A Data-Driven Approach using Machine Learning to Enable Real-Time Flight Path Planning

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As aviation traffic continues to grow, most airlines are concerned about flight delays, which increase operating costs for the airlines. Since most delays are caused by weather, pilots and flight dispatchers typically gather all available weather information prior to departure to create an efficient and safe flight plan. However, they may have to perform in-flight re-planning because weather information can significantly change after the original flight plan is created. One potential issue is that weather forecasts being currently used in the aviation industry may provide relatively unreliable information and are not accessible fast enough so that it challenges pilots to perform in-flight re-planning more accurately and frequently. In this paper, we propose a data-driven approach that uses an unsupervised machine learning technique to provide a more reliable and up-to-date area of convective weather. To evaluate the proposed methodology, we collect the American Airlines flight (AA1300) information and actual weather-related data on October 6th, 2019. Preliminary results show that the proposed methodology provides a better picture of the nearby convective weather activity compared to the most well-known convective weather product.

I. Introduction

According to the Federal Aviation Administration (FAA), the FAA's Air Traffic Organization (ATO) provides service to more than 44,000 flights and 2.7 million airline passengers across more than 29 million square miles of airspace every day [1]. This is already a large number of flights and passengers; however, the fact that aviation traffic continues to grow is becoming a problem. For example, the FAA forecasts the United States (U.S.) domestic carrier passenger growth over the next 20 years to average 1.8 percent per year as shown in Figure 1 [2].

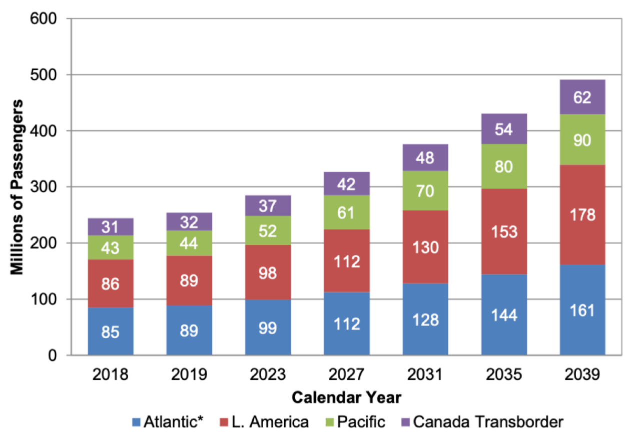

Fig. 1 Number of carrier passengers to/from the U.S. [2]

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As aviation traffic continues to grow, most airlines have growing concerns about flight delays, which are directly related to operating costs for the airlines. There are many factors that affect flight delays; however, most delays are caused by convective weather (e.g. thunderstorms) that peaks during the Summer months as shown in Figure 2 [3].

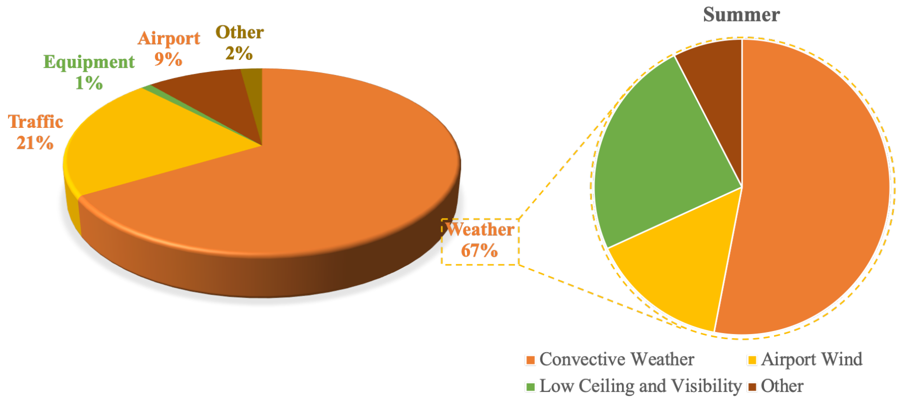

Fig. 2 Sources of flight delays in the U.S.

With the increase in aviation congestion, most airlines have also increasing concerns about fuel consumption given that fuel accounts for up to 35 percent of airline operating costs [4]. Airlines have a variety of options to reduce fuel consumption. For example, they can buy new aircraft; however, the required investment to purchase aircraft may be expensive for the airlines. As an operational solution, airlines can employ some of the less expensive options to optimize fuel consumption. The most common way used by airlines is to require pilots (or flight dispatchers) to plan a flight route by seeking favorable winds (i.e. riding a tailwind but avoiding headwinds) because winds can have a significant impact on an optimal route. For instance, there was the Virgin Atlantic flight from Los Angeles to London on February 19th, 2019 that achieved a record-breaking speed overnight over central Pennsylvania while flying through the jet stream. The ordinary cruising speed of the flight is approximately 561 mph; however, the Virgin Atlantic flight peaked at a whopping 801 mph due to tailwinds [5]. Although the flight did not remain in the jet stream for long, it still arrived 48 minutes early.

Given the aforementioned observations, it is an undeniable fact that weather is of primary concern for airlines because it affects not only flight delays but also fuel consumption as illustrated in Figure 3. In this paper, we specifically focus on weather metrics such as convective weather to account for weather-related flight issues. The remainder of this paper consists of the following sections: Research Motivation, Literature Review, Problem Formulation, Methodology, Results, Conclusion, and Future Work.

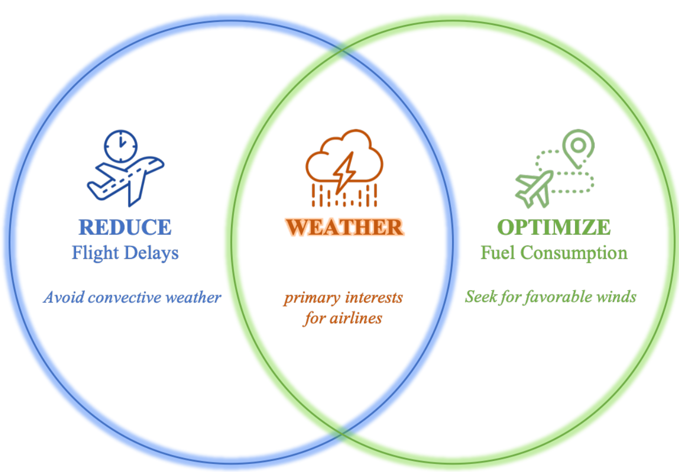

Fig. 3 The intersection of aviation research interests and impact of weather

II. Research Motivation

Flight planning is defined as the process of creating a flight plan to ensure that aircraft departs from an origin and arrives at a destination in a safe and efficient manner. Although airlines have different flight planning strategies that depend on policies, procedures, and aircraft capabilities, the most common flight planning strategy in the U.S. is to avoid areas of convective weather, especially during the Summer season [6]. For example, Figure 4 shows the trajectory of Delta Airlines Flight 1854 from Hartsfield-Jackson Atlanta International Airport (ATL) to Los Angeles International Airport (LAX) on May 18th, 2019. As shown in Figure 4, it appears that the pilots sought to avoid areas of convective weather when they encountered the areas in flight.

