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An Analysis Of Drop Outs And Unusual Behavior From Primary And Secondary Radar

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AN ANALYSIS OF DROP OUTS AND UNUSUAL BEHAVIOR FROM PRIMARY AND SECONDARY RADAR

by

Nicholas J. Allen Bachelor of Science, University of North Dakota, 2015

A Thesis

Submitted to the Graduate Faculty

of the

University of North Dakota

in partial fulfillment of the requirements

for the degree of

Master of Science

Grand Forks, North Dakota

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This thesis, submitted by Nicholas Allen in partial fulfillment of the requirements for the Degree of Master of Science from the University of North Dakota, has been read by the Faculty Advisory Committee under whom the work has been done and is hereby approved.

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This thesis is being submitted by the appointed advisory committee as having met all of the requirements of the School of Graduate Studies at the University of North Dakota and is hereby approved.

Grant McGimpsey Dean of the School of Graduate Studies

 30 2017 حدهمة k.

Date

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> Nicholas Allen June 23, 2017

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ABSTRACT

An evaluation of the radar systems in the Red River Valley of North Dakota (ND) and its surrounding areas for its ability to provide Detect and Avoid (DAA) capabilities for manned and unmanned aircraft systems (UAS) was performed. Additionally, the data was analyzed for its feasibility to be used in autonomous Air Traffic Control (ATC) systems in the future. With the almost certain increase in airspace congestion over the coming years, the need for a robust and accurate radar system is crucial. This study focused on the Airport Surveillance Radar (ASR) at Fargo, ND and the Air Route Surveillance Radar at Finley, ND. Each of these radar sites contain primary and secondary radars.

It was found that both locations exhibit data anomalies, such as: drop outs, altitude outliers, prolonged altitude failures, repeated data, and multiple aircraft with the same identification number (ID) number. Four weeks of data provided by Harris Corporation throughout the year were analyzed using a MATLAB algorithm developed to identify the data anomalies. The results showed Fargo intercepts on average 450 aircraft, while Finley intercepts 1274 aircraft. Of these aircraft an average of 34% experienced drop outs at Fargo and 69% at Finley. With the average drop out at Fargo of 23.58 seconds and 42.45 seconds at Finley, and several lasting more than several minutes, it shows these data anomalies can occur for an extended period of time. Between 1% to 26% aircraft experienced the other data anomalies, depending on the type of data anomaly and location. When aircraft were near airports or the edge of the effective radar radius, the largest proportion of data anomalies were experienced. It was also discovered that drop outs, altitude outliers, and

repeated data are radar induced errors, while prolonged altitude failures and multiple aircraft with the same ID are transponder induced errors. The risk associated with each data anomaly, by looking at the severity of the event and the occurrence was also produced. The findings from this report will provide meaningful data and likely influence the development of UAS DAA logic and the logic behind autonomous ATC systems.

CHAPTER I

INTRODUCTION

Overview

An analysis of radar performance in the Red River Valley of North Dakota (ND) and its surrounding area was completed to understand vulnerabilities and assess the current radar environment. From the literature review performed, this type of study is the first of its kind for information regarding radars open to the public. As unmanned aircraft systems (UAS) and autonomous air traffic control (ATC) towers are integrated into the aviation industry, the vulnerabilities of radar systems need to be understood to make reliable and robust designs. This study looked at radar sites in Fargo, ND and Finley, ND, which cover the states of North Dakota, South Dakota, Minnesota, and the provinces of Manitoba, Ontario, and Saskatchewan. These radars can be seen in Figure 1 [1, 2]. This study was funded by the Federal Aviation Administration's (FAA) Alliance for System Safety of UAS through Research Excellence (ASSURE), Harris Corporation, the University of North Dakota (UND) Mechanical Engineering Department, and the Unmanned Aircraft Systems Engineering (UASE) Laboratory. What began as supplemental work for the ASSURE A6 Project that investigated surveillance criticality for UAS, spun off into the research presented in this document.

ASSURE is an alliance of universities across the United States with partnerships from companies that help guide and fund the research being conducted. The mission of this group is to provide the FAA with the research needed to quickly, efficiently, and safely integrate UAS into the national airspace (NAS) [3]. This partnership between the government, research universities, and industry will allow the UAS industry to grow and support the needs of the world's economy.

Figure 1. Radars at Fargo and Finley

This study began by assessing the radar environment at Fargo and Finley on one day: June 15, 2015 for the ASSURE project. This analysis was all done by hand looking at the data, which showed many anomalies and unusual behavior exhibited by the radars. Some behaviors identified included: drop outs, altitude deviations, and multiple aircraft with the same aircraft identification number [4]. These behaviors, along with several others will be discussed in detail in Chapter II. This anomalous behavior can pose threats to the aircraft and people due to loss of well clear, additional stress on ATC personal, and failure of autonomous systems on UAS. After the realization of these data anomalies, follow on work was justified, which looked at one week of data in each season of the year. The dates of March 1-7, 2015; June 1-7, 2015; September 1-7, 2015; and December 1-7, 2015 were studied for both the Fargo and Finley radar locations. In order to process this extremely large amount of data, an algorithm was also developed to identify and classify the various

anomalous behavior initially discovered for the ASSURE study. What took weeks of time for the initial study just looking at June 15, took hours to process the months' worth of data with the algorithm.

Primary and Secondary Radar

Radar was originally an acronym that stands for radio detection and ranging. These systems have evolved substantially since their early days and are used for a wide variety of applications nowadays. A few of the many applications include: tracking aircraft, collision avoidance, weather observations, Earth resource monitoring, and mapping. Modern radars can track, identify, classify, and image targets while reducing or eliminating clutter and jamming [5].

While radar is one of the oldest technology to support the FAA's airspace monitoring, several other systems are used to supplement the radar systems, namely: traffic collision avoidance system (TCAS), automatic dependent surveillance – broadcast (ADS-B), and even simply the pilot's ability to see and avoid other aircraft. The current TCAS system was developed in the 1980's, and is a system that functions independently from the ground based ATC system [6]. TCAS provides pilots with traffic alerts and resolution advisories to prevent midair collisions with other transponder equipped aircraft. A traffic advisory instructs the pilot to visually search for other aircraft in the area. While a resolution advisory instructs the pilot to perform a certain maneuver to avoid the intruding aircraft which is inside the pre-defined envelope of the ownship aircraft. ADS-B is a realtime global positioning system (GPS) system which broadcasts the ownship's information, such as position, heading, and altitude [7]. This system allows the aircraft information to be received by any receiver within range of the aircraft. Lastly, every pilot is required, per the FAA to see and avoid all aircraft according to §14 CFR 91.113 [8]. All these systems help supplement the existing radar network across the United States.

The FAA uses two primary radar systems to monitor the NAS over the United States, namely: primary radar and secondary radar. Both types of radar are used to help ATC monitor and control the air traffic in their respective regions. With rich histories dating back before World War II, these systems have matured over the following years. While primary and secondary radars complement each other, they operate on different principles which are described in the subsequent subsections.

Primary Radar

Primary radar is often thought of as traditional radar. This system sends high frequency pulses that are reflected off the target and received again; this reply is typically referred to as an echo [9]. This system is passive, which means that no equipment on the aircraft is needed for detection. The only piece of equipment needed is the ground radar station. Having a passive system is very important, because it allows rogue aircraft to be detected. An example of this is during the terrorist attacks on September 11, 2001 in the United States. The terrorist pilots turned off the aircraft transponders which made the aircrafts invisible to ATC [10]. The primary radar systems couldn't detect the aircraft in the city skyline, but in most other environments they would have been. However, despite the advantages of being a passive system, primary radar has several disadvantages. A large antenna is typically required, the system provides only position information, and is prone to clutter (unwanted replies from buildings or antenna sidelobes) [11]. The power loss equation is given by

$$
P_{PSR} \sim \frac{1}{R^4},\tag{1}
$$

where P_{PSR} is the power of the primary surveillance radar and R is the range [9]. The basic schematic of a primary radar system can be seen in Figure 2 [5]. The major elements to this system are the transmitter, receiver, antenna, and signal processor.

Figure 2. Primary Radar Schematic

Secondary Radar

Secondary radar is slightly different, where the aircraft needs to have a transponder onboard that replies to interrogations [9]. The interrogations are high frequency impulses, just like primary radar. In fact, the secondary radar transmitter is usually mounted on the antenna of a primary radar unit. The primary disadvantage of secondary radar is that it is an active system, which requires a transponder. The advantages of this radar system include not being effected by ground clutter or weather, and also having a longer range, because the pulse sent out only needs to travel one direction (the transponder reply is a different pulse) [12]. The power loss equation for secondary radar is given by

$$
P_{SSR} \sim \frac{1}{R^2},\tag{2}
$$

where P_{SSR} is the power of the secondary surveillance radar and R is the range [9].

In fact, all aircraft are required to have a transponder that is capable of reporting the altitude and aircraft identification number according to the FAA's Aeronautical Information Manual section 4-1-20 [13]. These transponders can be broken down into many classes. The two that concern this study are Mode A and Mode C. Mode A reports the aircraft identification number, while Mode C reports the barometric altitude from the aircraft's barometric altimeter. A summary of a few of the aircraft identification numbers can be seen in Table 1 [14]. A full list of all the possible numbers are provided in Appendix A: Mode A Transponder Identification Numbers [14]. Each time an aircraft takes off, it is assigned one of the possible combinations of 4096 identification codes [15], which the pilot sets before takeoff.

Code	Description					
0000	Should never be assigned					
$0100 - 0400$	Allocated to Service Area Operations for assignment for use by Terminal/CERAP, NAS Stakeholder, Unique Purpose and Experimental activities.					
1200	Visual Flight Rules (VFR) aircraft that may or may not be in radio contact with an ATC Facility.					
$5000 - 5057$	Reserved for use by DOD					
$7601 - 7607$	Allocated by the FAA for special use by Federal Law Enforcement					
7400	Reserved for UAS experiencing a lost link situation					
7500	Hijack in accordance with FAA JO 7610.4.					

Table 1. Summary of Mode A Transponder Identification Codes

One of the biggest challenges of using two radar systems is syncing the data of both the primary and secondary radar systems. A brief schematic of the process can be seen in Figure 3 [16]. The ground unit, often called the interrogator sends a coded pulse to the transmitter. Following this the transponder receives the pulse, decodes it, and transmits the appropriate response. The interrogator on the ground receives the reply, decodes it, and syncs the data with the primary data on the radar display.

Figure 3. Secondary Surveillance Radar Schematic

Radar Site & Classifications

The Fargo and Finley radars cover a wide area around the Red River Valley and upper Midwest. Figure 4 shows the effective radar radius of both radars. The red circle represents the range of the Finley radar, while the blue circle represents the Fargo radar range. As a result, a wide variety of aircraft can be intercepted by the radars, while the exact aircraft can't be identified, because the Mode A transponder numbers change multiple times a day, even for the same aircraft. The general type of aircraft can be deciphered from the Mode A ID, along with knowledge of the type of aircraft that fly over the airspace. Figure 5 shows a few of the many aircraft that are intercepted by the Fargo and Finley radar, namely a Cessna and helicopter from the UND training fleet, a Delta commercial regional jet, and an Allegiant commercial jet [17-20].

Figure 4. Effective Radar Radii of the Fargo & Finley Radars

Figure 5. Aircraft Detected by the Fargo & Finley Radars

The location not only varies between Fargo and Finley, but also the radar type. Fargo is classified as an Airport Surveillance Radar (ASR), or an ASR-11; while Finley is classified as an Air Route Surveillance Radar (ARSR), or an ARSR-4. The ASR-11 is an integrated primary and secondary radar system that is deployed at terminal air traffic control sites. The range of this system is 60 nautical miles [21]. This radar system is primarily used for approaches and flight plans around towered airports. The ARSR-4 is a long range surveillance radar with a range of up to 250 nautical miles [22]. These radar systems are used primarily for cross country or long range flight paths, using both primary and secondary radar as well. Table 2 provides a summary of the power, frequency, rotation rate, and other factors of the ASR-11 and ARSR-4 radars (highlighted in yellow) [23]. With a rotation rate of 12.5 RPM, the ASR-11 has a scan rate of 4.8 seconds. The ARSR-4 has a rotation rate of 5.0 RPM, which indicates a scan rate of 12 seconds. The scan rate is the amount of time for the radar unit to turn one full rotation (360 degrees).

