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A Method for Anomaly Detection of Unmanned Aerial Vehicles (UAVs)

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Abstract— **The aim of this study is to detect anomalies and improve the safety of UAVs by analysing UAV flight data temporally and spatially. Flight parameters and sensor data were recorded on a UAV platform built using PIXHAWK3 autopilot hardware. The data analysed with Python and related libraries were converted into a weighted graph with 'networkx' and visualised with 2D graphics. In the flights performed in ten different scenarios, a total of 105 anomalies were detected, especially in the first flight and in the 1130-1160 m altitude range. The temporal and spatial graph neural network method stands out as a critical tool for flight safety by effectively identifying anomalies in UAV flights**

Keywords— UAV, flight data, anomaly detection, temporal and spatial analysis

I. INTRODUCTION

Unmanned Aerial Vehicles (UAVs) are remotely or autonomously guided aircraft without the physical presence of pilots or other operational personnel. In our age, UAVs are being developed in various sizes and capacities, and the main characteristic of these vehicles, regardless of their intended use, is the ability to communicate with ground stations (Taştan, 2022). UAVs are also considered as components of a wider unmanned aircraft system. According to the methodology of their use, UAVs fall into two main categories: those operated by remote pilot control and those with independent navigation capability. UAVs, also commonly referred to as 'drones', have a wide variety of take-off methods, configurations and application areas (Philip, Raghav & Johannes, 2017).

Recently, the application spectrum and usage areas of Unmanned Aerial Vehicles (UAVs) have expanded significantly. As the range of use of these vehicles expands, the integration and applicability of UAVs in every potential sector is being investigated and innovations in working methodologies are being sought. This evolution has encouraged the widespread use of UAVs in a wide range of sectors, from healthcare to construction. Some of the applications of UAVs include mapping with high-resolution imagery, object recognition and classification, detection and analysis of forest fires, civil cargo transport, agricultural spraying and aerial pattern detection. These developments have contributed to UAV technology becoming an indispensable tool for applications in various disciplines (Bown & Miller, 2018).

In recent years, developments in Unmanned Aerial Vehicles (UAV) technology have led to the expansion of their usage areas. The increasing use of UAVs, especially in civilian areas and crowded places, has increased the importance of safety and reliability. In order to ensure flight safety and flawless operation of UAVs, it is critical to evaluate flight data containing many parameters in terms of temporal and spatial aspects and to detect anomalies. In the literature, there are a number of studies in which different methods are used to predict and detect anomalies in flight systems in UAV systems:

In the study conducted by Güneş (2026), it was aimed to identify potential hazards that may arise during flight by analysing Automatic Dependent Surveillance-Broadcast (ADS-B) data with statistical methods. ADS-B is a surveillance system that continuously broadcasts the position, speed, altitude and identification information of aircraft. In this study, ADS-B data of flights from Istanbul Airport in June 2022 were used. In order to detect abnormal conditions in flights, the data were processed with median filter and convolution process and the vertical speed attribute was selected. The flights were divided into take-off, level flight and landing phases according to the altitude changes and the vertical speed data for each phase were visualised with point distribution and histogram plots. In addition, statistical tests were applied to determine the vertical speed differences and anomalies between the flight phases. The findings of the study show that ADS-B data is an important data source for flight safety and that statistical methods can effectively detect anomalies in flights.

The main objective of this study is to analyse the flight data of Unmanned Aerial Vehicles (UAVs) to detect anomalies in the context of time and space, thereby increasing the safety and reliability standards of UAV operations. In the research, Graph Neural Network (GNN) techniques were used to reveal the relationships of flight data over time and space, and the findings obtained played a critical role in determining the input variables of the anomaly detection model. With this method, it is aimed to make an important contribution to the monitoring and management of UAV systems.