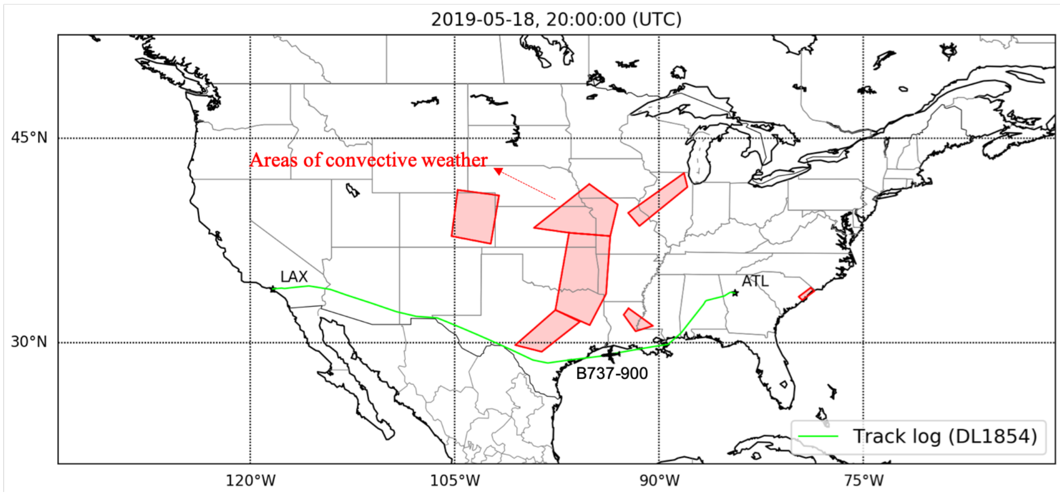

Fig. 4 DL1854 flight path visualization (Total travel time: 5 hours 31 minutes)

A flight from ATL to LAX, however, generally takes 4 hours and 30 minutes under ideal weather conditions. For instance, Figure 5 shows another previous Delta Airlines flight from ATL to LAX on October 17th, 2019. In comparison to the severe weather case shown in Figure 4, this indicates that convective weather may delay a flight and may be associated with large operating costs for airlines.

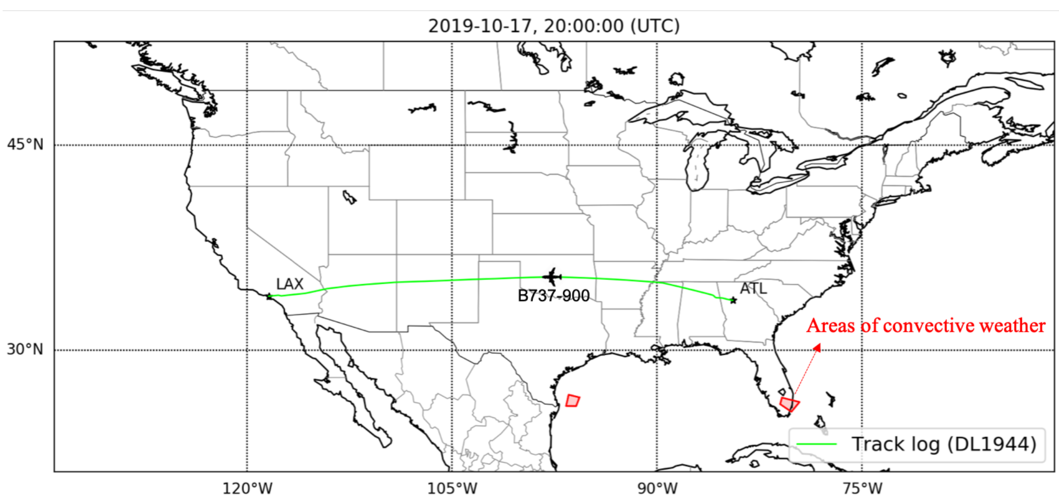

Fig. 5 DL1944 flight path visualization (Total travel time: 4 hours 23 minutes)

For this reason, pilots and flight dispatchers typically gather all available weather information prior to departure to create a safe and efficient flight plan. However, they may have to perform in-flight re-planning because weather information (e.g. areas of convective weather) can significantly change after the original flight plan is created. The good news is that they generally perform in-flight re-planning given weather information that is continuously changing. More specifically, an FAA-related facility, called the Air Route Traffic Control Center (ARTCC), typically communicates with pilots within controlled U.S. airspace. There are 21 ARTCC in the U.S. and each ARTCC supervises thousands of square miles encompassing several states; thus, pilots can perform in-flight re-planning if necessary by communicating with the centers [7]. Although pilots (or flight dispatchers) up to today are conscientious about their work, resulting in very few accidents in the U.S. airspace, there is one potential issue related to the current in-flight re-planning system as indicated below:

Issue: Weather forecasts being currently used in the aviation industry may provide relatively unreliable information and are not accessible fast enough so that it challenges pilots to perform in-flight re-planning more accurately and frequently

In this paper, we attempt to resolve the potential issue by proposing a data-driven approach that uses an unsupervised machine learning technique with multiple ground-based observational data.

III. Literature Review

Accurate weather information is critical for both a ground-based and a cockpit-based flight planning framework because pilots encounter weather every day when they are in flight in the U.S. airspace. Weather forecasting, however, has been considered one of the most challenging tasks and naturally drawn a large number of research interests in Aerospace Engineering and Meteorology. Many research groups such as the National Oceanic and Atmospheric Administration (NOAA) and the National Aeronautics and Space Administration (NASA) have been committed to developing weather forecast models. In particular, convective weather is one of the significant factors that must be addressed in a flight path planning framework. There have already been many efforts to create an accurate convective weather model that is currently in use or being developed by several research groups. For example, James E. Evans and Elizabeth R. Ducot from the Massachusetts Institute of Technology (MIT) Lincoln laboratory developed the Corridor Integrated Weather System (CIWS) to provide more accurate graphical areas of the convective weather activity that might be helpful to systematically control the congested U.S. airspace [8]. Figure 6 shows an example visualization of the CIWS product generated by the MIT Consolidated Storm Prediction for Aviation (CoSPA) [9].