	TDWR (Raytheon)	ASR-9 (Northrop Grumman)	ASR-11 (Raytheon)	ARSR-4 (Northrop Grumman)				
Transmitter								
Frequency	$5.5 - 5.65$ GHz \sim C Band	2.7-2.9 GHz	2.7-2.9 GHz	1.2-1.4 GHz				
Polarization	Linear	Linear or Circular	Linear or Circular	Linear or Circular				
Peak Power	250 KW	1.1 MW	20 kw	60 kw				
Pulse Width	$1.1 \mu s$	$1.0 \mu s$	1.0 μ s, 80 μ s	$150 \mu s$				
PRF	2000 (max)	2 CPIs (~ 1000 Hz avg.)	4 CPIs (~ 1000 Hz avg.)	9-pulse CPI at variable spacing (288 Hz avg)				
Receiver								
Sensitivity	0 dBz @ 190 km 1 m ² @ 460 km	0 dBz @ 20 km 1 m ² @ 111 km	0 dBz @ 20 km 1 m ² ω 111 km $*$	0 dBz @ 10 km 1 m ² @ 370 km				
Antenna								
Flevation Beamwidth	0.55 Degrees (min)	5 Degrees	5 Degrees	2 Degrees (stacked)				
Azimuth Beamwidth	0.55 Degrees	1.4 Degrees	1.4 Degrees	1.4 Degrees				
Power Gain	50dB	34 dB	34 dB	35 dB (transmit), 40 dB (receive)				
Rotation Rate	5 RPM (max)	12.5 RPM	12.5 RPM	5.0 RPM				
* 17dB sensitivity reduction in short-pulse processing range (0 - 6.5 nmi)								
Courtesy: [23]								

Table 2. Summary of Radar Specifications

Purpose of the Study

The primary purpose of this study was to assess the radar network in the surrounding area to understand vulnerabilities in the system. As UAS are integrated in the NAS, these vulnerabilities need to be understood to account for autonomous systems on the UAS and to better prepare pilots if radar data is used on the flight operations. With the New York Times dubbing North Dakota and specifically the Red River Valley area as the "Silicone Valley for drones" [24], it's only a matter of time before these aircraft fill the skies. This claim to fame makes this study in the area especially important. The FAA also just published Part 107 in August 2016, which is the first step forward for commercial operations of UAS in the United States [25]. In fact, the FAA is predicting that there will be 7 million drones that could be active in the airspace by 2020 [26]. The United States Government Accountability Office also predicts that UAS will add \$82.1 billion to the economy over the next 10 years [27]. These numbers just show the importance for this study, especially if UAS use radar for Detect and Avoid (DAA) operations.

In addition to UAS, ATC centers will likely one day be autonomous. In fact, one group of researchers has looked at how to how to deal with conflict resolution and flight operation services for an autonomous system [28]. Additional publications have worked on other aspects of an autonomous ATC system, such as algorithms for short term conflict avoidance for UAS in an autonomous ATC [29], a network based ATC paradigm [30], and an autonomous ATC system for non-towered airports [31]. Additionally, several articles have stressed the importance of autonomous ATC systems and ATC systems for UAS [32, 33], because the man force required for providing ATC services for manned and unmanned vehicles is not sustainable. Right now if an ATC tower loses radar contact with an aircraft

even for one radar scan rate, they need to reestablish contact. ATC personal also instruct pilots to turn off their Mode A transponders if they are providing erroneous data. These are just two examples of the many functions humans provide if the radar system is not functioning properly. Knowing what types of failures radar experience and how to address them will help build a robust autonomous system without the interaction of humans.

Previous Work

Radar systems have evolved substantially since their inception dating back to the early 1900's. Despite this fact, radar, just like any other complex system is prone to problems. Many researchers have performed studies identifying these issues. Some work has been done on the reliability/performance of current radars, while others look at future applications. However, from the literature review performed, no work to date has identified radar data anomalies to the scale of the study presented in this paper.

Several reports have been published covering surveillance resolution, measurement errors, and coverage of various radars. Lieutenant Colonel Thomas prepared maps of radar coverage throughout the continental U.S. to identify blind spots in the U.S. radar network [34]. Healy, McDonald, Pomrink, and Conklin developed an operational test and evaluation of the ARSR-4 radar system and found that most basic functions were performed well [35]. Weber and Schanne also performed a similar analysis for the ASR-11 radar system [36]. A comparison and analysis of azimuth errors between the ASR-11 and ASR-9 radars was completed by Mayer and Tzanos [37]. A system error assessment for the ARSR-4 radar was performed by Busch and Bradbury [38]. Some specific studies were done on secondary radar identifying the vulnerabilities [39, 40]. One vulnerability included the potential of having an aircraft interrogated up to 20 times in one radar scan,

leading to congestion in the bandwidth and erroneous data. Additionally, there is no difference between a Mode A or Mode C response from a transponder. If a Mode A interrogation is issued, a Mode A response is expected, and likewise for Mode C. This could lead to problems decoding the response if more than one ground station was interrogating an aircraft. Lemmon, Carrol, Sanders, and Turner even performed an assessment of the effects of wind turbines on radars [41].

While some studies have identified the problems of the radar network in the U.S., others have looked at addressing the problems by developing the next generation of radar systems. Immoreev and Taylor discuss new capabilities for civilian radar by simply increasing the bandwidth [42]. Buckler discusses the benefits of using a phased array radar to replace current radars [43]; the FAA even published a document highlighting the national requirements for a phased array radar [44]. When arrays are implemented, the multiple secondary radar signals will need to be separated, which is why Petrochilos, Galati, Mené, and Pracci developed a simple and robust algorithm to do so [45]. Additionally, ADS-B and radar data fusion will be essential for ATC in the future, so several studies have theorized and analyzed this data fusion [46, 47].

CHAPTER II

RADAR BEHAVIOR CLASSIFICATION ALGORITHM

This chapter will provide an overview and an explanation behind the logic of the MATLAB algorithm developed to analyze and classify the radar data into the various different anomalies described in in the first section of this chapter. The spreadsheets of data that Harris provided were separated by hour. For the analysis done in this paper, each hour of data for each day (24 hours total) was compiled into one spreadsheet. This was done for each day at each location, which resulted in 56 files, at a size of 4.28GB or 19,164,844 total lines long. This shear amount of data justifies the need for an algorithm to process it. What takes hours for the computer to process, would take months to process by hand. Of the 50 columns of data contained in each spreadsheet, the program reads only time, aircraft ID, altitude, azimuth, and range. The following sections describe how each function and the main script operates. The entire algorithm can be found in Appendix B: MATLAB Code.

Radar Data Anomaly Classification

From the initial study performed, a variety of data anomalies were identified which included: drop outs, altitude outliers, prolonged altitude failures, repeated data, and multiple aircraft with the same identification (ID) number. These behaviors directed how the algorithm described later in this chapter was written. The majority of the anomalies discovered were associated with altitude from the secondary radar. However, position from the primary radar was used to help identify repeated data and multiple aircraft with the same (ID) number. In some cases, aircraft experience several modes of unusual behavior. For example, the same aircraft may experience a drop out and an altitude outlier within a short period of time. The following sections in this chapter provide a description and a visual example of each data anomaly.

Drop Outs

A drop out occurs when there is a missed data point that should have been logged, which means the time between two data points is larger than the radar scan rate. Drop outs ranged in time from anywhere slightly greater than one radar scan rate to several minutes. The end limit was put in place to ensure that if aircraft went out of range for a period of time and came back into the radar's detection area it was not considered a drop out. A plot depicting a drop out can be seen in Figure 14 in Chapter III. Drop outs prevent ATC from getting updated information on the aircraft, which prevents up to date radar aircraft separation services. The typical separation of aircraft is 5 miles enroute and 3 miles in a terminal environment, or 1000 feet and 500 feet vertically, respectively [48]. To put the significance of drop outs in perspective, a drop out of just single scan rate forces ATC to reestablish contact with the aircraft. So a drop out just over 4.8 seconds at Fargo or just over 12 seconds at Finley puts additional strain on the ATC system. When aircraft are traveling several hundred miles an hour they can cover a great deal of distance in just one scan rate too. For example, an aircraft flying at 250mph would travel 0.33 miles in one radar scan at Fargo and 0.83 miles in one radar scan at Finley.

Altitude Discrepancies

Altitude Outliers

The first type of altitude discrepancy, an altitude outlier, happens when there is a significant deviation in the expected altitude for a given aircraft. A jump between data points is considered an outlier when the expected altitude is more than 800 feet off from nominal. Many times an outlier was accompanied by a drop out, where the data showed an outlier, and then a drop out occurred, or vice versa. Many of the outliers displayed an elevation of 0 feet above ground level (AGL) or over 120,00 feet. These readings were false because the aircraft was at an altitude above ground, and no commercial aircraft exists that can reach 120,000 feet. While altitude quantization and limitations on the barometric altimeter resolution are expected, large jumps observed are not nominal behaviors. The FAA requires altitude reported from Mode C to be quantized in 100 foot increments and be accurate within 2% of the actual value [49], so a properly functioning system shouldn't have more than a few hundred feet of variation from scan rate to scan rate. This data anomaly prevents ATC from providing accurate vertical separation between aircraft. An image showing altitude outliers can be seen in Figure 15 in Chapter III.

Prolonged Altitude Failure

The second type of altitude discrepancy is a prolonged altitude failure. This behavior occurs when there are a series of three or more zero altitude readings when the previous and/or past altitudes were greater than zero feet AGL. This failure is indicative of a transponder related issue, which will be expanded upon later in this paper. Again, this type of behavior prevents ATC from providing proper vertical separation between aircraft in the NAS. Figure 16 depicts a plot of a prolonged altitude failure in Chapter III.

Repeated Data

Repeated data is defined as receiving multiple data points with near identical altitude and position within a fraction of a second. The radar site needs to receive and log two or more data points with a time period less than one second to qualify as this type of behavior. While this anomaly may not necessarily be harmful for aircraft or ATC, it is a type of behavior that was identified from this study, nonetheless. This behavior is shown in Figure 17 in Chapter III.

Multiple Aircraft with the Same Identification Number

The final data anomaly is multiple aircraft with the same identification number. As the name implies, there are several aircraft with equivalent Mode A transponder numbers which the pilot sets before takeoff. While some transponder ID's are non-discrete, meaning the same class of aircraft are all assigned the same number, such as VFR traffic, others are intended to be discrete. Even the discrete ID numbers have multiple aircraft occasionally. This problem stems back to only having 4096 possible combinations of numbers to assign to aircraft in the entire United States. Typically, there are more aircraft than that number in the sky at once. This data anomaly puts additional stress on ATC to determine the difference between two aircraft with the same ID. Figures 18 and 19 show examples of discrete and non-discrete multiple aircraft examples in Chapter III.

Main Script

The main script titled *Combined* calls all the individual functions and outputs the required information for analysis. The main script starts with three different for loops to

allow all the files to be processed at once. The for loop with the counter *ll* dictates whether the data is from Fargo or Finley. The for loop with the counter *ii* indicates which month the data is from; with 1 representing March, 2 representing June, 3 representing September, and lastly 4 representing December. Finally, the last for loop's counter *kk* indicates which day of the month the data is from, with 1 representing the first of the month, ranging all the way to 7 which represents the seventh of the month.

The rest of the code in the *Combined* file is contained within the three for loops. Three if statements are next in the code to direct the algorithm to the correct file path where the radar data spreadsheets are saved. Once the file path is determined the *Data_Read* function is called to read the data from the spreadsheet. After the data is read in and stored in a matrix, all the rows with missing data are eliminated. The missing data is from the secondary radar, namely the aircraft ID and altitude. Some aircraft were detected by just primary radar, while others were detected by both primary and secondary radar. Aircraft ID was the method to differentiate different aircraft for this study, so those rows of data with the missing aircraft ID/altitude had to be eliminated. Table 3 summarizes the average, maximum, and minimum row size for the original data, the updated data with rows eliminated that contained missing data, and the difference between the two. The average reduction in rows for Fargo was 73,628, accounting for an average of 33% of the original data. While Finley had an average reduction in rows of 117, 324, approximately 25% of the original data.

	Fargo			Finley		
	Original Data	Updated Data	Difference	Original Data	Updated Data	Difference
Average	222,651	149,383	73,268	461,805	344,481	117,324
Maximum	393,112	225,151	186,210	749,859	459,712	357,503
Minimum	124,052	69,244	50,026	273,290	226,928	46,362

Table 3. Data Removal Summary

The next process is converting the azimuth and range to latitude and longitude. The azimuth is the angle in degrees between true north and where the target/aircraft is currently located. Range is the distance from the radar to the target/aircraft, given in nautical miles. An image showing these measurements is provided in Figure 6 [50]. The first step in converting azimuth and range to latitude and longitude is calculating the ground range, because the slant range is the range given in the data spreadsheets. This is calculated by Pythagoras Theorem,

$$
a^2 + b^2 = c^2,\tag{3}
$$

where *a* and *b* are the two legs of a right triangle, and *c* is the hypotenuse. In this case, the altitude is *a*, the ground range is *b*, and the slant range is *c*. The formula can be rearranged to solve for ground range,

$$
b = \sqrt{c^2 - a^2},\tag{4}
$$

because the altitude and slant range are provided in the spreadsheet and already stored within the program. However, in some cases, when the aircraft gets too close to the radar, the altitude becomes larger than the slant range, this is shown in Figure 7; where GR is ground range, SR is slant range, and alt is altitude. When this happens, the number under

the radical in Equation 4 becomes negative, making the solution undefined. To correct this, new equations need to be used:

$$
b' = \sqrt{a^2 - c^2},\tag{5}
$$

$$
\beta = \sin^{-1}\frac{c}{a},\tag{6}
$$

and

$$
b = b' + \sin \beta,\tag{7}
$$

where β and b' are the angle and length, respectively given in Figure 13.