II. MATERIAL AND METHOD

Purpose of the Study

This research aims to improve the safety and reliability of Unmanned Aerial Vehicles (UAVs) by analysing their flight data. The high-dimensional data sets obtained from the sensors of UAVs are correlated in both time and space. The design and flight dynamics of the UAV necessitate the interaction of these data. Anomaly detection methods are generally divided into two categories: temporal and spatio-temporal correlations. Temporal methods are based on temporal correlations between data and learn features based on historical data; a mismatch is considered an anomaly. However, these approaches ignore spatial correlations. Spatio-temporal methods, on the other hand, recognise that data are correlated in both time and space dimensions and use multi-parameter data to model these correlations. Deep learning is an effective method for exploring these correlations and LSTM is often favoured for time series data. Benkuan et al. successfully extracted correlations of UAV data using LSTM, but needed prior knowledge when determining the model inputs. In the absence of information, feeding all parameters directly into the model seems to be a simple solution, but too many parameters may adversely affect the performance of the model. In this study, the temporal and spatial relationships of the data are analysed using Graph Neural Networks (GNN) and the results obtained are used as a criterion for the selection of input parameters in the anomaly detection model.

Method

In the material and method section, anomaly detection is performed by classifying the data obtained from the flights of a UAV that can fly autonomously or manually, in the temporal and spatial graph neural network (GNN) model. In the first step of the research process, a ready-to-fly platform was created by assembling the components of the UAV and configuring the autopilot software. In the second step of the research, the data obtained as a result of the flights were classified by temporal and spatial graph neural networks with Python programme and anomaly detection was performed. Pandas was used for data manipulation and analysis, MinMaxScaler class of Scikit-learn library was used for data normalisation and Isolation Forest algorithm was used for anomaly detection. Matplotlib library was preferred for graphing. The model for the research process is shown in Figure 3.1.

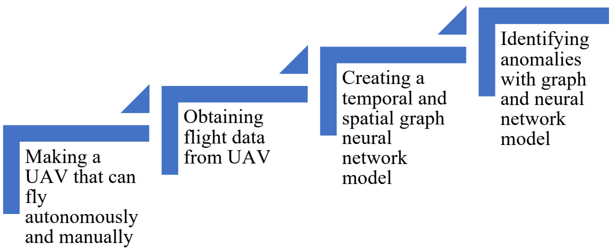

Figure 1. Research process model

Flight and Data Collection Process

UAV Production and Configuration Process

In this study, instead of using a pre-programmed UAV for UAV design and implementation, individually procured UAV hardware components were preferred. Among these components, PIXHAWK3, an open source and programmable autopilot hardware, plays an important role. The PIXHAWK3 autopilot hardware has the software interface required to perform software controls on the UAV. Thanks to this interface, functions such as flight parameters, sensor data, navigation information, mission planning and emergency management can be adjusted. After all the configuration procedures, the UAV can be managed by means of a control programme connected to a computer or a remote control (Figure 2).

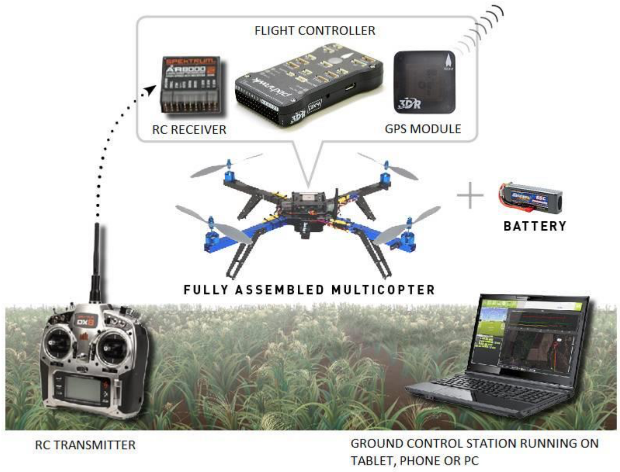

Figure 2. Configuration of the Project UAV Ready for Ground Tests

After successfully passing the tests, the UAV is ready for flight.

