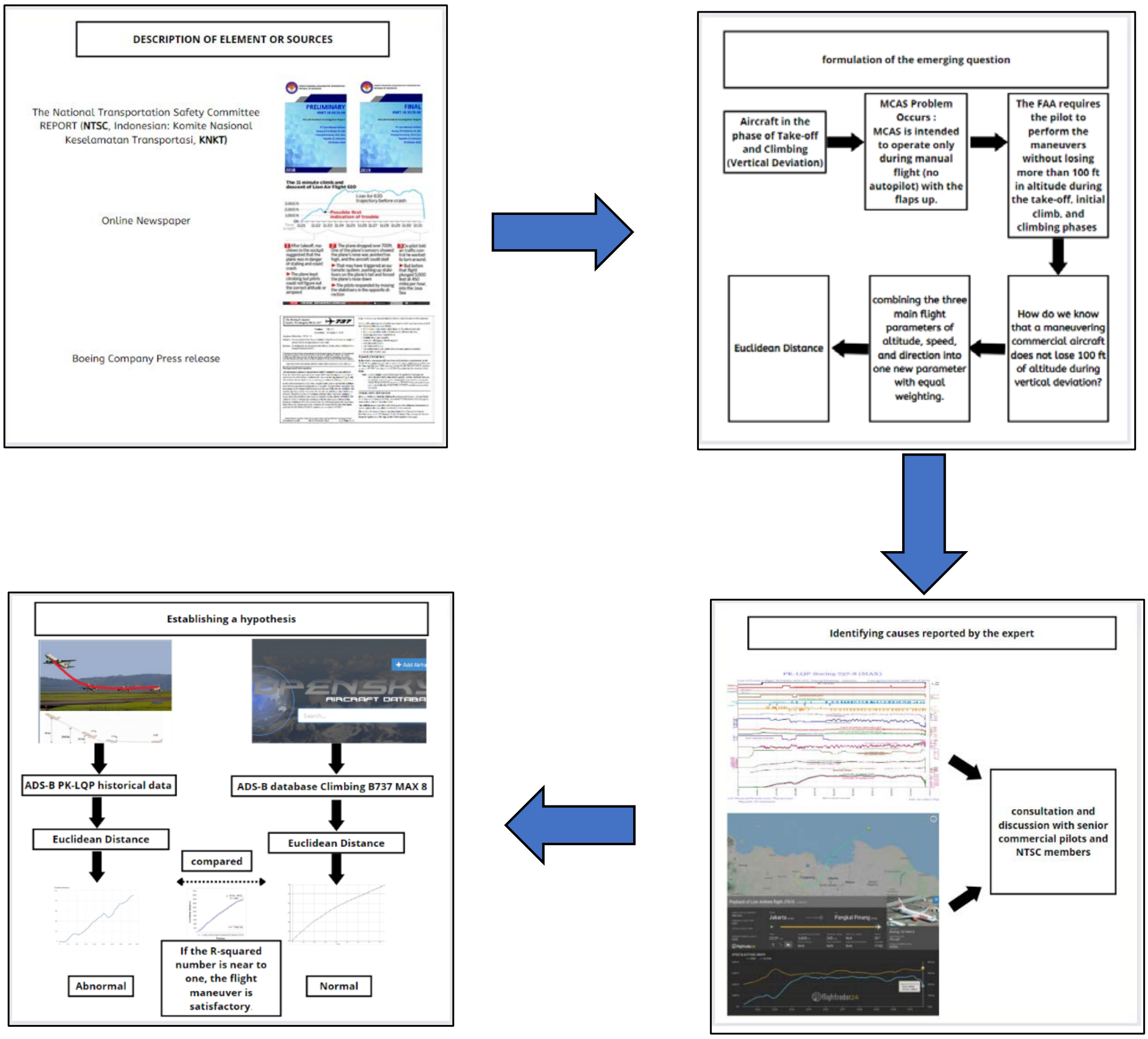


Fig. 1. Descriptive stages for hypothesis establishment.

The general process of developing the hypothesis is explained as follows: the first step is to collect relevant material such as the preliminary report of the PK-LQP accident, final report of the PK-LQP accident, online news regarding the PK-LQP accident, press releases from Boeing Company, and Publication Journals/conferences related to B737MAX8. Through these processes, the causes of the accident was mapped following the Fault Tree Analysis of the Lion Air 610 plane crash developed by [18], which informs the second stage – freezing of the findings, as the failure of the Maneuvering Characteristics Augmentation System (MCAS) software, which collects information from the AoA (Angle of Attack) sensor, has been noticed by Boeing [7][9][18].