Figure 6. Azimuth and Range Diagram

Figure 7. Ground Range, Slant Range, and Altitude of Aircraft

Once the ground range is calculated, the last step is to use latitude and longitude of the radar location, along with the azimuth and ground range to determine the latitude and longitude of the aircraft. This is given by Equation 8 which calculates the aircraft's latitude and Equation 9 which calculates the aircraft's longitude. These formulas calculate the latitude traveling along a great arc circle, knowing the start point, initial bearing (azimuth), and distance (ground range). Equations 8 and 9 are given by

$$
lat_{aircraft} = \sin^{-1} \left(\sin(lat_{radar}) \cdot \cos\left(\frac{b}{R}\right) + \cos(lat_{radar}) \cdot \sin\left(\frac{b}{R}\right) \cdot \cos(\emptyset) \right)
$$
 (8)
and

$$
long_{aircraft} = long_{radar} + \tan^{-1} \left(\sin(\phi) * \sin\left(\frac{b}{R}\right) * \cos(lat_{radar}), \cos\left(\frac{b}{R}\right) - \sin(lat_{radar}) * \sin(lat_{aircraft}) \right),
$$
\n(9)

where $lat_{aircraft}$ and lat_{radar} are the latitudes of the aircraft and radar, respectively. The variables $long_{aircraft}$ and $long_{radar}$ are the longitude of the aircraft and radar, respectively. R is the Earth's radius in nautical miles, b is the ground range in nautical miles, and lastly \emptyset is the azimuth.

This process to convert the azimuth and range to latitude and longitude is performed in a for loop, so the process is repeated for each row of data in the matrix stored within MATLAB. These locations are then added to the existing matrix in two new columns. There are two variants of the matrix that stores the time, aircraft ID, altitude, azimuth, range, latitude, and longitude. The first is titled *rd_sorted*, which has the data sorted by aircraft ID and within each ID number is chronological with respect to time. The second is a cell array, which has each aircraft data's array within a new cell, titled *rd_split*.

The remainder of the main script calls the various functions written and plots/saves the required data for analysis. Each type of data anomaly has its own function and after

each function is called, the locations of each occurrence are plotted on Google maps, along with the radar radius. A .png image and .fig MATLAB figure are saved for each map on each day, at each location for further analysis. At the very end of the script, all of the relevant data is output and saved for each day at each location. The data saved includes 32 different pieces of information, listed in Table 4. In addition to the Excel file saved, a .mat file was saved for each day at each location, so additional data could be referenced without running the algorithm again.

A flow chart summarizing the main script is shown in Figure 8. The algorithm starts and reads in the radar data with the data read function. Following that process, the missing data is eliminated and the position data is converted to latitude and longitude. The four data anomaly functions are then called which plot the location of the anomalies with open source software and the output from the four functions are also saved. Once this process is complete, the algorithm ends.
Number	Description
$\mathbf{1}$	Location (Fargo or Finley)
$\overline{2}$	Month
$\overline{3}$	Day
$\overline{4}$	Number of aircraft detected by the radar
5	Number of aircraft that experienced drop outs
$6 - 12$	Summary of drop out instances in 7 different time intervals
13	Average drop out time length
14	Minimum drop out time length
15	Maximum drop out time length
16	Number of drop out instances
17	Number of aircraft that experienced altitude outliers
18	Number of altitude outlier instances
19-25	Summary of prolonged altitude failures
26	Average prolonged altitude failure time length
27	Minimum prolonged altitude failure time length
28	Maximum prolonged altitude failure time length
29	Number of prolonged altitude failure instances
30	Number of aircraft ID numbers that experienced multiple aircraft
31	Number of aircraft that experienced repeated data
32	Number of repeated data instances

Table 4. Data Saved by the MATLAB Algorithm

Figure 8. Main Script Flow Chart

Data Read

The first function that is utilized, reads in the radar data from the Excel spreadsheet, and is titled *Data_Read*. The input to this function is the filename of the spreadsheet. The output is a matrix called *rd*, which contains all the necessary radar data. Each piece of information is separated by column that is read into the program. The plane ID, time, altitude, azimuth, and range correspond to columns A through E, respectively. Once the data is read in, the function checks to ensure all the columns are the same length. If there is missing information in the last row of any of the columns, a value of Not-a-Number (NaN) is added to ensure all the columns are the same length. The five columns of information are then input into the matrix *rd*.

Multiple Aircraft and Repeated Data

The function that is called in the main script to identify the multiple aircraft and repeated data is titled *MARD* (short for Multiple Aircraft and Repeated Data). This function has the following inputs: the location identifier (1 for Fargo or 2 for Finley), the number of planes, *rd_split*, and *rd_sorted*. The outputs are the multiple aircraft data matrix, the repeated data matrix, and a matrix called *rd_wo_ma*. The matrix *rd_wo_ma* contains the radar data contained in *rd_split* and *rd_sorted*, without the multiple aircraft data. The data that was associated with multiple aircraft was taken out because it would skew the rest of the data anomaly identification and analysis.

The majority of the function is split into two if statements, based on the location. Within either if statement, the same fundamental logic remains the same, however the thresholds and parameters vary based on location. Once the input data is read in, the data points for each aircraft in *rd_split* are run through a for loop. In the loop, the time difference is taken, along with the difference in latitude and longitude from row to row in in each cell. Data that is under the time threshold based on the radar scan rate then either falls into the multiple aircraft category or repeated data category. The differentiator between the two is the latitude and longitude difference. If the positional difference is greater than some threshold, the data is considered a multiple aircraft. If the difference is less than that threshold, it is classified as repeated data. This logic is used because multiple aircraft with the same ID will have a large difference in position, while repeated data have almost identical positions. Once this process is complete, a new cell array titled *rd_wo_ma* is created that excludes any aircraft ID that corresponded to multiple aircraft. A table summarizing the thresholds is given in Table 5. These thresholds were selected in degrees

of latitude and longitude for convenience to plot the behaviors in the algorithm. Additionally, when converting latitude or longitude to a standard measurement such as nautical miles, there is very little variation for the area of interest in this study.

Location	Time Threshold (seconds)	Latitude Threshold (degrees)	Longitude Threshold (degrees)
Fargo	3.8	.012	.035
Finley		.016	.16

Table 5. Thresholds Used in the Multiple Aircraft and Repeated Data Function

The thresholds provided in Table 5 were experimentally determined from the data. Five different days chosen at random from Fargo, and five days chosen at random from Finley, with at least one day from each season was used to set the thresholds. An initial threshold was set, then using the 10 total days, the data was processed by hand checking for false positives, false negatives, true negatives, and true positives. A false positive is when the algorithm labeled data as a positive (multiple aircraft or repeated data), and it was not in fact a positive. False negative is when the function marked data as multiple aircraft or repeated data when it should not have been. A true negative is when the system correctly identified data that was not multiple aircraft or repeated data. Lastly, a true positive is when the program correctly marked the data that was multiple aircraft or repeated data. These values were adjusted until all the all the multiple aircraft and repeated data were correctly identified. The time threshold is slightly below the radar scan rate for both Fargo and Finley because the aircraft may be moving against the rotation of the radar, so it is detected sooner than the radar scan rate of the radar. Another interesting note is the latitude threshold between Fargo and Finley are relatively similar, while the longitude threshold is

significantly apart. This indicates that aircraft move more longitudinally in Finley, rather than latitudinally. Finley is a long range radar, picking up many aircraft in cross county routes, which tend to fly more east to west, rather than north to south. Additionally, Fargo is a regional radar, near an airport, so planes move more uniformly in both longitude and latitude on the approach paths to the Fargo International Airport. This explains why the latitude and longitude threshold at Fargo are closer to each other than the Finley thresholds. At the geographical location of either radar, the distance of one degree latitude is about 1/3 larger in nautical miles than one degree longitude, which explains why the longitude threshold is larger for both Fargo and Finley as well. A flowchart describing the process of the multiple aircraft/repeated data function is provided in Figure 9.

Figure 9. Multiple Aircraft/Repeated Data Function Flow Chart

Drop Outs

The drop out function, titled *DropOut*, is called in the main script to identify drop outs in the radar data. This function has inputs of the location identifier and *rd* wo ma. Its outputs include: all the data that has drop outs associated with them, a statistical summary of the drop outs, and a categorization of drop outs into time categories.

Once the data is input into the function, for each aircraft, it takes the time difference between each data entry. The function then looks at the upper and lower bounds of the time threshold to determine if it is a drop out. The lower bound is slightly above the scan rate, and the upper bound is several minutes. These thresholds vary by location, because of the different radar scan rates. A summary of the thresholds is given in Table 6. These thresholds again were selected based of setting a nominal value and modifying the threshold, until all the data from five different days at both the Fargo and Finley locations gave correct outputs.

Once the drop outs are identified, statistics such as the average, minimum, and maximum values are taken. In addition, the drop outs are classified into seven different time intervals, to get an understanding of the time distribution of the drop outs. The number of drop outs are counted in each time interval. Due to the different radar scan rates, Fargo and Finley have different time intervals for the analysis. These time intervals are listed in Table 7.

Interval Number	Fargo	Finley
1	$<$ 10 sec	$<$ 24 sec
$\overline{2}$	$10-15$ sec	24-36 sec
$\overline{3}$	15-20 sec	36-48 sec
$\overline{\mathbf{4}}$	$20-25$ sec	48-60 sec
$\overline{5}$	25-30 sec	60-90 sec
6	$30-60$ sec	90-120 sec
$\overline{7}$	>60 sec	>120 sec

Table 7. Time Interval Classifications for Fargo and Finley

A flow chart depicting the logic behind the drop out function is shown in Figure 10.

Figure 10. Drop Out Function Flow Chart

Altitude Outliers

The function, titled *Outliers*, identifies and classifies altitude outliers in the radar data. The inputs to this function are again, the location identifier and *rd_wo_ma*. The output is a matrix summarizing the outliers. After the radar data is input, the time difference between each data point and the altitude difference between each data point is taken. The time difference is used to ensure that the data being compared doesn't occur at different times of the day, or different aircraft (one aircraft lands and another takes off). If the altitude difference is greater than 800 feet, and the following altitude difference is greater 800 feet, this indicates an altitude outlier. The value of 800 feet was chosen to ensure an aircraft descending at a rapid rate were not misidentified as an aircraft with outliers. This was based on research of the maximum ascent/descent rate of the UND Cessna 172 training aircraft, a Bombardier CRJ700, and an Airbus A320. All these aircraft are likely to be detected by the radars at Fargo and Finley. The rate of climb of a Cessna 172 is 730fpm [51], 2,000fpm for the Bombardier CRJ700 [52], and 2,400fpm for the Airbus A320 [53]. Just considering the largest ascent/descent rate of 2,400fpm, the distance traveled vertically in one scan rate at Fargo is 200 feet and 480 feet at Finley. These values are much less than the 800-foot threshold chosen for this function. The threshold was also verified by processing several hours of data by hand, to ensure there were no false classifications. Once the outliers are detected, a matrix is produced containing the aircraft information, time, and location information. A flow chart highlighting the process of the altitude outlier function is given in Figure 11.

Figure 11. Altitude Outliers Function Flow Chart

Prolonged Altitude Failure

The function titled *prolonged_alt_failure*, processed the data to identify prolonged altitude failures. Just like many of the other functions, the inputs are the location identifier, along with *rd* wo ma. The outputs are matrices summarizing the prolonged altitude failures, along with their time durations. In addition, time statistics and time interval instances are output for analysis. The altitude information is looked at for a series of zero values. The function notes the start and stop indices of these series of zero values. Then only the strings of more than a length of two are kept, denoting a prolonged altitude failure. Both a cell array, separated by aircraft ID and a matrix with the time duration of the prolonged altitude failure are output. Again, just like the drop outs, the time statistics and time interval instances are output as well. These values are calculated the same exact way

as described in the previous sections. A flow chart highlighting the logic of the prolonged altitude failure function is shown in Figure 12.

Figure 12. Prolonged Altitude Failure Function Flow Chart

Google Maps Plot & Draw Ellipse

The three functions used to plot the locations of the data anomaly locations and plot the effective radius on a Google Maps image were obtained online, through open source software. These functions were written for MATLAB. Due to these functions being open source and not authoring them myself, simply a broad description of how they are used will be provided in this section.

The function *plot_google_map*, allows a plot to be created with a static Google maps image to be inserted into the background [54]. The *plot* function within MATLAB is used, plotting latitude and longitude, then the *plot_google_map* function is called to place a static Google maps image in the background. The image is automatically taken to encapsulate the latitude and longitude plotted. Many options can be varied on the Google maps image and output, such as the size, resolution of the image, and map type (roadmap, satellite, hybrid, etc.). Additional documentation can be found on the source site [54]. The *export_fig* function is also used to save the Google Map output [55].

To draw the effective radar radius, an ellipse needs to be drawn. The reason an ellipse is used, even though it appears as a circle on the map is due to the measurement differences in nautical miles of the one degree of latitude and one degree of longitude. There was no built in ellipse function into MATLAB, so an open source function titled *ellipse*, was utilized [56]. The inputs to the function include: the semi-major axis length, the semi-minor axis length, angle of the semi-major axis, center point, color of the drawn ellipse, and the number of points used. Table 8 summarizes the inputs into the ellipse function. The semi-major and semi-minor axis lengths were calculated based on the conversion factor between nautical miles to one degree of latitude or longitude at the radar's location. At Fargo, one degree of latitude and longitude is 60.0266nmi and 41.1279nmi, respectively. At Finley, one degree of latitude and longitude is 60.03287nmi and 40.66041nmi, respectively. To calculate the semi-major and semi-minor axis length, the radar range in nautical miles is simply divided by the conversion factor for one degree of latitude/longitude at that location. While the measurement will vary slightly, once a location deviates from the radar's location, it is minimal for the distances considered in this study. So, the conversion factor at either Fargo or Finley is simply used for the entire radar's range.