Flight Process

The flight configuration and autopilot software settings required for the unmanned aerial vehicle (UAV) to be ready for flight have been completed. These settings are important for the flight performance, safety and stability of the UAV. For this reason, after the settings were made, the UAV was tested in detail on the ground. As a result of the test, the UAV was found to be ready for flight. Thereupon, the UAV took off for its first flight. During the first flight, the UAV's flight parameters, sensor data and autopilot system were monitored and evaluated. The first flight was successfully completed (Figure 4).

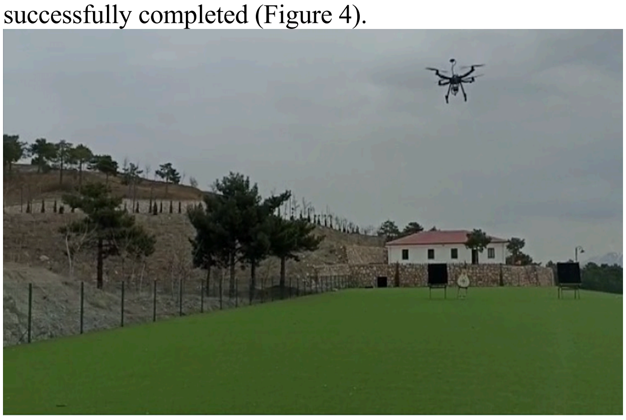

Figure 3. First flight of the project UAV

Collection of UAV Flight Data

In order to obtain a reliable data set suitable for the purpose of the research, the UAV was flown in 10 different scenarios and data were obtained.

Evaluation of UAV Flight Data

Unmanned aerial vehicles (UAVs) are used in many fields and collect data for different purposes. Analysing this data is important to evaluate the performance, safety and effectiveness of the UAV. However, data analysis does not only end with the collection of data, but also requires knowledge about the meaning, source and nature of the data. Therefore, the classification of UAV data ensures that the data can be interpreted correctly and contribute to decision-making processes.

In the classification of UAV data, the data related to the movement of the UAV has a special importance. Because, data such as the UAV's position, direction, speed, acceleration, rotation and inclination in the air are used to determine whether the UAV fulfils the desired mission, its status in the air, its relationship with its environment and its potential risks. These data can be expressed in Roll, Pitch and Yaw values that define the three-dimensional movement of the UAV. Roll is the angle of the UAV's wings with respect to the horizontal axis; Pitch is the angle of the nose of the UAV with respect to the vertical axis; and Yaw is the angle of the nose of the UAV with respect to the horizontal axis. These values are used to create mathematical models, algorithms and simulations to understand and control the movements of the UAV in the air.

Roll and DesRoll Data

Roll is the name of the movement in which an object rotates or tilts around its axis. This movement can change the direction and posture of the object. These data are instantaneous values that show how much the UAV's roll movement has occurred and how much it should occur. The Roll value is the actual roll angle of the UAV, while the Desroll value is the roll angle targeted by the UAV.

Pitch and DesPitch Data

Pitch movement can be defined as the upward or downward tilt of the nose of an aeroplane. The magnitude of this movement is measured by the pitch angle and the DesPitch data indicates the pitch angle that the aircraft wants to achieve. Roll motion can be defined as the rotation of the wings of the aeroplane on the horizontal axis. The magnitude of this movement is measured by the roll angle and the DesRoll data indicates the roll angle that the aircraft wants to achieve. During the flight, the pitch and roll movements of the aircraft are consistent with the DesPitch and DesRoll data, indicating that the aircraft is flying in a stable and controlled manner. However, environmental factors such as wind, temperature, pressure in the air during the flight may affect the pitch and roll movements of the aircraft. Therefore, the pitch angle of the aircraft must remain within the range of -5 to +5 degrees. If the aircraft's pitch angle moves outside this range or changes in a way that is inconsistent with the DesPitch data, this may indicate that the aircraft is making an abnormal movement or experiencing a problem. Such data anomalies can pose a significant risk to flight safety and should be carefully analysed.