Based on these steps, the hypothesis assumes that it would be able to identify evidence by extracting from the historical data of the aircraft. In case the MCAS has provided incorrect information, the pilot may have become confusing, resulting in an unusual movement to retaliate against the said error. However, apart from the Blackbox data, would there be other sources of data that may allow researchers to identify relevant parameters? Upon further research, Flightradar24 and OpenSky databases were identified as important sources that would provide data from ADS-B [14] [19] [20].

After having collected the data, the study examines the relations between the parameters or features provided by the two databases. According to [2], the three parameters have an equal weight to result in a standard flight climbing position. Hence, these parameters ought to be merged into a single unit to support the representation of a flight.

The study examined the historical data from the date reported by KNKT as having a notable issue within the climbing face – data that has been supported by the maintenance report logbook [8]. The dates are October 26, 2018, October 27, 2018, and October 28, 2018. While the historical data were collected from Flightradar24, each data contains various rows of data based on the flight time. Moreover, all flight data consists of six phases. Hence, all extraneous data from other phases were removed to match with the OpenSky dataset (ground truth).

The strategy employed to prepare readiness information has been shown in Fig 2. The raw data within this study has undergone three specific steps – preparation, preprocessing, and processing. The purpose of each step is as follows: data preparation is carried out to collect and convert raw data into the CSV (Comma Separated Values) format; preprocessing data is the organization of final data from both sources (ground truth and flightradar24) prior to the final step of processing.

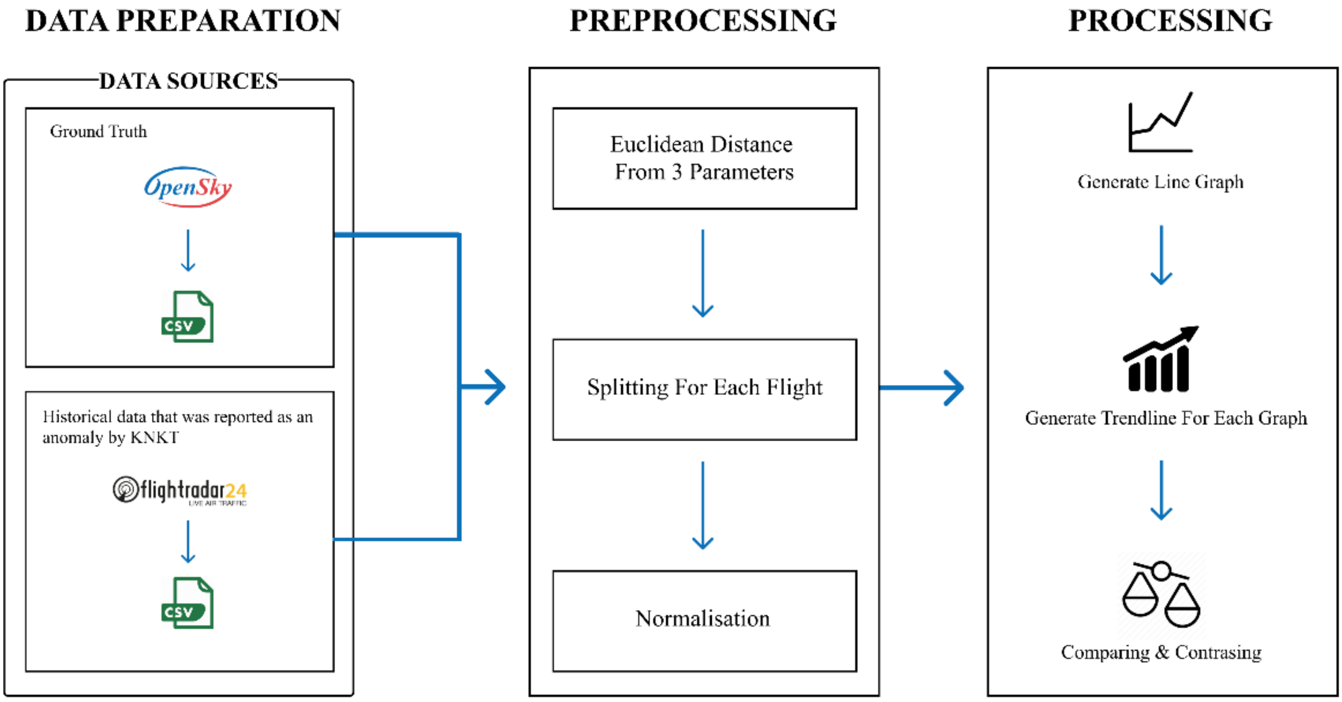


Fig. 2. Strategy to prepare readiness information

2.1 Data Sources

This section explains the data sources used in this study. The study used two data sources which are the B737 MAX 8 dataset on OpenSky data and Flightradar24 data. However, The OpenSky dataset has three types of data, which are training data, testing data, and validating data. On the other hand, the Flightradar24 data offer the historical data flight of accident aircraft (PK-LQP-B737 MAX8).