Description	Fargo	Finley
Semi-Major Axis Length	60 41.1279	250 40.6604
Semi-Minor Axis Length	60 60.0266	250 60.0329
Semi-Major Axis Angle	0 degrees	0 degrees
Initial Longitude location	46.9202 degrees	47.5282 degrees
Initial Latitude Location	96.8122 degrees	97.9006 degrees

Table 8. Ellipse Function Input Values

Overlapping Analysis

The script titled *Overlapping_Analysis* is a standalone algorithm that performs an overlapping analysis to understand whether the data anomalies were radar or transponder induced. If the data anomalies occurred at one location, it was considered a radar error, while if the data anomaly occurred at both locations it was considered a transponder error. This analysis will be described in more detail later in Chapter IV. The script reads in the .mat files that were created from the main script *Combined* for each of the Fargo and Finley locations. The script also has a nested for loop to process all the data at once from all 28 days. Once the .mat file is read in, the specific matrix associated to the data anomaly of interest is called. The program then looks for aircraft ID numbers that occur in both the Finley and Fargo data. Once those numbers are recorded, the timestamps associated with each location are analyzed. If the time difference was 17 seconds or less it was considered to occur at both the Fargo and Finley location (transponder error). The value of 17 seconds was obtained by adding the two scan rates together of both locations. This value was chosen because the aircraft could have just been missed by one radar and not be picked up by the

other radar until the end of its scan rate. The data points that did not occur at both sites are then considered radar failures. The script outputs the number of aircraft intercepted at each radar site, the number of transponder failures, and the percentage of aircraft with transponder or radar failures. This process is repeated for each data anomaly: drop outs, altitude outliers, prolonged altitude failures, repeated data, and multiple aircraft with the same ID. To summarize the logic of the overlapping analysis algorithm, a flow chart is provided in Figure 13.

Figure 13. Overlapping Analysis Algorithm Flow Chart

Algorithm Verification

Once the entire algorithm was finished, it was checked against data that was analyzed by hand from the previous June 21, 2015 study. In addition, the data from March 1, 2015 was also analyzed for the purposes for algorithm verification. The algorithm found

all of the data anomalies identified in both those studies, along with several other randomly selected groups of time throughout the other data from March, June, September, and December. In fact, the program was able to find data anomalies that were missed by the hand analysis, showing how significant human error can be in large data studies such as this. Once the algorithm was completed, it took seven hours, 18 minutes to process all the data from four weeks of data at both Fargo and Finley.

CHAPTER III

SUMMARY OF DATA ANOMALY RESULTS

Once the radar data was processed, the engineering and scientific analysis of the data could begin. By using an algorithm, the large, daunting amount of data became more reasonable to analyze and understand. This chapter will highlight a basic summary of the results, including graphical depictions of the anomalies, the number of each type of data anomaly, time durations, and locations of the anomalies. This summary is provided for each location, and is an average of the data for brevity. All the data for each day analyzed is provided in Appendix C: Radar Data Anomalies Summary. There are a number of sections in Appendix C: Aircraft Count/Location, Drop Outs, Altitude Outliers, Prolonged Altitude Failures, and Multiple Aircraft/Repeated Data. Each data anomaly was plotted on an altitude versus time plot to provide a visual representation in the Graphical Representation of Data Anomalies section. These plots were chosen to provide what a typical case for each anomaly looks like. The Aircraft Count/Location section summarizes the number of aircraft detected each day, at each location. The Drop Outs section provides a daily summary of the number of aircraft with drop outs, the number of instances of drop outs that occur in various time durations, the average drop out length, the minimum drop out length, the maximum drop out length, and the number of instances of drop outs. The Altitude Outliers section summarizes the number of aircraft that experienced outliers each day, along with the number of instances of outliers. The Prolonged Altitude Failure

section provides a nearly identical summary when compared to the Drop Out section. Lastly, the Multiple Aircraft/Repeated Data section provides aircraft counts for each day for each anomaly. A more thorough discussion of the results will be provided in Chapter IV.

Graphical Representation of Data Anomalies

Each data anomaly was plotted on an altitude versus time plot to provide a better understanding of what the behavior truly looked like. An example of a drop out is shown in Figure 14, which plots altitude versus time for a single aircraft. Notice how there are both large and small gaps where there are no data points, this indicates a drop out. Figure 15 depicts several outliers, going between the aircraft's cruising altitude of 900/1000 feet AGL and 0 feet AGL. An example of a prolonged altitude failure is shown in Figure 16, which has a zero-foot altitude reading for 17 radar scan rates, then the altitude returns to nominal. Repeated data is shown in Figure 17. The red boxes are zoomed areas of the data points to show a close up of what is happening. In this example, there are four instances of repeated data, each with two data points within a fraction of a second. Figure 18 shows a multiple aircraft example plotting altitude versus time. The non-discrete ID number of 1200 is shown in this example which is assigned to VFR traffic in the airspace by ATC. Figure 18 shows many aircraft making the plot very congested, this is because many of the aircraft in the sky are VFR traffic, which are all assigned the same ID number. Figure 19 shows two aircraft with a discrete code of 2603 in the same airspace. The ID is discrete in Figure 19, meaning that ideally there would only be one aircraft that was assigned that number. However, in this case the number was used twice.

Figure 14. Drop Out Example Plot

Figure 15. Outlier Example Plot

Figure 16. Prolonged Altitude Failure Example Plot

Figure 17. Repeated Data Example Plot

Figure 18. Non-Discrete Multiple Aircraft Example Plot

Figure 19. Discrete Multiple Aircraft Example Plot

Aircraft Count & Time Duration Summary

After the data was processed through the algorithm, the aircraft counts were analyzed, along with the time duration for drop outs and prolonged altitude failures. Table 9 summarizes the total number of aircraft observed each day at Fargo and Finley, along with the number of aircraft that experienced each type of anomaly. The number of aircraft is on the left column for each location, while the percentage of total aircraft effected is on the right hand column. The numbers in upper most section of Table 9 represent the average number over the four weeks of data analyzed, while each subsequent section is an average of each specific week. This provides a clear picture of the overall status of the radar network because the averages encapsulate four distinct different times of year over a wide variety of weather conditions.

When comparing the averaged data from each separate week to the to the overall averaged data, the results were relatively similar. It should be noted that more aircraft were intercepted in the fair weather months of June and September. While fewer aircraft flew in March and December when the weather typically is not as nice for flight. There also seemed to be a significantly larger number of drop outs in September compared to the nominal average percentage of drop outs for Fargo (37%) and especially Finley (84%). The opposite trend was observed in March for the percentage of drop outs at Finley with a significant decrease in drop outs, 52%, versus the overall average of 69%. There were not any noticeable trends for the other data anomalies from month to month. It is noteworthy that overall, 34% of aircraft experienced drop outs at Fargo, while 69% of aircraft experienced drop outs at Finley. Additionally, the other data anomalies ranged from 1-26% of aircraft at either location. Both altitude outliers and drop outs were the two types of data anomalies that happened most frequently.

To understand the severity of the drop outs and prolonged altitude failures, the time duration was looked at. The average, minimum, and maximum values of occurrence were identified for each location. The anomalies were then counted in different time intervals that were set based on the radar scan rate at each location. Table 10 provides this summary of the drop out times and Table 11 provides the summary of the PAF times. Again, these tables are the average values over the course of the four weeks of data. Just the overall averages for the time durations were chosen to be displayed in the main body of this document. This was decided, because from Table 9, there was not any drastic change when comparing the weekly averages to the overall averages. All required data to do a weekly average analysis is provided in Appendix C. In the time interval classification section for each table, the left column represents the instances (there can be multiple instances per aircraft), and the right column is the percentage of instances relative to the total number of instances.

			Fargo	Finley		
		Number of Aircraft	Percentage	Number of Aircraft	Percentage	
	Total Observed	450		1274		
	Drop Outs	155	34%	885	69%	
	Outliers	61	14%	326	26%	
Overall	PAF	$\overline{7}$	2%	9	1%	
	Repeated Data	11	2%	45	4%	
	Multiple Aircraft	14	3%	11	1%	
	Total Observed	433		1150		
	Drop Outs	147	34%	602	52%	
	Outliers	60	14%	190	17%	
March	PAF	6	1%	$\overline{7}$	1%	
	Repeated Data	11	3%	41	4%	
	Multiple Aircraft	6	1%	8	1%	
	Total Observed	459	\blacksquare	1328	$\overline{}$	
	Drop Outs	159	35%	936	70%	
	Outliers	61	13%	304	23%	
June	PAF	5	1%	6	1%	
	Repeated Data	11	2%	35	3%	
	Multiple Aircraft	16	4%	10	1%	
	Total Observed	440	$\overline{}$	1332	$\overline{}$	
	Drop Outs	161	37%	1116	84%	
mber	Outliers	55	12%	442	33%	
Septe	PAF	6	1%	6	1%	
	Repeated Data	6	1%	59	4%	
	Multiple Aircraft	15	3%	12	1%	
	Total Observed	467		1287		
	Drop Outs	153	33%	888	69%	
	Outliers	69	15%	366	28%	
December	PAF	9	2%	16	1%	
	Repeated Data	14	3%	44	3%	
	Multiple Aircraft	18	4%	15	1%	

Table 9. Aircraft Count Summary for Fargo and Finley

Table 10. Drop Out Summary for Fargo and Finley

Fargo		Finley			
PAF Duration			PAF Duration		
Average (sec)	124.99	$\qquad \qquad \blacksquare$	Average (sec)	170.15	-
Minimum (sec)	16.53	$\qquad \qquad -$	Minimum (sec)	39.40	$\overline{}$
Maximum (sec)	426.83	$\overline{}$	Maximum (sec)	495.42	-
Time Interval Classification			Time Interval Classification		
Number of PAF	6.5	$\overline{}$	Number of PAF	9.0	\blacksquare
Less than 10 sec	0.8	13%	Less than 24 sec	1.0	11%
$10 - 15$ sec	0.3	5%	24 - 36 sec	1.3	15%
$15 - 20$ sec	0.1	2%	36-48 sec	0.6	7%
$20 - 25$ sec	0.3	4%	$48 - 60$ sec	0.8	9%
25 - 30 sec	0.3	4%	60 -90 sec	1.0	11%
$30 - 60$ sec	1.1	17%	$90 - 120$ sec	0.7	7%
Greater than 60 sec	3.6	55%	Greater than 120 sec	3.6	40%

Table 11. Prolonged Altitude Failure Summary (PAF) for Fargo and Finley

There was an average drop out of 23.58sec at Fargo and 42.45sec at Finley. While 74% drop outs occurred for less than three radar scan rates at both Fargo and Finley; this is still a significant period of time to not have ATC receive information on the aircraft. It should also be noted that if ATC loses an aircraft for even one radar scan rate, they need to reestablish contact with them, so even having a short drop out adds more strain to the current ATC system. The maximum values show the drop outs can last for several minutes in some cases. Additionally, the average PAF was 124.99sec at Fargo and 170.15sec at Finley. This is a substantial amount of time for ATC to not have a correct altitude reading to help with vertical separation services. It is also noteworthy that 55% of PAF at Fargo lasted for more than one minute, while 58% of prolonged altitude failures at Finley occurred for greater than one minute.

Time of Day & Location Summary

Time of day and location were also investigated to understand if either factor impacted the drop outs and data anomalies. Other than the fact that more aircraft are flying during daylight hours, time of day not play a large role in the occurrence of the drop outs and data anomalies. However, despite that fact, location did appear to have an impact on the unique behavior observed. Figure 20 gives a typical plot of drop out locations at Fargo and Finley. Figure 21 provides a usual altitude outlier location plot for both locations. Figure 22 does the same for prolonged altitude failure, Figure 23 for repeated data, Figure 24 for multiple aircraft with the same discrete ID, and Figure 25 for multiple aircraft with the same non-discrete ID.

From Figures 20 and 21, it can be seen that majority of all outliers occur on the approach paths/near airports and on the edge of the effective radar radius. The prolonged altitude failure shown in Figure 22 appears to be a transponder related issue, with long trails showing the path of the aircraft. While Figure 23 show most repeated data occurs near airports as well. Figure 24 also shows that discrete multiple aircraft ID failures are transponder/aircraft specific. This is logical because ATC assigns each aircraft an ID before takeoff. However, Figure 25 shows that non-discrete ID failures are more sporadic. It is obvious there is a large concentration near airports and additionally transponder/aircraft flight paths can be seen. So this failure also appears to be transponder specific. The

behaviors that occurred near the edge of the radar effective radius occur because the radar is being pushed to its operational capacity to detect those aircraft. Additionally, airports are high traffic areas. As the airspace gets more congested, the radar is more likely to make mistakes. Based off Table 9 and Figures 20-25, drop outs and outliers are the most prominent unique behavior observed.