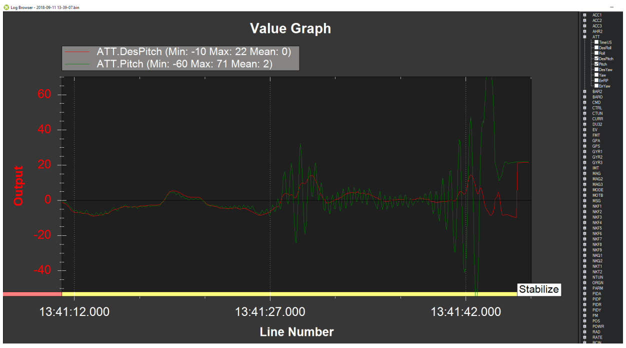

Figure 5. Example of Discordant Pitch and DesPitch Graph

Yaw and DesYaw Data

Yaw motion can be defined as the rotation of the nose of an aeroplane to the right or left. The magnitude of this movement is measured by the yaw angle, and the DesYaw data indicates the yaw angle that the aircraft wants to achieve. During the flight, if the yaw motion of the aircraft is consistent with the DesYaw data, it indicates that the aircraft is correctly orientated. However, environmental factors such as wind, temperature, pressure in the air during the flight may affect the yaw movement of the aircraft. Therefore, the change of the yaw angle of the aircraft should be within the range of +1 or -1 degrees. If the yaw angle of the aircraft falls outside this range or changes in a way that is inconsistent with the DesYaw data, this may indicate that the aircraft is making an abnormal movement or experiencing a problem. Such data anomalies can pose a significant risk to flight safety and should be carefully analysed.

AEKF Data

The Extended Kalman Filter (EKF) is an algorithm for modelling the flight dynamics of an Unmanned Aerial Vehicle (UAV). The EKF combines data from various on-board sensors to estimate the position, velocity, and orientation parameters of the UAV in motion. These sensors include velocity gyroscopes, accelerometers, compass, GPS, airspeed and barometric pressure sensors. The EKF relates this sensor data to a state space model describing the motion of the vehicle and calculates the most probable values of the state variables. The EKF data is presented in flight as an indication of the current state estimation.

Drawing Anomaly Graphs

In this study, Python programming language was used for the analysis of flight data. Python is an open-source, high-level and multi-purpose programming language that is widely preferred in the field of data science. The data were cleaned, organised and statistically analysed using the Pandas library for data manipulation and analysis. Pandas is a library developed for Python that allows easy data manipulation with data structures called data frames. For data normalisation, the data was scaled to a range between 0 and 1 with the MinMaxScaler class of the Scikit-learn library. Data normalisation is a process to prevent problems caused by data being at different scales and to ensure that the data is comparable. The MinMaxScaler class is a method that scales the data to a range between 0 and 1 using the minimum and maximum values of the data. For anomaly detection, the Isolation Forest algorithm was applied to identify outliers in the data. Anomaly detection is a machine learning technique used to find abnormal or unexpected behaviours or values in data. The Isolation Forest algorithm is an algorithm that tries to isolate outliers in the data by randomly dividing the data into subsets and calculating the separation depth of each subset. Various graphs were created with the Matplotlib library for data visualisation. Matplotlib is a library developed for Python, used to present data visually. Many types of graphics such as line graphs, pie charts, histograms, scatter plots can be created with Matplotlib. In this context, the procedures performed during the analysis process are given below respectively:

Feature selection: Among the flight data obtained in the research, features such as flight number, flight date, flight time, flight altitude, flight speed and flight distance were selected. The data belonging to these features were separated as a sub-data frame. A sub-data frame is a data structure that forms a part or subset of the data frame. The altitude value was used for anomaly detection on the sub-data frame. Data with an elevation value less than 1100 metres or greater than 1170 metres were considered as an anomaly condition. An anomaly condition is a term that describes abnormal or unexpected values in the data. Anomalous data were selected from the sub-data frame and stored as a list.