In this paper, only the validating dataset of B737 MAX 8 that is stored in the OpenSky dataset is used [12]. This validating data is known as the ground truth behaviour of the climbing flight. Besides ground truth, the historical data of PK-LQP (flightradar24) are only choosing for three flights, which were reported by KNKT and confirmed by the pilot as an anomaly [8].

2.2 Aircraft Related Parameters

The Aircraft parameters were sourced from Flightradar24.com, which is a web platform. ADS-B is the essential innovation method that Flightradar24 has used to access flight data [19]. The first step involved in this innovation is the reception of the aircraft's location from a GPS route source (satellite). After this, the ADS-B transponder on the aircraft transmits a signal that carries its location (and perhaps, further information). Next, the ADS-B signal is intercepted by a receiver associated with Flightradar24. After this, the receiver feeds the received data to Flightradar24. Finally, the information appears on the website and applications associated with Flightradar24 [21].

ADS-B is a global innovation that has been implemented and developed. This implies that the Air Traffic Control (ATC) has made use of this system within their environment as well. Presently, almost 70% of all business traveler aircraft (80% in Europe, 60% in the US) are furnished with an ADS-B transponder. For general aeronautics, this number is likely beneath 20%. The level of aircraft outfitted with ADS-B receivers is consistently expanding. However, as they shall eventually be required for nearly all the aircraft across the world by 2020, ADS-B is bound to supplant the present radar as an essential observation technique used by the ATC [22].

The data parameters provided by ADS-B are shown in Table 1, with features such as the timestamp, UTC (Coordinated Universal Time), callsign, position, altitude, speed, and direction. Equation (1) is used to calculate the Euclidean distance between 3 parameters (features); the results of this calculation shall be positioned among the new attribute data.

$$ED = \sqrt{(A-S)^2 + (A-D)^2 + (S-D)^2} \tag{1}$$

Where ED stands for Euclidean Distance, A refers for Altitude, Acronym stands for aircraft speed, and D represents for aircraft direction.

Table 1. Data sources of ADS-B flightradar24.

Timestamp	Position (LAT, LONG)	Altitude (Feet)	Speed (Knots)	Direction (Degree)
1539533683	6.1441,106.637894	800	179	251
1539533692	6.14662,106.63065	1150	180	251
1539533703	6.14983,106.62188	1450	184	249
1539533712	6.15453,106.61444	1625	189	233
1539533723	6.16173,106.60984	1800	194	207
1539533732	6.17093,106.60877	1975	200	181

In the Aviation Glossary & Flight Tracking Terminology determined by flightradar24, the altitude of the flight refers to the elevation of the distance between aircraft and terrain. However, it is important to note that the calibrated altitude has been computed into the Flightradar24 system, implying that the values reflect the aircraft's altitude above Mean Sea Level. The speed of the flight is known as ground speed.

The historical data from Flightradar24 in the cluster has been highlighted in 3 merger features with an equal assessment weight consisting of altitude, speed, and direction. The equal assessment weight is indicative that each of the features of the data flight significantly contributes to the behavior of the flight route (See Fig. 3).

2.3 Anomaly

Specific investigations into flight abnormalities started to take place in 1996 [23]. According to [24], anomalies are defined as patterns in data that do not conform to a well-defined notion of normative behavior. Anomaly detection is a significant issue that has been investigated within various fields of research and application. Anomalies in data provide a vast amount of noteworthy information across a wide range of applications; hence, its significance. In the context of aircraft, many works of anomaly research have reported using trajectory data (historical data) [25][26].

As stated in [23], two aspects are worth noting within anomaly detection – the nature of the data and the type of the anomaly. As per the nature of the data, the flight trajectory is recorded by point data that represent the behavior of the pilot. The data recorded by ADS-B consist of a whole trajectory for a specific flight number. Point anomalies represent a data point that is not normal or is considered to be out of the ordinary.