Figure 20. Drop Out Location Plots for Finley (left) and Fargo (right)

Figure 21. Altitude Outlier Location Plots for Finley (left) and Fargo (right)

Figure 22. Prolonged Altitude Failure Plots for Finley (left) and Fargo (right)

Figure 23. Repeated Data Location Plots for Finley (left) and Fargo (right)

Figure 24. Multiple Aircraft with the Same Discrete ID Location Plots for Finley (left) and Fargo (right)

Figure 25. Multiple Aircraft with the Same non-Discrete ID Location Plots for Finley (left) and Fargo (right)

CHAPTER IV

DISCUSSION OF RESULTS

While Chapter III provided a summary of the results based on aircraft count, time duration, and location. This chapter will provide a more through explanation and conjecture for why some of these anomalies are occurring. The overlapping analysis mentioned earlier will be presented in this chapter, along with a correlation of weather/climate conditions on each day of this study. The final sections will cover a risk matrix/hazard assessment to understand the true severity of data anomalies, and lastly a comparison to previous studies will be assessed.

Overlapping Analysis

To understand if the data anomalies were radar or transponder induced errors, an overlapping analysis was performed. Only the aircraft that were intercepted at both Fargo and Finley were considered. Fargo's radar radius fits entirely inside Finley's radar radius, as shown by Figure 4, so theoretically all of the aircraft detected by Fargo should be detected by Finley. The two primary exceptions to that rule are if the aircraft were detected by Finley, but in Fargo's radar cone of silence, or the aircraft were too low to be intercepted by Finley's radar beam. If the data anomalies occurred at both sites, it was considered a transponder error, because it is highly unlikely both radar sites were experiencing failures at the same time. If the data anomalies occurred only at one site, it was considered a radar error. Only the drop outs and altitude outliers produced statistically significant results for this analysis, so only those behaviors were considered. Table 12 summarizes the percentage of aircraft that experienced transponder induced errors and radar induced errors for drop outs and outliers. These percentages consider the average value of over the time period listed in the far left hand column of the table. The overall average, and average for each week of data was considered. For a complete day by day breakdown, a more detailed table can be seen in Appendix D: Overlapping Analysis Results.

	Data Anomaly Description	Percentage of Aircraft w/ Radar Error	Percentage of Aircraft w/Transponder. Error
	Drop Outs	93%	7%
Overall	Outliers	51%	49%
	Drop Outs	94%	6%
Mar.	Outliers	49%	51%
	Drop Outs	95%	5%
June	Outliers	52%	48%
	Drop Outs	93%	7%
Sep.	Outliers	53%	48%
	Drop Outs	91%	9%
Dec.	Outliers	50%	50%

Table 12. Radar and Transponder Failure Summary

Table 12 shows there isn't a drastic change from season to season when compared to the overall results for the method of failure. In this study, the overall results showed 93% of drop outs were radar errors, while only 51% of altitude outliers experienced radar errors. The largest deviation from these values were by $\pm 2\%$ considering the weekly averages.

The most probable explanation for why outliers have roughly equal percentages for the source of error, between the radar and transponder, while drop outs are mostly caused by the radar is the number of systems that can contribute to the data anomalies. Outliers have many more systems involved than drop outs. The altimeter, system to convert the altitude reading to binary for the transponder, transponder, and all the systems at the ground station can all contribute to altitude outliers. The increase in sources of error, make the distribution more uniform between radar or transponder induced errors for the altitude outliers.

It should be noted that prolonged altitude failures and multiple aircraft with the same ID are also transponder induced errors, which can be seen from Figures 22, 24 and 25. However, there were not enough data points of those anomalies to be considered for the overlapping analysis.

Hazard Assessment

To assess risk, the FAA and other organizations use Safety Risk Management (SRM), which is a process to analyze, assess, and accept risk for designs, policies, and many other aspects. One tool that is used in SRM is a risk matrix to help quantify the amount of risk. The risk matrix takes into account the severity and likelihood of an event, then using the combination of both interactions, assigns a rating in terms of risk: unacceptable risk, acceptable risk with mitigation, and acceptable risk. Table 13 provides the FAA severity definitions [57] and Table 14 provides the FAA likelihood definitions [57]. Due to the broad nature of the likelihood definitions, a revised table, specific for this study was developed; this is shown in Table 15. Table 16 provides the generic FAA risk matrix [57].

Minimal	Minor	Major	Hazardous	Catastrophic
Negligible safety effect	Physical discomfort to persons - Slight damage to aircraft/vehicle	- Physical distress or injuries to persons Substantial damage to aircraft/vehicle	Multiple serious injuries; fatal injury to a relatively small number of persons (one or two); or a hull loss without fatalities	Multiple fatalities (or fatality to all on board) usually with the loss of aircraft/ vehicle
Courtesy: Federal Aviation Administration [57].				

Table 13. FAA Severity Definitions

Table 14. FAA Likelihood Definitions

Frequent	Expected to occur routinely	
Probable в	Expected to occur often	
Remote С	Expected to occur infrequently	
Extremely Remote	Expected to occur rarely	
Extremely Improbable	So unlikely that it is not expected to occur, but it is not impossible	
Courtesy: Federal Aviation Administration [57].		

Table 15. Radar Data Anomaly Likelihood Definitions

Table 16. Generic FAA Risk Matrix

In the risk assessment used for the radar anomalies, the ratings were assigned under the assumption that no other DAA system were in place, including the pilot's ability to see and avoid. The risk assessment performed assumes only the radar system is in place, providing the five pieces of information run through the algorithm: time, aircraft ID, altitude, range, and azimuth. A study incorporating other DAA systems is beyond the scope of this project. By performing the risk analysis under these underlying assumptions, a true sense of the severity of these issues can be understood. Using the likelihoods assigned in Table 15 and severity ratings from Table 13, a risk matrix was assembled for the data anomalies. The severity was taken for each data anomaly to assume the worst case scenario,

given that condition. It should be noted that typically the severity at Finley was higher than Fargo for the data anomalies studied for the risk matrices. This is because the scan rate is larger and the radar covers a larger area, so there is an increase in the potential severity of events, if they do happen. An overall risk matrix, looking at the averages from the four weeks of data is shown in Table 17. Tables 18-21 show the averages from each week, starting in March and ending in December. The number from the severity rating and the letter from the likelihood rating, along with the risk color (green, yellow, or red) are shown in each risk matrix. This done for each location, with Fargo in the left column, and Finley in the right column. This work provides one of the biggest findings from this study, because it shows the true severity of the data anomalies. Risk matrices are one of the most commonly used methods for analysis in the aerospace industry, so this helps individuals with more of an aerospace background understand the significance of the engineering analysis in this report.

When comparing the overall results to each week, there weren't very many significant changes. The likelihood varied slightly from week to week in some categories. In fact, the only time the risk rating changed was from the prolonged altitude for greater than 6 scan rates in June, which went from unacceptable risk to acceptable risk with mitigation. Other than that specific case, the risk ratings stayed consistent. While the results look problematic, keep in mind that the risk assessment considers only the radar DAA system. The current airspace is safe, with near midair collisions (NMAC) and midair collisions (MAC) happening very infrequently. This is due to other DAA technologies and over 100 years of policy and technology going into the current NAS system. However, as UAS are incorporated into the NAS, they may only have one or two DAA systems, so the

results shown from Tables 17-21 may be more representative of that system. This shows that a robust logic to handle these anomalies is required to create a safe, efficient DAA system for UAS if radar was used. It also shows that multiple DAA systems may be required on UAS.

Additional findings show that Finley has more cases for unacceptable risk, when compared to Fargo. This is can be explained by the increased surveillance area and scan rate, and typically an increased severity rating. Drop outs, altitude outliers, and prolonged altitude failures greater than six scan rates all pose unacceptable risk. Drop outs and altitude outliers are also considered the most catastrophic data anomalies. Every scenario with these behaviors poses either acceptable risk with mitigation or unacceptable risk. They also have identical risk ratings when comparing Fargo or Finley. Completely losing an aircraft with a drop out or having inconsistent altitude readings from altitude outliers poses the biggest risk for aircraft and ATC. Prolonged altitude readings are not as problematic because with a prolonged altitude reading of zero feet elevation, it is obvious that the aircraft is not at that elevation, so ATC can make more informed decisions on aircraft separation services. Additionally, an algorithm could do the same thing for an autonomous UAS. Multiple aircraft is the fourth lowest data anomaly in terms of risk, because ATC has protocols in place and is aware of the problem of assigning multiple aircraft with the same ID number. Lastly repeated data is the lowest risk, with acceptable risk for both locations. Receiving multiple data points doesn't contribute any harm to knowing the aircraft position. About the only potential harm is increasing bandwidth congestion in the airspace.

Table 17. Overall Radar Phenomena Risk Matrix

Table 18. March Radar Phenomena Risk Matrix

Table 19. June Radar Phenomena Risk Matrix

Table 20. September Radar Phenomena Risk Matrix

Table 21. December Radar Phenomena Risk Matrix

Climate Effects

Weather is one of the factors that can impact the performance of a radar system. While clutter from weather, namely: rain and hail are important for professionals who study climate and the environment, they can severely hinder the performance of radars used to detect aircraft or other large objects. A significant portion of radar design goes into reducing the amount of clutter picked up. Typically, the Doppler frequency shift is the method to detect moving objects from the clutter of stationary objects. Circular polarization is another method to enhance the detection of aircraft in rain, because rain drops are symmetrical/spherical and aircraft are typically asymmetrical [58].

This section aims to understand the correlation between weather conditions and the data anomalies, if any. To do this weather information for each day of study was obtained [59]. For the Fargo analysis, the weather data from the Fargo International Airport was used. For the Finley study, the weather information from the Grand Forks Air Force Base was used, because this was the closest major airport with weather information dating back to 2015. Once the data was obtained, the weather was classified as fair weather and poor weather. The conditions were considered poor when the visibility was less than 1 mile, which is the minimum requirement for VFR traffic to take off and land in day light hours [60]. Conditions were also considered poor if the maximum wind speed exceeded 30mph, there was measured precipitation during the day, or any events were recorded (snow, fog, rain, or thunderstorms). If the weather during each day didn't experience any of the above conditions, it was considered fair weather.

The climate conditions were then compared to the percentage ratio of the instances of each type of data anomaly to the total number of aircraft detected that day. In some cases, the ratios were greater than 100% because an aircraft can experience multiple instances of that specific data anomaly. Table 22 summarizes the instance/aircraft number ratio for each type of data anomaly in poor and fair weather at Fargo. The overall average results are listed first, with average of each week listed afterwards. Table 23 provides the same information, except for Finley.

	Weather Condition	Drop Outs	Altitude Outliers	Prolonged Altitude Failure	Repeated Data	Multiple Aircraft
Overall	Poor	94%	18%	1%	5%	4%
	Fair	134%	30%	2%	31%	2%
Mar.	Poor	75%	15%	2%	11%	1%
	Fair	118%	24%	1%	49%	1%
June	Poor	86%	14%	1%	7%	4%
	Fair	174%	38%	1%	15%	3%
Sep.	Poor	129%	22%	1%	2%	4%
	Fair	119%	26%	2%	82%	3%
Dec.	Poor	36%	9%	0%	0%	22%
	Fair	120%	30%	2%	23%	2%

Table 22. Fargo Climate Effects

	Weather Condition	Drop Outs	Altitude Outliers	Prolonged Altitude Failure	Repeated Data	Multiple Aircraft
Overall	Poor	256%	38%	0%	4%	1%
	Fair	240%	47%	1%	8%	1%
Mar.	Poor	134%	20%	0%	2%	1%
	Fair	110%	28%	1%	8%	0%
June	Poor	201%	29%	0%	2%	1%
	Fair	269%	47%	1%	9%	1%
Sep.	Poor	388%	52%	0%	7%	1%
	Fair	487%	70%	1%	6%	1%
Dec.	Poor	246%	50%	1%	1%	2%
	Fair	232%	54%	1%	9%	1%

Table 23. Finley Climate Effects

The effects on weather at Fargo can be seen much more easily than Finley, because Fargo covers a much smaller area than Finley. Finley may also be experiencing different climate conditions in different parts of its scan path, so it's difficult to draw meaningful conclusions. However, when looking at Table 22 for Fargo, drop outs, altitude outliers, and repeated data all seem to be effected by weather. It's interesting to see the ratio go down for poor weather days, while it increases for good weather days. This demonstrates the method of failure for those three anomalies listed above. With the poor weather, fewer aircraft are in the sky, however, for fair weather more aircraft are in the sky. This implies that drop outs, altitude outliers, and repeated data are a function of aircraft density. As more aircraft are airborne, the density goes up, along with the ratio of instances to aircraft. The opposite trend can be seen with a lower aircraft density. The only exception to this behavior is the drop out average from September at Fargo. There was a slight increase in the instance to aircraft ratio for poor weather, rather than the typical increase for good weather. This was likely because of the small sample size in fair weather days (two days) versus the sample size in good weather days (five days). Other factors could also be in play to effect the results from that week of data.

The multiple aircraft with the same ID and prolonged altitude failures had minimal correlation with weather, with only a few percentage points separating the fair and poor weather days. The one exception to this rule was for multiple aircraft with the same ID in December at Fargo. Again, this is likely due to small sample size, with only one day of poor weather, versus six days of fair weather. This shows that transponder induced errors are not as susceptible to changes in climate conditions, because multiple aircraft with the same ID and prolonged altitude failures are the two behaviors that are most exclusively transponder induced. In the introduction, it was mentioned that secondary radar is better at handling poor weather conditions; these results further verify that statement.