Normalisation: In order to detect UAV flight anomalies, data normalisation was applied to overcome problems such as the variables in the data set being at different scales and their distributions being unequal. Data normalisation aims to reduce the values in the data set to a certain range, making them more suitable for data analysis and modelling. In this study, the data were scaled in the range [0, 1] using Min-Max normalisation.

Anomaly detection: In order to detect UAV flight anomalies, the Isolation Forest algorithm was applied on the normalised data set. The Isolation Forest algorithm is a decision tree-based algorithm that aims to separate outliers in the dataset by dividing the dataset binary using a randomly selected attribute and a randomly selected threshold between the minimum and maximum values of this attribute. This algorithm is based on the assumption that outliers are fewer and more diverse in the data set. Therefore, it requires fewer splitting operations to isolate outliers. The splitting operations are represented by a tree structure called Isolation Tree. The number of splits required to isolate a data point is interpreted as the path length from the root node to the last node in the tree structure. This path length is calculated as the anomaly score of the data point, averaged over a forest of multiple random trees. The anomaly score is inversely proportional to the path length. That is, shorter path length means higher anomaly score [35]. In this study, the Isolation Forest algorithm was trained on the normalised dataset and the anomaly score of each data point was calculated. These anomaly scores were classified according to a certain threshold value and the data points were labelled as normal or outlier. This method is an effective and fast method for detecting UAV flight anomalies.

Graph creation and visualisation: In the research, a graph was created using the Matplotlib library to show whether the data points are normal or abnormal. The graph shows the height and speed parameters of the UAV as x and y axes. On the graph, normal data points are marked in blue and abnormal data points are marked in red.

Drawing Graph Neural Network Diagrams

This study presents a method for the geographical analysis of flight data. The first step of the method is reading the flight data provided in Excel file format. For this purpose, the data has been transferred to a dataframe using the Pandas library. The dataframe includes the roll, pitch, and yaw parameters of the flight data. The second step involves filtering and optimizing the parameters within the dataframe. This is achieved by filtering the data with altitude information (Alt), ensuring the most accurate representation of the flight data. The third step is the creation of a weighted graph from the geographical data. Utilizing the 'networkx' library, each piece of data has been defined as a node. The weights of the nodes are assigned based on the altitude information of the data. The edges between nodes are determined by the distances between the data points. The fourth step is the visualization of the weighted graph as a 2D graphic. For this purpose, the positions of the nodes have been calculated using the 'spring_layout' function. Subsequently, the weighted graph has been drawn using the 'nx.draw' function. The graphic has been formatted with the desired shape and color settings. The final step is the display and recording of the graphic. For this purpose, the graphic has been displayed on the screen (plt.show()) and also saved as a PNG file named 'graph.png'."

Please note that the technical terms such as 'dataframe', 'networkx', 'spring_layout', and 'nx.draw' are specific to the Python programming language and its libraries, and have been kept in their original form. If you need any further assistance or another type of translation, feel free to ask!

III. Result and Discussion

In the study, it was determined that anomaly detection can be performed effectively as a result of analysing the UAV flight data recorded using the PIXHAWK3 interface with graph neural networks (GNN). By analysing the roll, pitch and yaw data, both time saving and flight safety were increased in the anomaly detection process. The details of the first flight scenario are presented in Table 2 and the related anomaly and graph neural network graph are presented in Figure 8.

Table 2. General information about flight scenario-1

Flight date	:	05.03.2023-08:21
Flight location coordinates	:	38,6596525 Lat-39,1516682 Long
Flight time	:	0:23:41
Temperature	:	17 ^{0}C- Cloudy

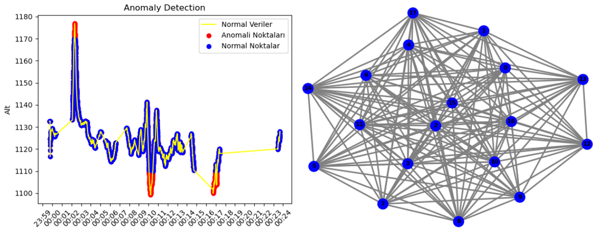

Figure 8. Anomaly plots for flight scenario-1

According to the analysis in Figure 8, anomalies were detected in the flight data of the UAV between 13:00-13:15, especially at values other than 1150-1170 m altitude. In the graph neural network analysis, 23 anomaly points concentrated at 13:03, 13:06 and 13:12 were identified. These anomalies are associated with sudden altitude changes, sharp manoeuvres, GPS loss, sensor errors, piloting errors and meteorological changes.