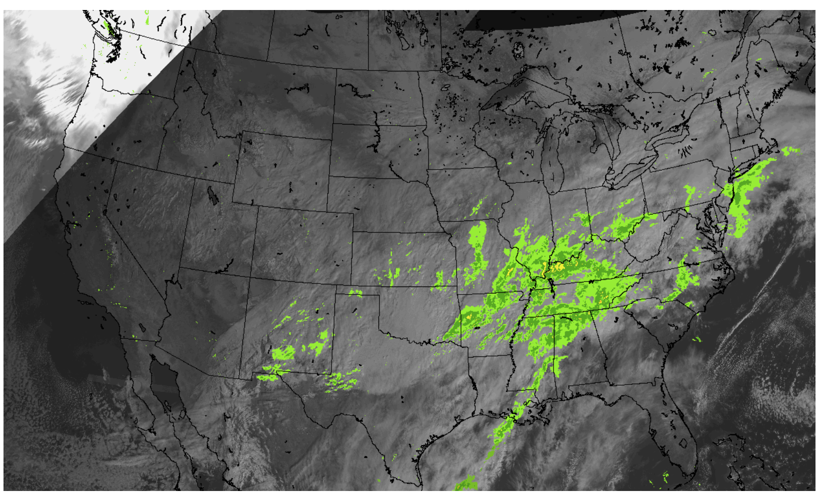

Fig. 6 CIWS product visualization by MIT CoSPA [9]

Although the CIWS was originally designed for automatically generating graphical depictions of the convective weather, the integration of convective weather data into a flight planning framework had been noted as a key factor among the aviation industry. In order to transform the CIWS graphical areas into grid-based convective weather avoidance fields, Michael P. Matthews and Rich DeLaura developed the Convective Weather Avoidance Model (CWAM) by employing more than 500 aircraft-convective weather encounters in the Indianapolis airspace [10]. The CWAM identified convective weather areas in which pilots are potentially guided to avoid the areas by investigating the planned and real flight trajectories in the areas [11]. Mikhail Rubnich and Rich DeLaura, however, noticed that one significant problem actually reduced the effectiveness of CWAM. To be more specific, the CWAM sometimes generated complex avoidance areas due to the fact that the model considers a deviation probability, leading to unrealistic cases. They were determined to develop the Convective Weather Avoidance Polygon (CWAP) to increase the effectiveness of the CWAM [12]. Furthermore, with the aim of managing the U.S. airspace tactically, Michael P. Matthews and Rich DeLaura proposed a model that accounts for the scale, severity, and permeability of the convective weather in a way that it provided an assessment of the impact of the areas of convective weather [13].

While the MIT Lincoln laboratory's convective weather model is an excellent product with which the NASA has experience in the context of several research projects, it must be noted that it is not an operational product and there is no guarantee of its availability in future years; therefore, one has to sign a Memorandum of Agreement (MOA) with the FAA for access. The Weather Company (i.e. formerly WSI) also provides the convective weather product, which has been coded as an in-house tool, to only customers [14]. The Aviation Weather Center (AWC), however, publicly issues convective weather products in the form of convective Significant Meteorological Information (SIGMET) that is currently prevalent among aviation researchers. Due to limitations in the text version of the convective SIGMET, the most vertices that the AWC typically define are five as shown in Figure 7 [15].

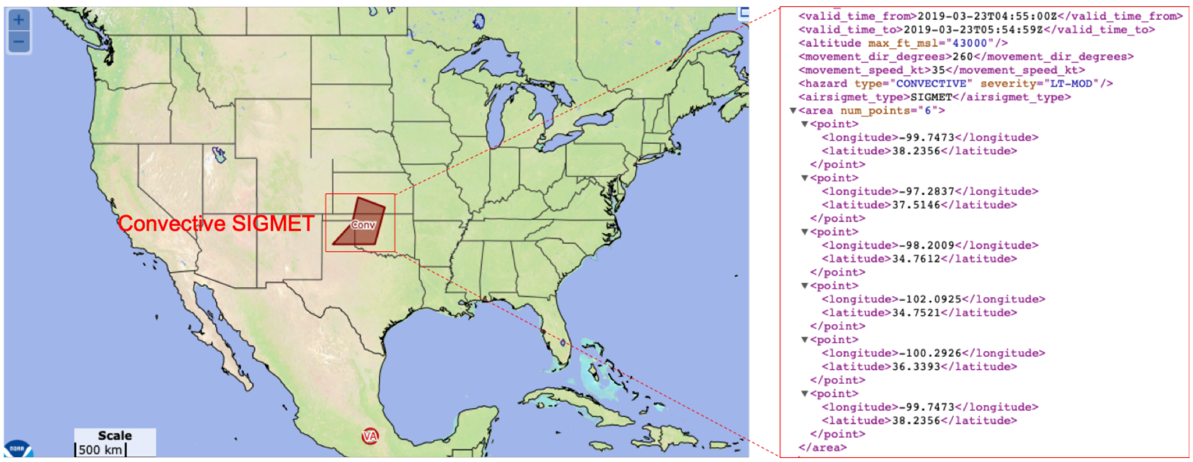

Fig. 7 AWC convective SIGMET polygon visualization

IV. Problem Formulation

While the MIT Lincoln laboratory's products are not publicly accessible, the AWC, which is a part of the NOAA, publicly issues convective weather products in the form of convective SIGMET that are prevalently used by aviation researchers. In particular, the AWC uses radar and satellite data to define convective SIGMET polygon areas that are potentially hazardous to all aircraft. The convective SIGMET is issued on a scheduled basis when the following conditions are expected to occur [16]: 1) a line of thunderstorms at least 60 miles long with thunderstorms affecting at least 40 percent of its length, 2) an area of active thunderstorms judged to have a significant impact on the safety of aircraft operations covering at least 40 percent of the area concerned and exhibiting a very strong radar reflectivity intensity or significant satellite or lightning signature, 3) embedded or severe thunderstorms expected to occur for more than 30 minutes during the valid period regardless of the size of the area, and 4) a special case may be issued when wind gusts greater than or equal to 50 knots are reported.

Although the AWC convective SIGMET product is currently utilized by many flight planning tools, the tools do not raise a question about the resolution/quality of convective SIGMET data. In fact, there are some limitations of the convective SIGMET product as follows. First, the convective SIGMET product is only updated hourly. This means that the convective SIGMET polygons do not change their shape during an hour while moving in a given direction at a given speed. Second, the convective SIGMET product may contain inherent uncertainty because the product consists basically of human-drawn polygons, which tend to be prone to human error. Therefore, a graphical area of the AWC convective SIGMET may not represent the convective activity in reality. For example, Figure 8 shows the previous American Airlines flight trajectory from ATL to Chicago O'Hare International Airport (ORD) on October 6th, 2019 indicating that the pilots actually penetrated one of the convective SIGMET polygons issued by the AWC at 15:10 Universal Time Coordinated (UTC). However, it is impossible to penetrate polygons in a computer simulation because the polygons are treated as a hard constraint. Based on these observations, the following research question can be constructed:

Research question: How can we more accurately and frequently draw the boundaries of convective weather activity as part of an algorithm for a computer simulation?