To further show the correlation of climate and the data anomalies, a day to day summary for the June data at Fargo is provided in Table 24. When the weather is poor (rows highlighted in yellow/orange), the general trend is for the ratio of instances to aircraft to decrease when compared to fair weather days. A detailed day to day summary for all the data analyzed in this study at both Fargo and Finley is provided in Appendix E: Climate Effects Summary.

Table 24. Fargo Climate Effects for the Week of June

Additionally, with poor weather there are likely better pilots and better aircraft in

more likely to operate the equipment correctly. This may also explain why the ratio of data anomaly instances to total number of aircraft decreases for poor weather as well.

Comparison of Results to Previous Studies

While many studies have been performed on the performance and problems with radar, no study of this scale or scope has been done. This section will compare some previous work to the research presented in this document. Particularly the secondary radar vulnerabilities, the ADS-B/radar comparisons, and the wind turbine study. While the all the other research is relevant and important work, it is difficult to directly relate it to the findings from this study. If more specifics on the radar measurements were provided from Harris, studies looking at azimuth and range accuracy could also be addressed in the future.

The secondary radar vulnerability studies [39, 40] stated that aircraft transponders could be interrogated up to 20 times per scan rate depending on where the aircraft was relative to the radar site. This phenomenon likely explains why repeated data is occurring. With repeated data, many nearly identical data points were received within a fraction of a second. Although logic exists in the current radar system's computer to filter out most of the erroneous data, no software is ever perfect. The bandwidth congestion with interrogating the aircraft up to 20 times per scan rate, along with TCAS and ADS-B sharing some of the same frequencies as radar may contribute to the data anomalies observed as well. For the climate effects summary, it was shown as aircraft density increased, the ratio of data anomaly instances to total number of aircraft increased for drop outs, altitude outliers, and repeated data. When traffic density increases, so does the bandwidth congestion. In one of the ADS-B/radar studies [47], the authors struggled with correlating radar data to ADS-B data because of erratic radar and radar drop outs around the

Philadelphia airspace. This demonstrates that these radar data anomalies are occurring in other parts of the country, and especially in congested airspaces.

Additionally, the wind turbine study [41], has indicated that wind turbines around ATC radars can cause undesired effects, such as: electromagnetic shadowing, effects on Doppler, and clutter effects. While these effects are most often seen on primary radar resulting in erroneous data, the author suggests secondary radar could be effected as well. Some of the observed phenomenon from secondary radar effects were bearing and azimuth error, along with target splits (i.e. altitude outliers). A map depicting the over 47,000 wind turbines locations in the U.S. was obtained from the U.S. Geological Survey [61]. A map of the coverage area in the U.S. from both radars is provided in Figure 26, with a close up near Fargo and Finley provided in Figure 27. Each dot (the colors vary based on power output) represent a single wind turbine. The blue circle with an X represents Fargo and the red circle with an X represents Finley in both Figures 26 and 27.

Figure 26. Wind Turbine Locations in the Fargo/Finley Radar Coverage Area

Figure 27. Close Up of the Wind Turbine Locations Near Fargo and Finley

It can be seen from Figures 26 and 27 there are quite a few wind turbines located close to the Fargo and Finley radar sites and in their scan areas. There are two wind turbines right next to the Fargo radar site, and a large wind turbine farm just south of the Finley radar site. It is likely these wind turbines may have contributed to the some of the drop outs and outliers due to interference with the radar's performance.

While many external factors may have contributed to the observed data anomalies, such as weather conditions, bandwidth congestion, traffic density, multiple interrogations per scan, and wind turbines. Other factors such as jamming (intentional or unintentional), engineering limitations of the radars, or simply design flaws could have contributed as

well. While it is important to understand where these data anomalies originated from, it is just as important to understand the anomalies themselves and know how to handle them if they do occur. Especially when radar data is used in UAS autonomy or DAA logic and for autonomous ATC systems.

CHAPTER V

CONCLUSIONS

The goal of this study was to understand the current state of the radar environment around the Red River Valley. To understand the status of the radar network, vulnerabilities needed to be understood. Chapter II described the five different types of data anomalies identified through this work, namely: drop outs, altitude outliers, prolonged altitude failures, repeated data, and multiple aircraft with the same ID. A MATLAB algorithm was developed to classify and sort out the data anomalies from the four weeks of data at both the Fargo radar site and the Finley radar site. This algorithm is described in detail in Chapter III.

Once the data was processed through the computer program developed, the results were analyzed by occurrence rate, time duration, and location. Finley always detected more aircraft each day because it is a long range radar, while Fargo is primarily used around the Fargo International Airport. The drop outs were the most prevalent data anomaly, with an average of 34% of aircraft at Fargo and 69% of aircraft at Finley experiencing at least one drop out. The other data anomalies ranked in order from most common (behind drop outs) to least common are altitude outliers, repeated data, multiple aircraft with the same ID, and prolonged altitude failures. These data anomalies occurred on 1-26% of the aircraft, depending on anomaly and location. Drop outs and prolonged altitude failures were analyzed by time duration. It was discovered the average drop lasted 23.58 seconds and 42.45 seconds, at Fargo and Finley, respectively. While 74% of drop outs occurred for less

than three scan rates at both locations, there were some drop outs lasting several minutes. The average prolonged altitude failure was 124.99 seconds at Fargo and 170.15 seconds at Finley, showing a much longer time duration than drop outs. Location was also analyzed, showing that many of the data anomalies occur near airports or on the edge of the effective radar radius.

Error source (radar or transponder induced), risk, weather impacts, and a correlation to previous studies was also done. The overlapping analysis, along with the location of data anomaly plots showed that drop outs, repeated data, and outliers are predominately radar induced errors. Multiple aircraft with the same ID and prolonged altitude failures are primarily transponder induced errors. While the weather conditions were not shown to directly impact the data anomalies, an indirect correlation was discovered. With poor weather, fewer aircraft are in the sky, decreasing the traffic density. It was also shown the ratio of instances to total number of aircraft detected decreased in poor weather as well. The opposite trend was observed with good weather, showing radar induced data anomalies are potentially a function of traffic density in the airspace. The risk assessment showed that multiple aircraft with the same ID and repeated data pose the lowest risk to aircraft, while prolonged altitude failures, altitude outliers, and drop outs pose the greatest risk. The comparison to previous studies also showed bandwidth congestion with multiple interrogations per scan rate and wind turbines can cause erroneous radar behavior.

While identifying the various data anomalies, their duration, and severity are eye opening. The airspace is still safe with the additional systems in place such as TCAS and ADS-B. However, with the addition of autonomous ATC systems and especially UAS into the NAS, the effect of these data anomalies could be compounded. If autonomous DAA

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systems use radar data, work definitely needs to be done either on improving the radar systems or a robust logic to handle the data anomalies onboard the aircraft. Other systems will likely need to supplement UAS DAA, just like manned aircraft today. This will ensure that if there is a failure in one system, the aircraft is not flying without guidance. Future work could look at replicating the data anomalies to further understand how they are caused. This could be done at the Northern Plains UAS Test Site with their mobile radar unit. Additionally, to understand how radar data could be used for a DAA system onboard UAS, algorithms could be developed to handle the data anomalies and fuse other sources of data from other systems, such as: vision, ADS-B, or Light Detection and Ranging (LIDAR).

The information presented in this document can be used by developers of DAA logic for UAS and autonomous ATC systems. While knowing what types of behaviors radars are experiencing is important for radar designers, it is just important for users of this data to know how to handle data anomalies. To create a robust DAA system and autonomous ATC system, understanding how to deal with radar data anomalies is crucial if that information is used for those systems. While newer technologies will supplement radar in the coming years, radar will likely be used for the foreseeable future.