Table 3. General information about flight scenario-2

Flight date	:	10.03.2023-11:20
Flight location coordinates	:	38,6596540 Lat-39,1518027 Long
Flight time	:	0:06:55
Temperature	:	16°C-Partly cloudy

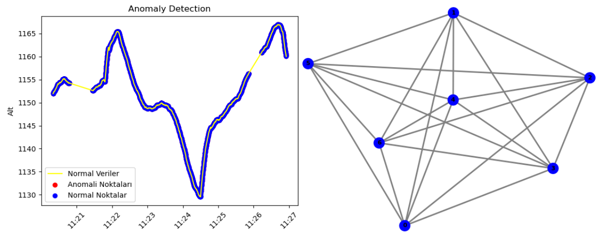

Figure 9. Anomaly plots for flight scenario-2

When Figure 9 is examined, it is observed that anomalies in UAV flight data occurred between 11:21 and 11:27; altitude values outside the range of 1130-1160 meters have been characterized as anomalies. In the temporal and spatial graph neural network diagram, anomalies were observed at seven points, with the most significant occurrence detected between 11:24 and 11:25. It is believed that sudden altitude changes, rapid turns, loss of GPS signal, sensor failure, piloting errors, and changes in weather conditions have contributed to these anomalies.

Table 4. General information about flight scenario-3

Flight date	:	10.03.2023-12:29
Flight location coordinates	:	38,6792354 Lat-39,1816057 Long
Flight time	:	0:13:02
Temperature	:	16°C-Partly cloudy

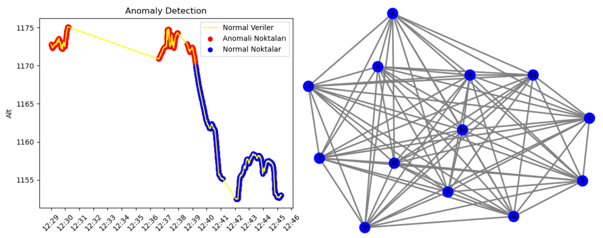

Figure 10. Anomaly plots for flight scenario-3

Upon examining Figure 10, it is observed that anomalies in the UAV flight data were detected between the times of 12:29 and 12:46; altitude values outside the range of 1160-1175 meters have been characterized as anomalies. In the temporal and spatial graph neural network, anomalies were observed at fifteen points, with the most significant occurrences noted at 12:31, 12:34, and 12:42. It is believed that sudden altitude changes, rapid turns, loss of GPS signal, sensor malfunctions, piloting errors, and variations in weather conditions have contributed to the emergence of these anomalies.

Table 5. General information about flight scenario-4

Flight date	:	25.04.2023-14:57
Flight location coordinates	:	38,6791317 Lat-39,1812956 Long
Flight time	:	0:13:02
Temperature	:	16°C-Partly cloudy

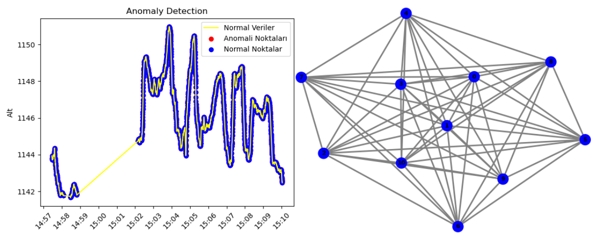

Figure 11. Anomaly plots for flight scenario-4

Upon reviewing Figure 11, it has been noted that anomalies in the UAV flight data were observed between 11:21 and 11:27; altitude values that deviated from the range of 1130-1160 meters have been identified as anomalies. In the temporal and spatial graph neural network, anomalies were detected at seven points, with the most pronounced occurrences identified at 11:24 and 11:25. It is hypothesized that factors such as sudden altitude changes, rapid maneuvers, loss of GPS signal, sensor failure, piloting errors, and fluctuations in weather conditions may have contributed to the manifestation of these anomalies.