According [24], the anomaly detection for time-series determined by data-based approaches is of four types - Euclidean distance, dynamic time warping distance, probability-based distance, and correlation-based distance. In this paper, the Euclidean distance is chosen as an approach for the preliminary study to verify the hypothesis using evidence that is produced from historical trajectory data.

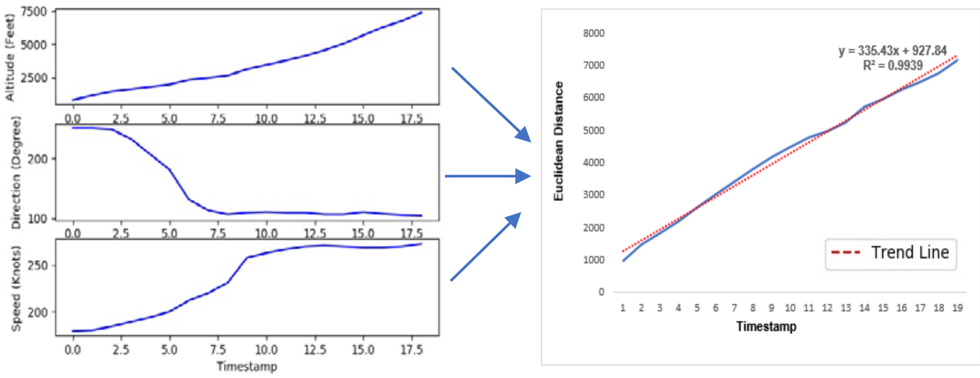


Fig. 3. Merging three parameters into a single line with the trendline generated.

3 RESULTS AND DISCUSSION

The results and analysis of this preliminary study consider the ground-truth data to develop a graph. Moreover, the history of the aircraft from the accident reflects the very same thing. Ultimately, this study compares results between ground-truth and accident data to verify whether relevant evidence is produced to prove the hypothesis.

3.1 Data Set B737 MAX 8 (OpenSky)

The ground truth data has 1780325-row data with 25,433 flights in the climbing phase of B737 MAX 8 that has been validated (Table 2). The data have eight features which are timestep, time, callsign, latitude, longitude, Baro altitude, velocity, and heading. Baro altitude in this data knows as an altitude of aircraft, velocity, also known as a speed of the aircraft, and then heading is representing the direction of the flight.

Table 2. Dataset of the ground-truth (climbing) - B737 MAX 8 (OpenSky).

No	Time step	Time	Call sign	latitude	longitude	Baroaltitude (Feet)	Velocity (Knots)	Heading (degree)
1	0	1504225936	12929	37.6230	-122.3726	100.98	75.83	28.87
2	15	1504225951	12929	37.6315	-122.3663	283.56	79.39	28.17
3	30	1504225966	12929	37.6426	-122.3628	435.54	82.01	2.1
4	45	1504225981	12929	37.6548	-122.3629	511.1	94.7	359.38
5	60	1504225996	12929	37.6677	-122.3629	647.7	101.92	358.47
6	75	1504226011	12929	37.6813	-122.3687	815.34	111.62	319.03
7	90	1504226026	12929	37.6892	-122.3855	1106.99	112.25	287.42
8	105	1504226041	12929	37.6892	-122.4044	1372.17	115.58	253
9	120	1504226056	12929	37.6806	-122.4203	1615.5	116.98	219.28
10	135	1504226071	12929	37.6667	-122.4280	1875.61	115.09	187.12
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
1780 325	780	1509490891	11914	43.7272	-77.066	11704.33	250.51	88.81

The ground-truth data are considered significant with 25,433 climbing flights from B737 MAX8, and the descriptive statistics of this data have been shown in Table 3. Descriptive statistics are fundamental to understanding any arrangement of data being studied as it provides the researcher with information regarding patterns observed in addition to the mode, median, mean, and range, as well as standard deviation, variance, skewness, count, and maximum and minimum. Descriptive statistics allow one to summarize a vast amount of data in a simple review.

A critical task in various measurable investigations (statistical analyses) is to describe the area and fluctuation of an informational data set. Further characterization of the data incorporates skewness and kurtosis. Skewness is a proportion of the balance, or all the more correctly, the absence of symmetry. A dataset is symmetric when it appears to be identical to the left and right sides of the center point

Table 3. Descriptive Statistics of ground truth data.