APPENDIX A: MODE A TRANSPONDER IDENTIFICATION NUMBERS

APPENDIX B: MATLAB CODE

```
Main Script
```

```
clc
clear all
close all
all data=[;;counter=0;
%Read file data
for 11=1:2 location=ll
for ii=1:4
     for kk=1:7
         if 3*ii<10
             Date= ['2015.0', num2str(3*ii), '.0', num2str(kk)]
         else
             Date= ['2015.', num2str(3*ii), '.0', num2str(kk)]
         end
Filepath='C:\Users\nicholas.allen\OneDrive - North Dakota University 
System\UAS Research\Radar Analysis\Radar Data Merged Short\';
if location==1
 Location='Fargo';
 file=['Short Merged ', Date,' ', Location];
 filename= [Filepath, file, '.xlsx'];
end
if location==2
Location='Finley';
file=['Short Merged ', Date,' ', Location];
filename= [F\overline{i}]lepath, file, '.xlsx'];
end
rd=Data_Read(filename);
% New data ==> deletes all the rows with missing data
rd new = rd(all(\sim isnan(rd),2),:);%Convert Range & Azimuth to Latitude and longitude
if location ==1
lat=46.920222; 
lat1=deg2rad(lat);
long=-96.812167; 
long1=deg2rad(long); 
radii1=60/41.1279;
radii2=60/60.0266;
%1 degree of latitude = 60.02647nmi
%1 degree of longitude = 41.1279nmi
end
```

```
if location ==2
lat=47.528167; 
lat1=deg2rad(lat);
long=-97.90061; 
long1=deg2rad(long);
radii1=250/40.6604;
radii2=250/60.0329;
%1 degree of latitude = 60.0329nmi
%1 degree of longitude = 40.6604nmi
end
ER=3440.27694; %Earth's radius in nautical miles 
count= size(rd new(:,1)); %count how many data points
lat in=[;]long in=[];
for i=1: count (1,1)alt(i)=0.000164578833693*rd new(i,2); %feet to nmi
    if alt(i)< rd new(i,5)
        ran(i)=sqrt(rd_new(i,5)^2-alt(i)^2); %ground range (range in
data is slant range)
     else
        ran prime(i)=sqrt(alt(i)^2-rd new(i,5)^2);
        beta(i)= asind(rd new(i,5)/alt(i));ran(i)=ran prime(i)*sind(beta(i));
     end
    b(i)=ran(i)/ER; sconversion
    rad(i)=deg2rad(rd new(i,4));
    lat2(i)=asin(sin(lat1)*cos(b(i))+cos(lat1)*sin(b(i))*cos(rad(i)));
    a(i)=atan2(sin(rad(i))*sin(b(i))*cos(lat1),(cos(b(i))-
sin(lat1)*sin(lat2(i)));
    long2(i)=long1+a(i);long f(i)=rad2deg(long2(i));lat f(i)=rad2deg(lat2(i));long in=[long in long f(i)];
    lat \overline{in}=[lat in lat f(\overline{i})];
 end
latitude=lat_in';
longitude=long_in';
rd new pos= [rd new, ran', latitude, longitude];
% Sorted rows ==> sorts the data based on the aircraft ID number
rd sorted= sortrows(rd new pos);
%split data ==> splits rd_sorted matrix into a cell array based on the 
aricraft ID number
 rd split=arrayfun(\mathcal{C}(x) rd sorted(rd sorted(:,1) == x, :),
unique(rd sorted(:,1)), 'uniformoutput',false);
   fprintf('done split rd \n')
 %Count planes
```

```
count planes= size(unique(rd new(:,1))); %count how many planes there
are
%% Multiple Aircraft & Repeated Data
[ multiple aircraft repeated data, multiple aircraft, repeated data,
rd wo ma ] = MARD( location, count planes, rd split, rd sorted );
Filepath ma="C:\Users\nicholas.allen\OneDirive - North Dakota UniversitySystem\UAS Research\Radar Analysis\Multiple Aircraft Maps\';
addpath('altmany-export_fig-5be2ca4')
%Plot Multiple Aircraft
if length(unique(multiple aircraft(:,2)))>2
ma_loc=[];
for mm=1:length(multiple_aircraft)
    if multiple aircraft(mm, 2) \sim=0if multiple aircraft(mm, 2) \sim=1200ma loc=[ma loc;multiple aircraft(mm,:)];
         end
     end
end
plot(ma_loc(:,9),ma_loc(:,8),'.r','MarkerSize',10)
h=ellipse(radii1, radii2,0, long,lat, 'b');
set(gca,'visible','off')
set(gcf, 'Units', 'Inches', 'Position', [0, 0, 9, 9], 'PaperUnits', 
'Inches', 'PaperSize', [9, 9])
plot google map('maptype', 'hybrid','scale', 2, 'resize', 2)
savefig([Filepath_ma,file,'_multiple_aircraft_map.fig'])
set(gcf,'renderer','zbuffer') 
export_fig([Filepath_ma,file,'_multiple_aircraft_map.png'])
close all
end
Filepath rd='C:\Users\nricholas.allen\OneDirive - North Dakota UniversitySystem\UAS Research\Radar Analysis\Repeated Data Maps\';
%Plot Repeated Data
plot(repeated data(:,9),repeated data(:,8),'.r','MarkerSize',10)
h=ellipse(radii1, radii2,0, long,lat, 'b');
set(gca,'visible','off')
set(gcf, 'Units', 'Inches', 'Position', [0, 0, 9, 9], 'PaperUnits', 
'Inches', 'PaperSize', [9, 9])
plot_google_map('maptype', 'hybrid','scale', 2, 'resize', 2)
savefig([Filepath_rd,file,'_repeated_data_map.fig'])
set(gcf,'renderer','zbuffer') 
export fig([Filepath rd,file,' repeated data map.png'])
close all
%% Drop Outs
[ data do, drop out summary, do time categorization ] = DropOut(
location, rd wo ma );
```

```
Filepath do='C:\Users\nicholas.allen\OneDrive - North Dakota University
System\UAS Research\Radar Analysis\Drop Out Maps\';
plot(data do(:,7), data do(:,6), '.r', 'MarkerSize',10)
h=ellipse(radii1, radii2,0, long,lat, 'b');
set(gca,'visible','off')
set(gcf, 'Units', 'Inches', 'Position', [0, 0, 9, 9], 'PaperUnits', 
'Inches', 'PaperSize', [9, 9])
plot google map('maptype', 'hybrid','scale', 2, 'resize', 2)
savefig([Filepath do, file,' drop out map.fig'])
set(gcf,'renderer','zbuffer') 
export fig([Filepath do,file,' drop out map.png'])
close all
%% Outliers
\lceil outliers \rceil = Outliers (location, rd wo ma );
Filepath_out='C:\Users\nicholas.allen\OneDrive - North Dakota
University System\UAS Research\Radar Analysis\Outlier Maps\';
plot(outliers(:,9),outliers(:,8),'.r','MarkerSize',10)
h=ellipse(radii1, radii2,0, long,lat, 'b');
set(gca,'visible','off')
set(gcf, 'Units', 'Inches', 'Position', [0, 0, 9, 9], 'PaperUnits', 
'Inches', 'PaperSize', [9, 9])
plot_google_map('maptype', 'hybrid','scale', 2, 'resize', 2)
savefig([Filepath_out,file,'_outlier_map.fig'])
set(gcf,'renderer','zbuffer') 
export_fig([Filepath_out,file,'_outlier_map.png'])
close all
%% Prolonged Altitude Failure
[p alt failure pre, p alt failure, p alt failure time,
alt failure summary, alt failure time categorization ] =prolonged alt failure( rd wo ma, location );
%obtain lat and long values
p_alt_lat_long=[];
for zz=1:length(p_alt_failure)
p_alt_lat_long=[p_alt_lat_long;p_alt_failure{zz}(:,7:8)];
end
Filepath paf='C:\Users\nicholas.allen\OneDrive - North Dakota
University System\UAS Research\Radar Analysis\Prolonged Altitude 
Failure Maps\';
if length(p_alt_lat_long)>=1
plot(p alt lat long(:,2),p alt lat long(:,1),'.r','MarkerSize',10)
h=ellipse(radii1, radii2,0, long,lat, 'b');
set(gca,'visible','off')
set(gcf, 'Units', 'Inches', 'Position', [0, 0, 9, 9], 'PaperUnits', 
'Inches', 'PaperSize', [9, 9])
plot google map('maptype', 'hybrid','scale', 2, 'resize', 2)
```

```
savefig([Filepath_paf,file,'p_alt_failure_map.fig'])
set(gcf,'renderer','zbuffer') 
export fig([Filepath paf,file,'p alt failure map.png'])
end
close all
%% Store all data
counter=counter+1;
 repeated data instances=size(repeated data);
 alt failure summary size=size(alt failure summary);
 if alt failure summary size(1) == 0alt failure summary=cell(1,4);
     alt failure summary{1}=0;
     alt failure summary{2}=-0;alt failure summary{3}=-0;alt failure summary{4}=-0;alt failure time categorization=cell(1,7);
     alt fature-time categorization{1}=0;alt failure time categorization{2}=0;
      alt_failure_time_categorization{3}=0;
      alt_failure_time_categorization{4}=0;
     alt failure time categorization{5}=0;
     alt failure time categorization{6}=0;
     alt failure time categorization{7}=0;
 end
 if repeated data instances(1)>0
 all_data=[all_data; ll, 3*ii, kk, count_planes(1),
length(unique(data do(:,1))), do time categorization{:,:},
drop out summary\{:,:\}, length(unique(outliers(:,1))),
length(outliers(:,1)), alt failure time categorization{:,:},
alt failure summary{:,:}, length(unique(multiple aircraft(:,1))),
length(unique(repeated data(:,1))), repeated data instances(1)];
elseif repeated data instances(1) == 0all data=[all data; ll, 3*ii, kk, count planes(1),
length(unique(data do(:,1))), do time categorization{:,:},
drop out summary\{:\,:\,\}, length(unique(outliers(:,1))),
length(outliers(:,1)), alt failure time categorization{:,:},
alt failure summary{:,:}, length(unique(multiple aircraft(:,1))), 0,
repeated data instances(1)];
end
 if counter==28
      xlswrite('Summary of Fargo Data Anomalies.xlsx', all_data)
elseif counter==56
     xlswrite('Summary of Fargo & Finley Data Anomalies.xlsx', 
all data)
 end
%% Save .mat file
matFileDir= 'C:\Users\nicholas.allen\OneDrive - North Dakota 
University System\UAS Research\Radar Analysis\mat Files\';
```

```
save([matFileDir,file, '.mat'])
 disp('done data write')
% Clear variables
clearvars -except ii kk ll location all_data counter
    end
end
end
```
Data Read

```
function [ rd ] = Data_Read( filename)
%This function reads in the data from the Excel sheets & creates the 
radar
%data matrix with the required information in the matrix titled rd
% Location 1 is Fargo & Location 2 is Finley
% The output contains columns of the data in the following order: 
planeid, time, altitude, azimuth, range
planeid = xlsread(filename, 'A:A');
time = xlsread(filename, 'B:B');
 altitude = xlsread(filename, 'C:C');azimuth = xlsread(filename, 'D:D');range = xlsread(filename, 'E:E');length1=length(planeid);
 length2=length(altitude);
 length3=length(time);
 length4=length(azimuth);
 length5=length(range);
 length comb=[length1, length2, length3, length4, length5];
max size=max(length comb);
 for i=1:5
    diff=abs(max_size-length_comb(i));
     if diff>0
         if i==1
             planeid= [planeid; NaN(diff,1)];
         elseif i==2
             altitude= [altitude; NaN(diff,1)];
         elseif i==3
            time= [time; NaN(diff, 1)];
         elseif i==4
            azimuth= [azimuth; NaN(diff,1)];
         elseif i==5
             range= [range; NaN(diff,1)];
         end
     end
end
rd= [planeid, time, altitude, azimuth, range]; 
end
```
Multiple Aircraft and Repeated Data

```
function [ multiple aircraft repeated data, multiple aircraft,
repeated data, rd wo ma ] = MARD( location, count planes, rd split,
rd_sorted )
%This function identifies the plane ID's with multiple aircraft and
%repeated data
% Inputs: location = location number defined previously in the 
script, count planes=number of aircraft, rd split=radar data split into
a cell array, rd sorted= radar data
% Outputs: multiple_aircraft_repeated_data= a combination of the 
multiple aircraft and repeated data, multiple_aircraft= data that has 
multiple aircraft, repeated data= data that has repeated data,
rd_wo_ma= radar data without multiple aircraft 
multiple aircraft repeated data=[];
multiple aircraft=[];
if location==1
for kk=1: count planes (1,1)
      datapts=size(rd split{kk}(:,2)); %Count how many data points
there are for each aircraft
      for l = 1: (datapts(l, 1) - 1)
          delta t ma= rd split{kk}(ll+1,2) - rd split{kk}(ll,2);
          delta<sup>lat=</sup> rd \overline{split{kk}(l1+1,7)} - rd \overline{split{kk}(l1,7)};
          delta long= rd split{kk}(ll+1,8) - rd split{kk}(ll,8);
          if rd split\{kk\}(11,1) == 0multiple aircraft=[multiple aircraft;kk,rd split{kk}(ll,:),delta t ma,
delta lat, delta long];
           end
           if delta_t_ma<3.8
multiple aircraft repeated data=[multiple aircraft repeated data;kk,rd
split{kk}(ll,:), delta t ma, delta lat, delta long];
               if abs(delta_lat)>0.012 
                    if abs(delta_long)>0.035 
multiple aircraft=[multiple aircraft;kk,rd split{kk}(ll,:),delta t ma,
delta lat, delta long];
                    end
                end
           end
       end
end
%Repeated Data
repeated data potential=setdiff(multiple aircraft repeated data,
multiple_aircraft, 'rows');
     %Eliminate multiple aircraft from repeated data matrix
    repeated data=repeated data potential;
    ma unique=unique(multiple aircraft(:,2));
     for qq=1:length(ma_unique)
       repeated data(any(repeated data(:, 2) == ma unique(qq), 2), :)=[];
     end
end
```

```
if location==2
for kk=1: count planes (1,1)
      datapts=size(rd split{kk}(:,2)); %Count how many data points
there are for each aircraft
      for l = 1: (datapts(l, 1) - 1)
          delta t ma= rd split{kk}(ll+1,2) - rd split{kk}(ll,2);
          delta lat= rd split{kk}(ll+1,7) - rd split{kk}(ll,7);
          delta long= rd split{kk}(ll+1,8) - rd split{kk}(ll,8);
           if delta_t_ma<10
multiple aircraft repeated data=[multiple aircraft repeated data;kk,rd
split{kk}(ll,:), delta t ma, delta lat, delta long];
               if abs(delta_lat)>0.016
                   if abs(delta_long)>0.16
multiple aircraft=[multiple aircraft;kk,rd split{kk}(ll,:),delta t ma,
delta lat, delta long];
                   end
               end
           end
       end
end
%Repeated Data
repeated data potential=setdiff(multiple aircraft repeated data,
multiple_aircraft, 'rows');
     %Eliminate multiple aircraft from repeated data matrix
    repeated data=repeated data potential;
    ma unique=unique(multiple aircraft(:,2));
     for qq=1:length(ma_unique)
        repeated_data(any(repeated_data(:,2)==ma_unique(qq),2),:)=[]; 
     end
end
% Sort out multiple aircraft from data
%Find indices in drop out data that correspond to multiple aircraft
indices=[];
for oo=1:length(ma_unique)
        indices=[indices;find(rd sorted(:,1)== ma unique(oo))];
end
rd wo ma combined=rd sorted;
rd wo ma combined(indices,:)=[]; \frac{1}{2}Remove indices that correspond to
multiple aircraft
%split data ==> splits rd_sorted matrix into a cell array based on the
%aircraft ID number without multiple aircraft
rd wo ma=arrayfun((\theta(x)) rd wo ma combined(rd wo ma combined(:,1) == x,
:), unique(rd wo ma combined(:,1)), 'uniformoutput',false);
```

```
end
```
Drop Outs

```
function [ data do, drop out summary, do time categorization ] =
DropOut( location, rd wo ma )
%This function identifies drop outs from the radar without the multiple
%aircraft
% Inputs: location = location indicated by user (1 or 2, for Fargo or 
Finley), rd wo ma= radar data without multiple aircraft
% Outputs: data do= drop out data, drop out summary=avg, min, max and
% total number of drop outs, do_time_categorization= time 
categorization of drop outs
data do=[];
   if location==1
   for ii=1:length(rd_wo_ma)
      datapts=size(rd wo ma{ii}(:,2)); %Count how many data points
there are for each aircraft
      for jj=1: (datapts(1,1)-1)
          delta t= rd wo ma{ii}(jj+1,2) - rd wo ma{ii}(jj,2);
           if delta_t>5.5 && delta_t<300
data do=[data do;ii,rd wo ma{ii}(jj,1),delta t,rd wo ma{ii}(jj,2:3),rd
wo ma{ii}(jj,7:8)];
           end
       end
   end
   end
   if location==2
  for ii=1:length(rd wo ma)
      datapts=size(rd wo ma{ii}(:,2)); %Count how many data points
there are for each aircraft
      for jj=1: (datapts(1,1)-1)
          delta t= rd wo ma{ii}(jj+1,2) - rd wo ma{ii}(jj,2);
                     if delta_t>13 && delta_t<400
data do=[data do;ii,rd wo ma{ii}(jj,1),delta t,rd wo ma{ii}(jj,2:3),rd
wo ma{ii}(jj,7:8)];
           end
       end
   end
   end
%% Categorize drop outs
average do=mean(data do(:,3)); %average
```

```
min do=min(data do(:,3)); %minimum
max do=max(data do(:,3)); % max = maxtotal_do=length(data_do(:,3)); %total number of drop outs
drop out summary=table(average do, min do, max do, total do);
%Time interval classification
do count1=[;]do_count2=[];
do_count3=[];
do count4=[;]do_count5=[];
do_count6=[];
do_count7=[];
if location==1
for aa=1: length (data do(:,3))
    if data do(aa,3)<10
        do count1=[do count1;data do(aa,3)];
    elseif data do(aa, 3) >=10 && data do(aa, 3) <15
         do count2=[do count2;data do(aa,3)];
    elseif data do(aa,3) >=15 && data do(aa,3) <20
         do count3=[do count3;data do(aa,3)];
    elseif data do(aa,3) >=20 && data do(aa,3) <25
         do count4=[do count4;data do(aa,3)];
    elseif \overline{data} do(aa, 3) >=25 && data_do(aa, 3) <30
         do count5=[do count5;data do(aa,3)];
    elseif data do(aa,3) >=30 && data do(aa,3) <60
         do count6=[do count6;data do(aa,3)];
    elseif data do(aa,3) >=60
         do count7=[do count7;data do(aa,3)];
     end
end
do_less10=length(do_count1);
do 10 15=length(do count2);
do 15 20=length(do count3);
do 20 25=length(do count4);
do\overline{25} 30=length(do count5);
do 30 60=length(do count6);
do greater60=length(do count7);
do_time_categorization= table(do_less10,do_10_15, do_15_20, do_20_25, 
do 25 30, do 30 60, do greater60);
end
if location==2
   for aa=1: length (data do(:,3))
    if data do(aa, 3) <24
        do count1=[do count1;data do(aa,3)];
    elseif data do(aa,3) >=24 && data do(aa,3) <36
          do_count2=[do_count2;data_do(aa,3)];
    elseif data do(aa,3) >=36 && data do(aa,3) <48
         do count3=[do count3;data do(aa,3)];
    elseif \overline{data} do(aa,3) >=48 && data_do(aa,3) <60
         do count4=[do count4;data do(aa,3)];
    elseif data do(aa,3) >=60 && data do(aa,3) <90
         do count5=[do count5; data do(aa,3)];
```

```
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```