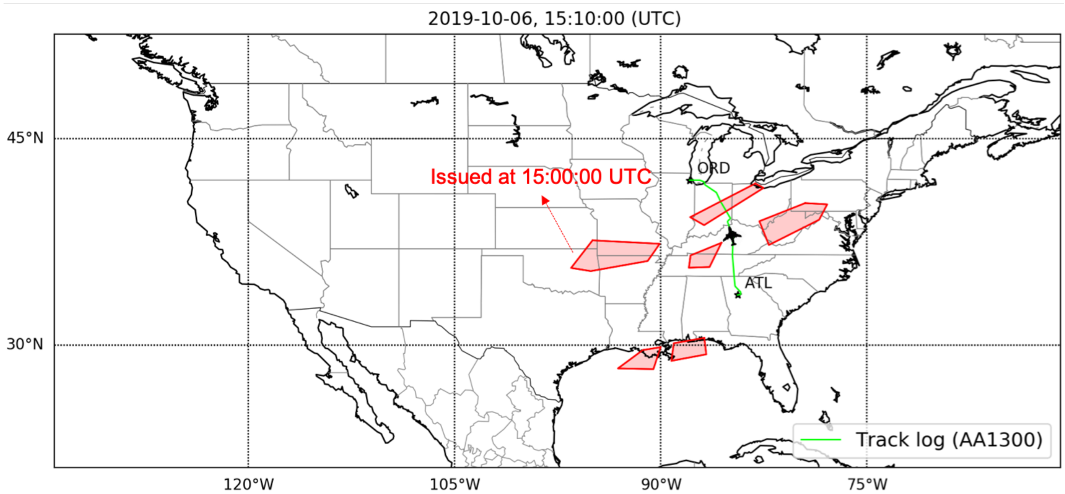

Fig. 8   AA1300 flight path visualization with AWC convective SIGMETs

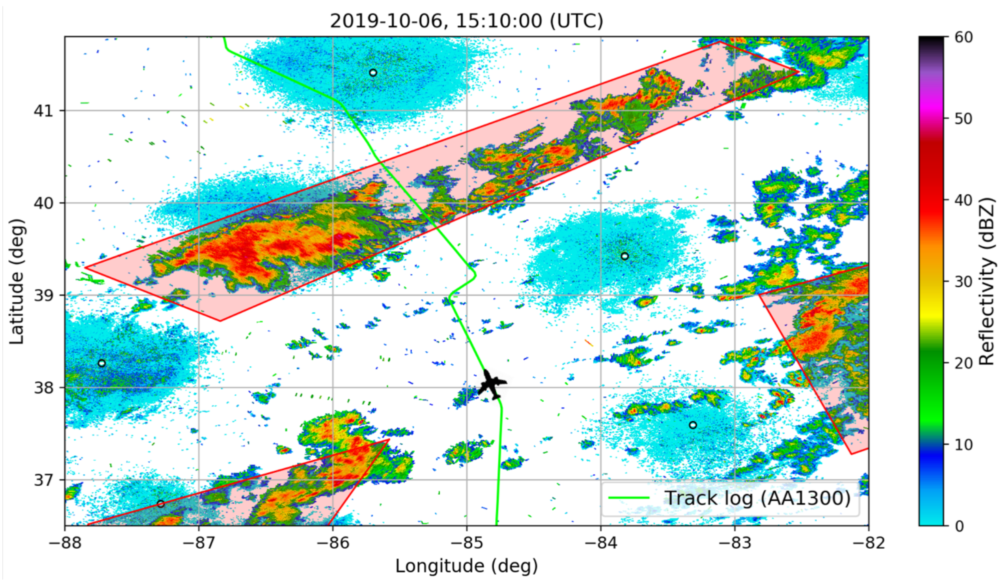

Fig. 9   AA1300 flight path in-depth analysis with weather radar data

The question is "how could the AA1300 pilots penetrate the polygon in reality?" It could be hypothesized that some of the graphical area portions are not actually convective. The hypothesis can be easily demonstrated by retrieving all historical ground-based observational information such as weather radar data. Figure 9 illustrates that the pilots might seek to avoid the areas in which radar reflectivity values (i.e. intensity of rainfall) were approximately above 40 dBZ. Here, it must be noted that the radar reflection does not have altitude information; thus, in reality, we may not really know if the pilots went or not in an area with a rainfall reflectivity exceeding 40 dBZ but we may claim the aforementioned hypothesis according to the historical data. Based on these observations, the following research hypothesis can be developed:

Research hypothesis: Convective SIGMET polygons can be generated in a more accurate and frequent manner by employing multiple ground-based observational data.

To prove the above research hypothesis, in this paper, we performed short-term (i.e. every 10 minutes) convective SIGMET predictions using an unsupervised machine learning technique with multiple ground-based observational data. Additional details will be discussed in the next section.

V. Methodology

A. Data Pre-processing

We developed a Python code (*DATA.py*) that retrieves various datasets from open-source websites in real-time and automatically goes through data pre-processing steps. Details of the datasets are described below.

1. Next Generation Radar (NEXRAD)

The Next Generation Radar (NEXRAD) system in the U.S. currently consists of 159 radar sites in which the Weather Surveillance Radar 1988 Doppler (WSR-88D) technology is implemented as shown in Figure 10 [17]. The radar sites have an automated system that transmits precipitation information by sweeping around 360 degrees. Typically, each scan takes roughly 5 minutes to complete and it is then broadcast over the NOAA satellite network, which takes approximately 10 minutes in total [18].