Statistic Parameters	Baroaltitude (Feet)	Velocity (Knots)	Heading (Degree)
Mean	6669.582997	197.8169	177.5985
Standard Error	2.518071	0.033951	0.076816
Median	7109.766688	208.7164	186.2258
Mode	11887.2	232.5975	90
Standard Deviation	3359.831915	45.29978	102.4943
Sample Variance	1.13E+07	2.05E+03	1.05E+04
Kurtosis	-1.095445	0.113546	-1.23424
Skewness	-0.251976	-0.84409	-0.02966

Statistic Parameters	Baroaltitude (Feet)	Velocity (Knots)	Heading (Degree)
Range	12584.72708	259.9748	360
Minimum	-68.189231	51.96903	0
Maximum	12516.53785	311.9438	360
Sum	1.19E+10	3.52E+08	3.16E+08
Count	1780325	1780325	1780325

As illustrated in Table 3, the information is indicated to have been skewed/slanted to the left as the normal distribution while the skewness should originally be of zero value. Skewness/Slanted-ness to the left implies that the left tail is long as compared to the right tale. As per the skewness values for parameters in Table 3, the distribution of data appears to be almost symmetric as the skewness remains between -0.5 and 0.5, which are acceptable values to demonstrate univariate distribution. In contrast, the value of standard error from the three features (Baro altitude, Velocity, and Heading) gives a value that ranges between 0 and 3. As the standard error demonstrates how accurately a sample represents the dataset population, a small value would imply better representation. After having confirmed that the descriptive statistics are representative and acceptable, preprocessing and processing phases are initiated.

The ground-truth data is then sent to the Python program to provide a single line trajectory to be compared with the trendline, which fits with all the data points. A simple linear data set is considered a best-fit straight line if used as a linear trendline. The data is linear if it has a pattern of data points resembling a line. A straight trendline generally shows that something is expanding or diminishing at a steady rate. The linear trendline also provides the researcher with the R-squared value, which may be used to measure the trendline reliability. If the value of R-squared is nearer to 1, the trendline appears to fit with the data. The linear trendline is considered suitable for use in the climbing phase due to the continuous rise of data in perspective time.

According to the results, all graphs confirm that the trajectory constantly intersects with the trendline, giving the R-squared average value being assigned 0.98, meaning the value for R-squared below the established denotes abnormal behaviour and vice versa. The sample result graph of ground-truth data is shown in Fig. 4. The value of flight with callsign 12925 gives a value of R-squared = 0.9983, while the flight with callsign 3566 gives R-squared 0.9901, which signifies normal flight behavior. Moreover, the Euclidean distance from the merged three features (Baro altitude, velocity, and heading) demonstrates an intersection with the linear trendline.

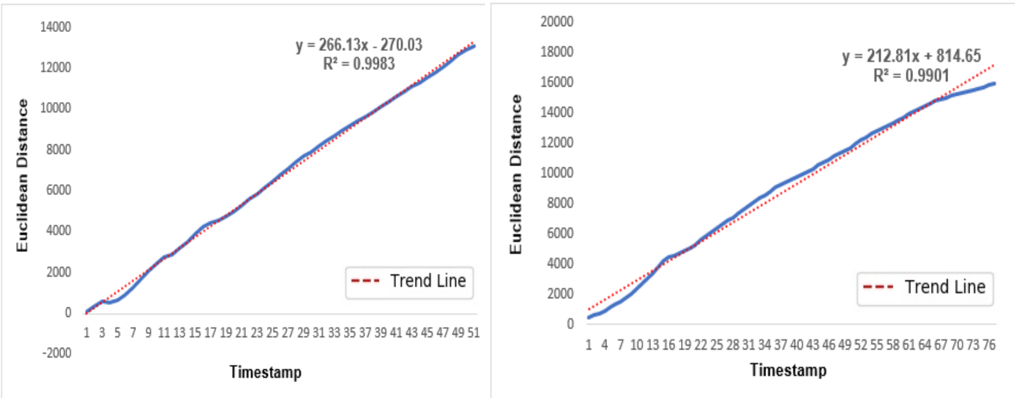


Fig. 4. The sample graph results from ground truth data;(A) Flight from callsign 12925;(B) Flight from Callsign 3566.

3.2 Data PK-LQP (Boeing 737 MAX 8 – Flightradar24)

The sample data corresponding with the climbing of PK-LQP demonstrates for three flights: JT2657, JT043, and JT610. The detailed descriptive statistics of the sample historical data for PK-LQP (Table 4) are shown. The median altitude is 1875 feet, the speed is 237 knots, and the direction of the flight is 158 degrees. Furthermore, the skewness and kurtosis from the three parameters show values below 0.46 and -0.21, which implies symmetry in the distribution of data. However, the standard error of altitude is very high (180.5); hence, the data characterizes low distribution in comparison with mean data. On the other hand, the number of the data sample is unsatisfying in perspective statistics; however, the number of flights in the climbing phase from the accident aircraft in this study are based on the reports by KNTK, to verify the hypothesis in this study.