Table 6. General information about flight scenario-5

Flight date	:	06.05.2023-10:22
Flight location coordinates	:	38,6731491 Lat39,1852486 Long
Flight time	:	0:14:06
Temperature	:	25°C - partly cloudy with scattered showers

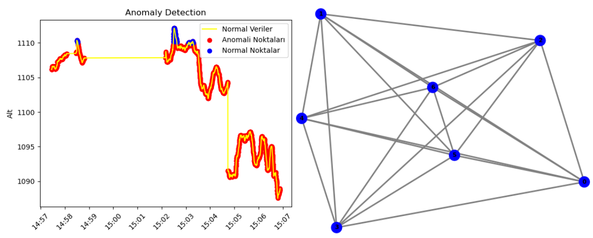

Figure 12. Anomaly plots for flight scenario-5

Upon analysis of Figure 12, it is discernible that anomalies were detected in the UAV flight data between 11:21 and 11:27; altitude readings falling outside the 1130-1160 meter range were deemed anomalous. The temporal and spatial graph neural network chart revealed anomalies at seven distinct points, with the most significant instances occurring at 11:24 and 11:25. A notable surge in anomaly count at 11:24 suggests the possibility of an incident during flight. The clustering of anomalies at 11:24 and 11:25 indicates their close temporal proximity, which may suggest the detection of the same event by multiple sensors. The extension of anomaly points beyond the data range signifies a considerable deviation during flight. It is conjectured that abrupt altitude shifts, swift turns, GPS signal loss, sensor malfunctions, piloting errors, and changes in weather conditions may have played a role in the emergence of these anomalies.

IV. DISCUSSION AND CONCLUSION

The temporal and spatial graph neural Unmanned Aerial Vehicles (UAVs) have begun to be widely used in various fields at both global and national levels. It is anticipated that this technology will further develop and play an effective role in numerous sectors in the future. In this context, it is clear that if UAVs are frequently used in cities and living spaces, issues of flight safety and reliability will gain importance. UAVs constitute a system composed of complex systems, multiple system data, and flight system controls. The analysis of this data reveals the necessity for the system to predict abnormalities in advance, inform its user, and autonomously take preventive measures.

Graph Neural Networks (GNNs) are becoming an increasingly popular and widely used concept day by day. The development of models, their non-specificity to any field, and the application of models developed for a certain field in different areas contribute to the proliferation of graph neural networks. This study aims to identify anomalies that occur during the flight process of unmanned aerial vehicles using graph neural networks. There are numerous international studies on graph neural networks, which perform well in non-Euclidean spaces, focusing on different fields. However, it is assessed that there are few studies conducted in Turkey and that this type of network has not gained popularity in our country.

In this study, the Temporal and Spatial Graph Neural Network (TSGNN) method was used to detect anomalies in UAV flights. This method employs a neural network model that learns the attributes of nodes and edges on a graph by converting flight data into a graph structure. The method was applied for 10 different flight scenarios in the study, and the times and points where anomalies were observed during the flights were determined. The research found anomalies at a total of 105 points across different times and altitude ranges. The flight scenario with the most anomalies was found to be the first flight scenario, with 23 points of anomalies detected during this flight process. It is thought that piloting errors due to it being the first flight contributed to this situation. The flight scenarios with the least anomalies were found to be the 2nd, 4th, and 5th scenarios, with anomalies detected at 7 points in each of these flights. The study also concluded that anomalies were more frequently observed at altitude values in the range of 1130-1160 meters.

The results obtained demonstrate that the Temporal and Spatial Graph Neural Network method can successfully detect anomalies in UAV flights. This method can be used as an important tool for flight safety and performance.

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