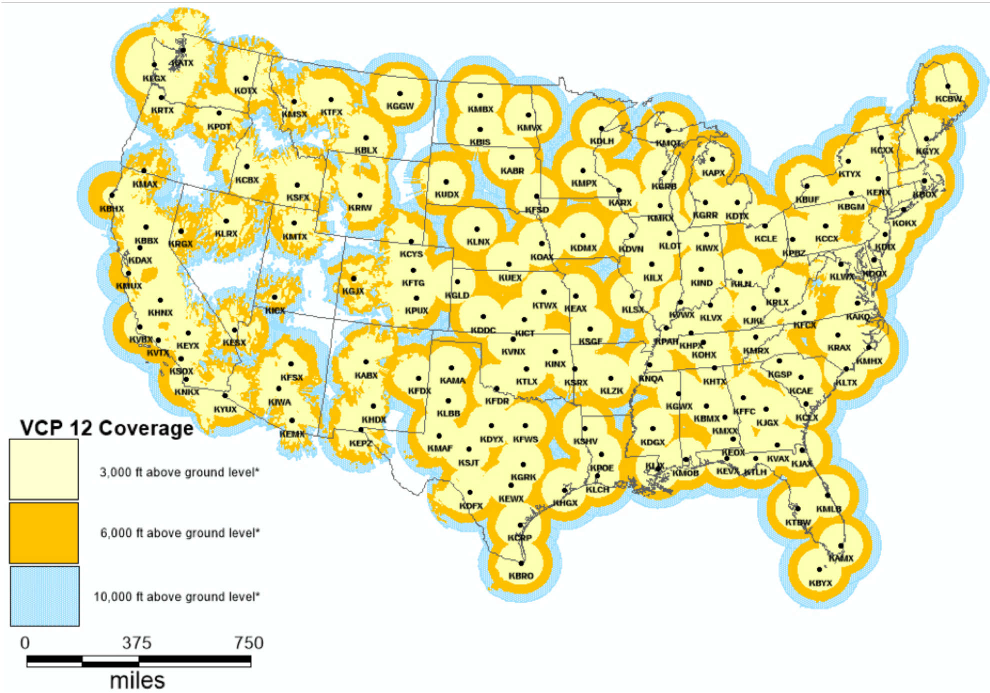

Fig. 10 NEXRAD coverage visualization [17]

Based on the fact that weather forecasters primarily use the precipitation information for generating convective SIGMET polygons, we developed another Python code (*SIGMET.py*) that automatically goes through the data pre-processing steps on the reflectivity information and performs short-term (i.e. every 10 minutes) convective SIGMET predictions. Figure 11 shows an example visualization of the selected NEXRAD location and reflectivity values at a specific time.

2. Convective Significant Meteorological Information (SIGMET)

The AWC publicly issues weather alerts in the form of either an Airmen's Meteorological Information (AIRMET), non-convective SIGMET, or convective SIGMET for different weather-related phenomena. For example, a SIGMET is generally issued for the following reasons: 1) severe icing, 2) severe turbulence, 3) dust storms, and 4) volcanic ash. In

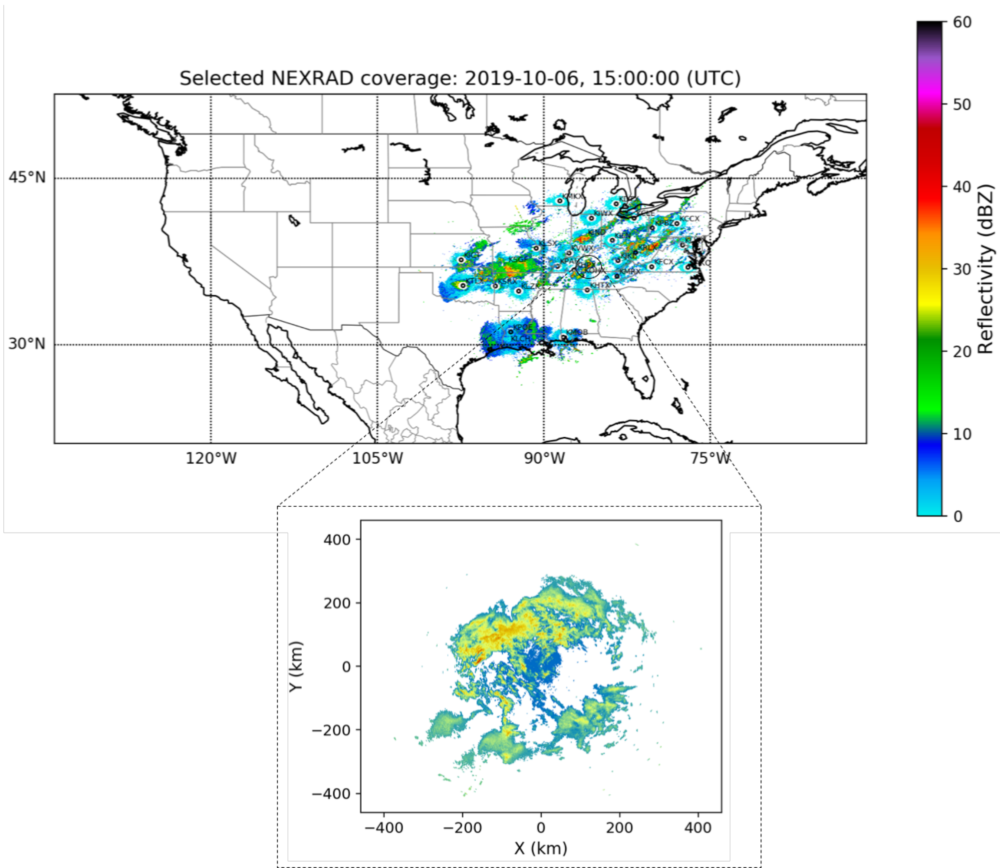

Fig. 11 The selected NEXRAD visualization at 2019-10-06 15:00 UTC

this paper, we only collected the convective SIGMET, which is representative of areas with weather that is potentially hazardous to aircraft, because it is typically responsible for a majority of weather-related flight delays.