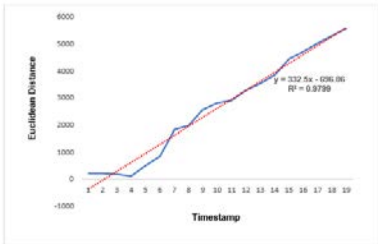
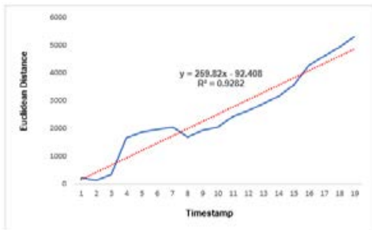
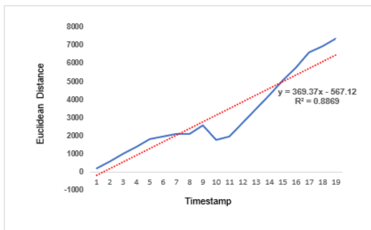
Hence, from the method used to identify early evidence from the 3 historical flights of PK-LQP, it was demonstrated that the flight trajectory is represented by lines that are always far apart from the trend lines as long as the flight time is in the climbing phase (Table 5). Furthermore, it was also found that the value of R-squared denoted 0.9799 (JT2657), 0.9282 (JT043), and 0.8869 (JT610). The different results elicited from the valid dataset of OpenSky (ground truth) that the flight trajectory always intersects with the trendline (Fig. 4).

Table 4. Descriptive Statistics of historical data PK-LQP

Statistic Parameters	Altitude (Feet)	Speed (Knots)	Direction (Degree)
Mean	2127.193	232.0175	174.2807
Standard Error	180.5427	6.70262	11.31713
Median	1875	237	158
Mode	1525	172	270
Standard Deviation	1363.067	50.60367	85.44249
Sample Variance	1857953	2560.732	7300.42
Kurtosis	-0.46821	-0.28848	-1.91177
Skewness	0.421898	-0.21157	0.026928
Range	5350	233	214
Minimum	0	101	57
Maximum	5350	334	271
Sum	121250	13225	9934
Count	57	57	57

From Table 5, it may be viewed that on October 26, 2018, the aircraft (PK-LQP) was scheduled from Denpasar (Indonesia) to Tianjin (China). The graph shows that after initial take-off and climbing, the aircraft struggled to climb smoothly. After a few attempts, the pilot managed to bring the aircraft back to a typical trajectory. The next day, on October 27, 2018, the aircraft was scheduled from Denpasar (Indonesia) to Tangerang (Indonesia). As per the graph, the aircraft behavior trajectory appears to unfollow the trendline, which repeats on the "Crash Day" on October 28, 2018, when the aircraft was scheduled from Tangerang to Pangkal Pinang (Indonesia).

Table 5. Graph results from 3 selected flights of PK-LQP

Date	Flight Number	Departure	Arrival	Graphs
October 26,2018	JT2657 (LNI2657)	DPS (Denpasar, Indonesia)	TSN (Tianjin, China)	
October 27,2018	JT043 (LNI043)	DPS (Denpasar, Indonesia)	CGK (Tangerang, Indonesia)	
October 28, 2018	JT610 (LNI610)	CGK (Tangerang, Indonesia)	PGK (Pangkal Pinang, Indonesia)	

4 CONCLUSION

This preliminary study was conducted using three parameters - altitude (Baroaltitude), speed (Velocity), and direction (Heading), which were found to have contributed to the flight behavior outcome. From the results of ground-truth data and historical flight accident data, the former was shown to be near the trendline during the climbing phase while the latter demonstrates a contrasting result. Moreover, the value of the R-squared shows the value from the ground-truth is an average of 0.98, while the R-squared value from the accident data of PK-LQP range below 0.98, which shows that the behavior flight history of PK-LQP does not meet with the ground-truth. The results were as predicted by the study hypothesis. Now that the hypothesis has been proven, it is imperative to investigate all data from PK-LQP from its first flight (August 8, 2018) until the crash day (October 29, 2018) using our method to support the claim by KNKT – that the aircraft is characterized by an abnormal behavior flight trajectory.

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