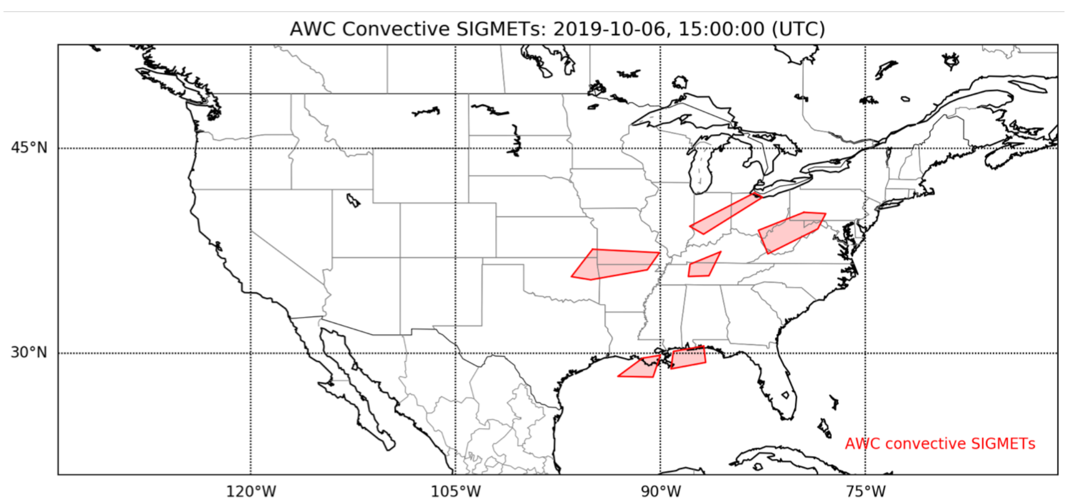

Fig. 12 AWC convective SIGMET visualization at 2019-10-06 15:00 UTC

In particular, we developed a Python code (*DATABASE.py*) that automatically connects to the AWC Text Data Server (TDS) at regular intervals because the AWC has limited access to historical data. Figure 12 shows an example visualization of convective SIGMETs at a specific time, represented as red polygons. It is important to note that the polygon shapes are forecasted based on a highly trained meteorologist's assessment of the hazard and typically defined with five vertices due to limitations in the text version of the SIGMET. Furthermore, the shapes are valid up to two hours into the future and include information with respect to initial position and velocity.

3. Meteorological Aerodrome Report (METAR)

Weather stations in the U.S. report weather-related information such as wind speed and direction every hour in the form of a Meteorological Aerodrome Report (METAR). The METAR report typically contains the following information in sequential order [18]: 1) type of report, 2) station identifier, 3) date and time of report, 4) wind, 5) visibility, 6) weather phenomena, 7) sky condition, 8) temperature, and 9) dew point. Figure 13 shows an example of the METAR symbols.

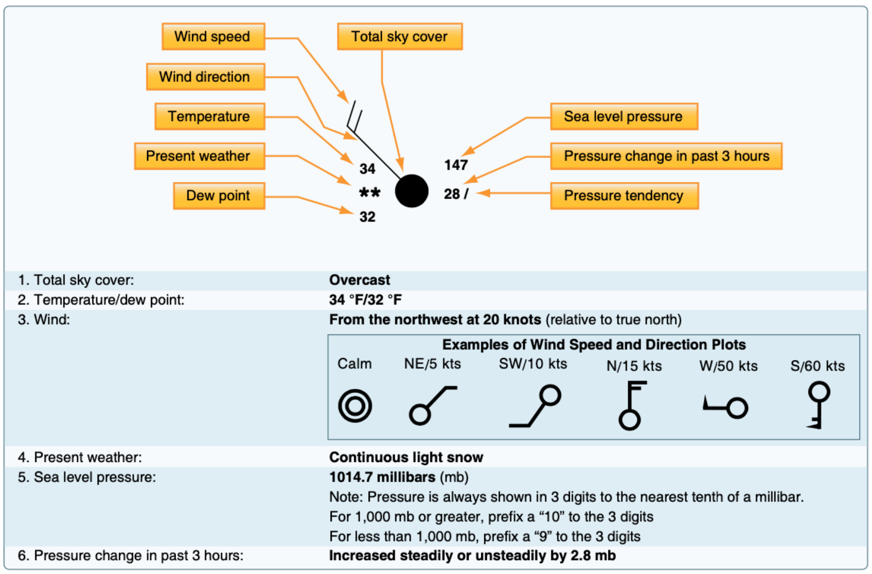

Fig. 13 METAR symbol sample [18]

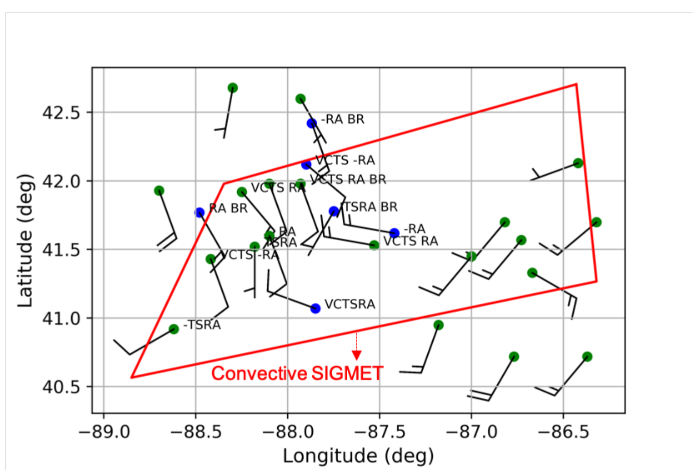

Fig. 14 AWC METAR visualization at 2019-05-18 21:00 UTC

Although each METAR covers only a small area of the U.S. territory, we developed a Python code (*DATA.py*) that automatically downloads and decodes the text version of the METAR because viewing many METARs together would provide a better picture of the convective activity over the U.S. territory. Figure 14 shows an example visualization of the METARs at a specific time and location. The weather phenomena information TS, RA, VC, and BR in Figure 14 stand for Thunderstorm, Rain, Vicinity, and Mist respectively.

4. Pilot Report (PIREP)

The Pilot Report (PIREP) is a report that is based on dangerous weather conditions such as turbulence encountered by a pilot in flight. It is not mandatory for pilots to file a PIREP when they encounter unexpected weather conditions; however, pilots are encouraged to make a report because it provides valuable information regarding real weather conditions. Once pilots decide to file a PIREP, it is typically transmitted as an individual report in real-time to a ground station. While the convective SIGMET polygon areas are useful because they typically cover relatively large geographic areas, the PIREP may provide a more accurate information of the current convective weather, compared to the blanket guidance generally provided by the AWC convective SIGMET product. For this reason, we developed a Python code (*DATA.py*) that automatically downloads and decodes the text version of the PIREP. Figure 15 shows an example visualization of the PIREP with the raw text data at a specific time.

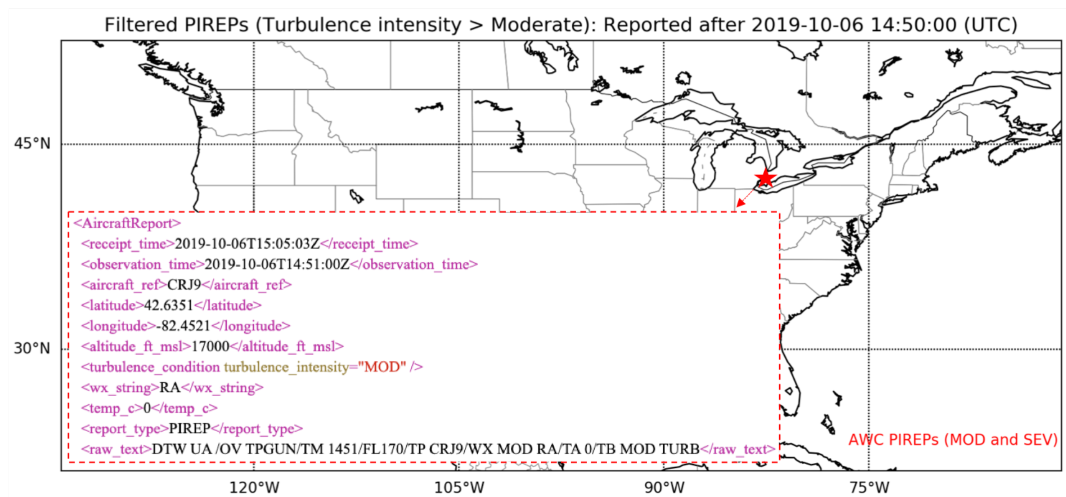

Fig. 15 AWC PIREP visualization with the raw text data at 2019-10-06 14:50 UTC

B. Short-Term Convective SIGMET Modeling

We developed a Python code (*SIGMET.py*) that performs short-term (i.e. every 10 minutes) convective weather predictions using the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) technique with multiple ground-based observational data (e.g. NEXRAD) to provide a more reliable and up-to-date area of the convective SIGMET polygons across the U.S. territory. Details of the proposed methodology are described as follows.

1. Density-Based Spatial Clustering of Application with Noise

The DBSCAN is a data clustering algorithm first proposed by Martin Ester [19]. The key idea of the algorithm is to locate regions of high density that are separated from one another by regions of low density [20]. We decided to implement the DBSCAN algorithm [21] for several reasons as follows. First, the algorithm does not require users to specify the number of clusters before they run the algorithm. This is particularly suitable for this research because the weather domain typically requires minimum knowledge. Second, the algorithm can discover clusters of arbitrary shape and is robust to outliers. This is also appropriate for this research because the weather domain normally contains data that is noisy as well as irregular; thus, they are not well-separated cluster datasets.

2. Convective SIGMET Polygon Generation

The convective SIGMET polygon generation process proposed in this paper is described in Figure 16. Details of the process are as follows. First, the Python code (*SIGMET.py*) connects the TDS to retrieve current convective SIGMET polygons issued by the AWC. Second, the code downloads the ground-based observational data, namely NEXRAD, from the radar sites and saves the files in temporary directories. It is important to note that the code only connects radar sites close to the current convective SIGMET polygons. Third, the code performs additional data pre-processing to filter out radar reflectivity values. More specifically, we examined levels of reflectivity intensity as avoidance options and used 40 dBZ, which represents the level of moderate-to-heavy [16], to draw the boundaries of convective weather activity. For the filtering process, the code also parses moderate-severe PIREPs and TS (Thunderstorm) METAR reports from the server to delineate the convective weather activity. Fourth, the code computes a center for the polygons and evaluates distances between the centers and all filtered points. The points are then re-configured based on the moving speed and direction information of the SIGMET polygons. Fifth, the code employs an unsupervised machine learning technique, namely DBSCAN, to cluster the data points. Last, the code generates a convex hull for the data points and adds lateral buffer layers to ensure a safety margin. In particular, the buffer layer is determined based on interview surveys, operational manuals, and feedback from airline pilots [22]. For example, according to section 8.3.8 of the Boeing 777 Quick Reference Handbook, it mentions that strong weather detected by the radar should be avoided by at least 10 nautical miles at or below FL200 and by a minimum of 20 nautical miles above FL200.

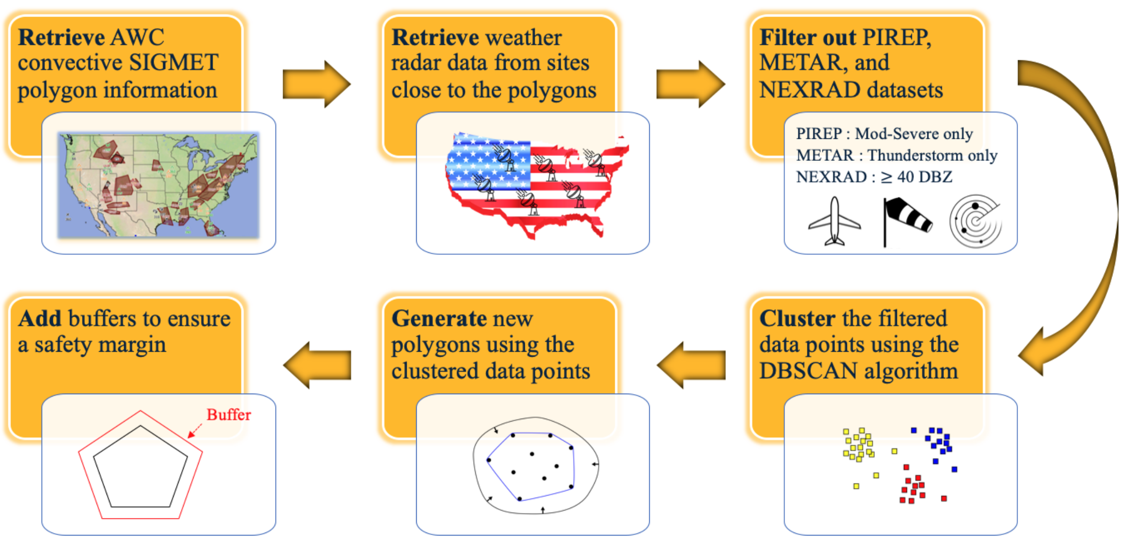

Fig. 16 Overview of the convective SIGMET polygon generation process

VI. Results

To evaluate the proposed methodology, we collected the American Airlines (AA) flight information and actual weather-related data on October 6th, 2019. We utilized the *DATA.py* module to retrieve the following weather-related data: 1) PIREP, 2) METAR, 3) SIGMET, and 4) NEXRAD. The scenario sequence of the case study is described in Figure 17.

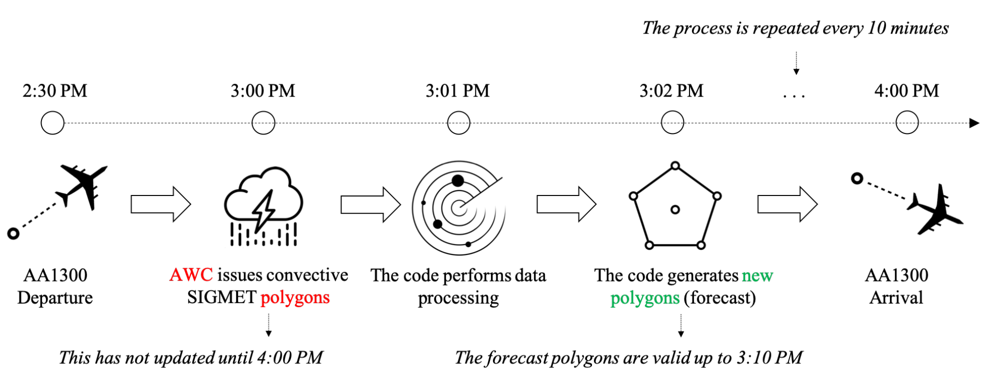

Fig. 17 Scenario sequence of the case study

Since it was found that the AWC convective SIGMET product does not always accurately reflect the actual convective activities in the vicinity of a hazard, we employed the *SIGMET.py* module to perform short-term convective SIGMET predictions that enable the algorithm to draw boundaries of convective activity in a more accurate and frequent manner. As a result, it was observed that the proposed methodology would provide a better picture of the nearby convective activity compared to the AWC convective SIGMET product as shown in Figure 18.

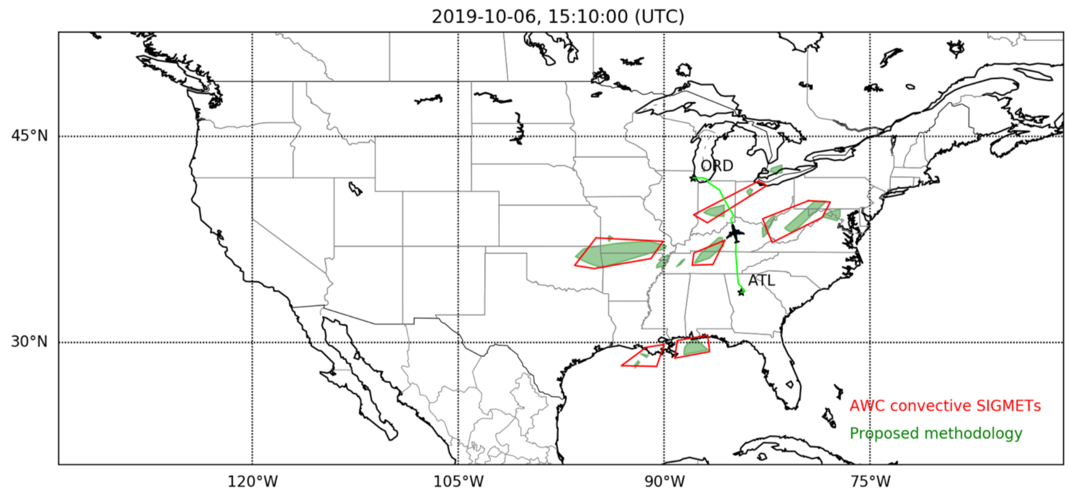

Fig. 18 AWC convective SIGMET polygon vs. Proposed methodology

More specifically, this result implies that the uncertainty of a AWC convective SIGMET polygon area could be broken into some measurable shapes without losing the key information of the AWC convective SIGMET product. This result also means that the proposed methodology would treat AWC convective SIGMET polygon areas as soft constraints in a way that it would allow the algorithm to avoid excessive deviations from a flight route. In other words, if the proposed methodology informs that it is not necessary to avoid the AWC convective SIGMET polygon areas completely, it would tactically select more acceptable flight routes that are supposed to fly between polygon areas. This helps pilots to take a shorter flight route in reality; thus, they can minimize fuel consumption and reduce carbon emissions into the atmosphere.

VII. Conclusion

The most common flight planning strategy in the U.S. is to guide aircraft away from convective weather and to seek favorable winds in order to have an efficient and safe flight. For this reason, pilots and flight dispatchers today typically gather all available weather information prior to departure; however, they may have to perform in-flight re-planning because weather information can significantly change after the original flight plan is created. Major airlines in the U.S. generally hire flight dispatchers to ensure that aircraft departs from an origin and arrives at a destination in a safe and efficient manner. Although pilots and flight dispatchers today are conscientious about their work and rarely cause accidents in the U.S. airspace, there was one potential issue related to the current in-flight re-planning system identified in this paper. The potential issue is that weather forecasts being currently used in the aviation industry provide relatively unreliable information and are not accessible fast enough so that it challenges pilots to perform in-flight re-planning more accurately and frequently.

This paper attempts to resolve the potential issue by proposing a data-driven approach that uses an unsupervised machine learning technique, namely DBSCAN, with multiple ground-based observational data such as NEXRAD. The preliminary result shows that the proposed methodology would provide a better picture of the nearby convective activity compared to the AWC convective SIGMET product that is currently prevalent in the aviation industry. This implies that the uncertainty of an AWC convective SIGMET polygon area could be broken into some measurable shapes without losing the key information of the AWC convective SIGMET product; therefore, the proposed methodology would allow the algorithm to avoid excessive deviations but could tactically select more acceptable flight routes (e.g. flying between polygon areas) in a computer simulation.

VIII. Future Work

This paper mainly accounted for the short-term convective SIGMET modeling problem. In the end, the author aims to develop an algorithm that performs in-flight re-planning automatically in a more accurate and frequent manner. To achieve this goal, the author will work on developing a data-driven approach that uses machine learning techniques for real-time flight path optimization as depicted in Figure 19.

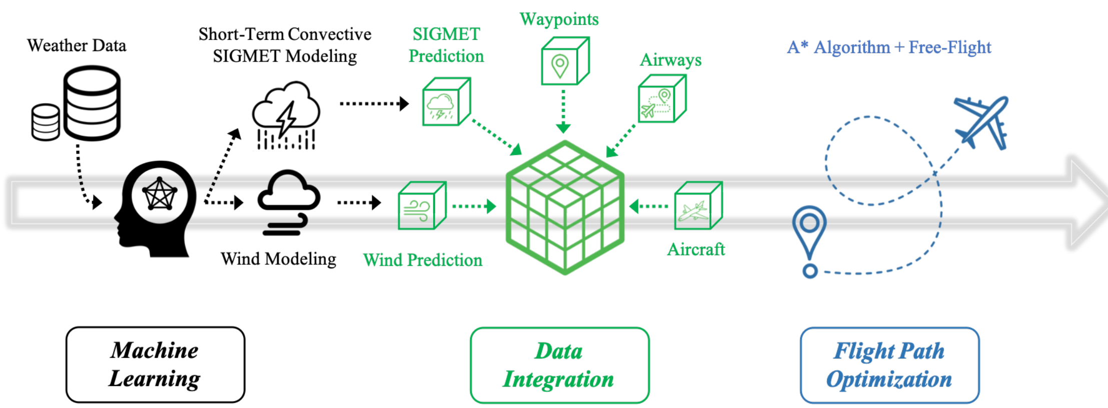

Fig. 19 Overview of the proposed methodology

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