```
elseif data do(aa,3) >=90 && data do(aa,3) <120
          do count6=[do count6;data do(aa,3)];
     elseif data_d do (aa,3) >=120
           do_count7=[do_count7;data_do(aa,3)];
      end
end
do_less24=length(do_count1);
do 24 36=length(do count2);
d\overline{o}36 48=length(do count3);
do48<sup>-60=length(do-count4);</sup>
d\overline{o} 60<sup>-</sup>90=length(do<sup>-</sup>count5);
d_0_90_120=length(d_0_count6);
do_greater120=length(do_count7);
do time categorization= table(do less24,do 24 36, do 36 48, do 48 60,
d\overline{o}6090, do 90 120, do greater120);
end
```
end

Altitude Outliers

```
function [ outliers ] = Outliers ( location, rd wo ma )
%This function identifies drop outs from the radar without the multiple
%aircraft
% Inputs: location = location indicated by user (1 or 2, for Fargo or 
Finley), rd wo ma= radar data without multiple aircraft
% Outputs: outliers= data with outliers, outlier summary=average
time, min time, max time, and number of outliers 
outlier time categorization= outliers categorized by time
outliers=[];
rd split outliers=cell(length(rd_wo_ma),1);
if location==1
for bb=1:length(rd_wo_ma)
      rows to last row=size(rd wo ma{bb}(:,2));
      last row=rd wo ma{bb}(rows to last row(1,1),:);
      rd split outliers{bb}=[rd wo ma{bb}(:,:);last row];
      datapts=size(rd split outliers{bb}(:,2)); % Count how many data
points there are for each aircraft
      if datapts(1,1) >2
      for cc=1: (datapts(1,1)-2)
          delta t out= rd split outliers{bb}(cc+1,2) -
rd split outliers{bb}(cc,2);delta alt out= rd split outliers{bb}(cc+1,3) -
rd split outliers{bb}(cc,3);delta alt out prev= rd split outliers{bb}(cc+2,3) -
rd split outliers{bb}(c^{-1},3); if delta_t_out>4 && delta_t_out<300
              if delta_alt_out>800 || delta_alt_out<-800
                   if abs(delta_alt_out_prev)<800 
outliers=[outliers;bb,rd_split_outliers{bb}(cc,:),delta_alt_out,delta_a
lt out prev, delta t out];
                   end
              end
          end
       end
       end
end
end
if location==2
for bb=1:length(rd_wo_ma)
      rows to last row=size(rd wo ma{bb}(:,2));
      last row=rd wo ma{bb}(rows to last row(1,1),:);
      rd split outliers{bb}=[rd wo ma{bb}(:,:);last row];
      datapts=size(rd_split_outliers{bb}(:,2)); % Count how many data
points there are for each aircraft
      if datapts(1,1)>2
      for cc=1: (datapts(1,1)-2)
```

```
delta t out= rd split outliers{bb}(cc+1,2) -
rd split outliers{bb}(cc,2);
           delta_alt_out= rd_split_outliers{bb}(cc+1,3) -
rd_split_outliers{bb}(cc,3);
          delta alt out prev= rd split outliers{bb}(cc+2,3) -
rd split outliers {b\overline{b}}(c-1,3); if delta_t_out>10 && delta_t_out<400
             if delta alt out>800 || delta alt out<-800
                  if abs(delta alt out prev)<800
outliers=[outliers;bb,rd_split_outliers{bb}(cc,:),delta_alt_out,delta_a
lt_out_prev, delta_t_out];
                   end
              end
           end
       end
       end
end
end
if length(outliers)<1
    outliers=[];
     return
end
```
Prolonged Altitude Failure

```
function [p_alt_failure_split_pre, p_alt_failure, p_alt_failure_time,
alt failure summary, alt failure time categorization ] =prolonged alt failure( r\bar{d} wo ma, location )
%This function finds all the prolonged altitude failures at 0ft
% Inputs: rd_wo_ma= radar data without multiple aircraft
% Outputs: p_alt_failure: data with prolonged altitude failure,
% p alt failure time= time duration of failures,
alt failure summary=avg, min, max and total number of alt failures,
alt failure time categorization= time categorization of alt failures
start stop=cell(length(rd wo ma), 1);
all indices=cell(length(rd wo ma), 1);
p alt failure pre=[;]for ii=1:length(rd wo ma)
      datapts=size(rd wo ma{ii}(:,2)); %Count how many data points
there are for each aircraft
          alt= rd wo ma{ii}(:,3)';
           %logical array for when alt is equal to 0 ft
          t alt= (abs(alt) \geq 1);\overline{\text{F}}ind the starting and ending indices and duration of the
string of zeroes
            d alt = diff([1 \t{all } 1];startIndex = find(d alt < 0);
            endIndex = find(d alt > 0)-1;
            duration = endIndex-startIndex+1; %Find the strings of zeros with a duration greater than 2 
to indicate a prolonged altitude failure
            stringIndex = (duration \geq 2);
            startIndex = startIndex(stringIndex);
            endIndex = endIndex(stringIndex);
            start stop{ii}= [startIndex; endIndex];
             %Find indices corresponding to prolonged altitude failure
            indices = zeros(1, max(endIndex)+1);indices(startIndex) = 1;
            indices(endIndex+1) = indices(endIndex+1)-1;
            indices = find(cumsum(indices));
            all indices{ii}=indices;
            if length(endIndex)>=1
                  for kk=1:length(endIndex)
                      p_alt_failure_pre=[p_alt_failure_pre;
rd wo ma{ii}(startIndex(kk):endIndex(kk),:)];
                  end
            end
end
%Output matrix with altitude readings of 0ft 2 more times in a row
p_alt_failure_split_pre=arrayfun(@(x)
p alt failure pre(p alt failure pre(:,1) == x, :),
unique(p_alt_failure_pre(:,1)), 'uniformoutput',false);
```

```
%Separate aircraft at different time of day & only include aircraft 
w \textbf{i} + h%readings of 3 or more 0ft alt readings in a row
p_alt_failure=[];
for mm=1:length(p_alt_failure_split_pre)
    current length=length(p alt failure);
    time_diff=find(diff(p_alt_failure_split_pre{mm}(:,2))<300);
    index=setdiff(1:(length(p_alt_failure_split_pre{mm}(:,2))-
1),time_diff);
    index=[0, \text{index}, \text{length}(p \text{ alt failure split pre}{\text{fmin}}); if length(index)>2 
            ind count=length(index);
                 for hh = 1: (ind count-1)
                     p_alt_failure{current_length+hh}= 
p_alt_failure_split_pre{mm}((index(hh)+1):index(hh+1),:);
                  end
         else
p_alt_failure{current_length+1}=p_alt_failure_split_pre{mm}(:,:);
         end
end
for qq=1:length(p_alt_failure)
    length matrix=size(p alt failure{qq});
    if length matrix(1) < 3p_alt_failure{qq}=[];
     end
end
%eliminate empty arrays
TF=[];
for aa=1:length(p_alt_failure)
TF=[TF; isempty(p all failure{aa})];end
p_alt_failure=p_alt_failure(find(TF==0));
p_alt_failure=p_alt_failure';
 if length(p_alt_failure)<1
     p_alt_failure=[];
     p alt failure time=[];
     alt failure summary=[];
     alt failure time categorization=[];
      return
 end
%Categorize by time interval & stats
p alt failure time=[];
 for mm=1:length(p_alt_failure)
     points=length(p alt failure{mm}(:,1)); %Count how many data points
there are for each aircraft
p_alt_failure_time=[p_alt_failure_time;p_alt_failure{mm}(points,2)-
p alt failure{mm}(1,2)];
```
end

```
alt failures=p alt failure time;
average_alt_failure=mean(alt_failures(:,1)); %average
min alt failure=min(alt failures(:,1)); \frac{1}{2} minimum
max alt failure=max(alt failures(:,1)); \frac{1}{2} maximum
total alt failures=length(alt failures(:,1)); %total number of alt
failure
alt failure summary=table(average alt failure, min alt failure,
max alt failure, total alt failures);
%Time interval classification
alt failure count1=[];
alt failure count2=[];
alt failure count3=[];
alt failure count4=[];
alt failure count5=[];
alt failure count6=[];
alt failure count7=[];
if location==1
for aa=1:length(alt_failures(:,1))
    if alt failures (aa,1) < 10alt failure count1=[alt failure count1;alt failures(aa,1)];
    elseif alt failures(aa,1)>=10 && alt failures(aa,1)<15
         alt failure count2=[alt failure count2;alt failures(aa,1)];
    elseif alt failures(aa,1) >=15 && alt failures(aa,1)<20
         alt failure count3=[alt failure count3;alt failures(aa,1)];
    elseif alt failures(aa,1)>=20 && alt failures(aa,1)<25
         alt failure count4=[alt failure_count4;alt failures(aa,1)];
    elseif alt failures(aa,1)>=25 && alt failures(aa,1)<30
         alt failure count5=[alt failure count5;alt failures(aa,1)];
    elseif alt failures(aa,1) >=30 && alt failures(aa,1)<60
         alt failure count6=[alt failure count6;alt failures(aa,1)];
    elseif alt failures(aa, 1) >=60
         alt failure count7=[alt failure count7;alt failures(aa,1)];
     end
end
alt failure less10=length(alt failure count1);
alt failure 10 15=length(alt failure count2);
alt failure 15 20=length(alt failure count3);
alt failure 20 25=length(alt failure count4);
alt failure 25 30=length(alt failure count5);
alt failure 30 60=length(alt failure count6);
alt failure greater60=length(alt failure count7);
alt failure time categorization=
table(alt failure less10,alt failure 10 15, alt failure 15 20,
alt failure 20 25, alt failure 25 30, alt failure 30 60,
alt_failure_greater60);
end
if location==2
   for aa=1: length(alt failures(:,1))
     if alt_failures(aa,1)<24
        alt failure count1=[alt failure count1;alt failures(aa,1)];
```

```
elseif alt failures(aa,1)>=24 && alt failures(aa,1)<36
         alt failure count2=[alt failure_count2;alt failures(aa,1)];
     elseif alt_failures(aa,1)>=36 && alt_failures(aa,1)<48
         alt failure count3=[alt failure count3;alt failures(aa,1)];
    elseif alt failures(aa,1)>=48 && alt failures(aa,1)<60
         alt failure count4=[alt failure count4;alt failures(aa,1)];
    elseif alt failures(aa,1)>=60 && alt failures(aa,1)<90
         alt failure count5=[alt failure_count5;alt failures(aa,1)];
    elseif alt failures(aa,1)>=90 && alt failures(aa,1)<120
         alt failure count6=[alt failure count6;alt failures(aa,1)];
    elseif alt failures(aa, 1) >=120alt failure count7=[alt failure count7;alt failures(aa,1)];
     end
end
alt failure less24=length(alt failure count1);
alt failure 24 36=length(alt failure count2);
alt failure 36 48=length(alt failure count3);
alt_failure_48_60=length(alt_failure_count4);
alt_failure_60_90=length(alt_failure_count5);
alt_failure_90_120=length(alt_failure_count6);
alt_failure_greater120=length(alt_failure_count7);
alt failure time categorization=
table(alt failure less24,alt failure 24 36, alt failure 36 48,
alt failure 48 60, alt failure 60 90, alt failure 90 120,
alt failure greater120);
end
```
end
Plot Google Map

```
function varargout = plot google map(varargin)
% function h = plot google map(varargin)
% Plots a google map on the current axes using the Google Static Maps 
API
\frac{6}{10}% USAGE:
% h = plot_google_map(Property, Value,...)
% Plots the map on the given axes. Used also if no output is specified
\approx% Or:
% [lonVec latVec imag] = plot google map(Property, Value,...)
% Returns the map without plotting it
\mathbf{Q}% PROPERTIES:
% Axis - Axis handle. If not given, gca is used.
% Height (640) - Height of the image in pixels (max 640)
% Width (640) - Width of the image in pixels (max 640)<br>% Scale (2) - (1/2) Resolution scale factor. Using S
% Scale (2) - (1/2) Resolution scale factor. Using Scale=2 will
% double the resulotion of the downloaded image (up
% to 1280x1280) and will result in finer rendering,
% but processing time will be longer.
% Resize (1) - (recommended 1-2) Resolution upsampling factor. 
% Increases image resolution using imresize(). This 
results
% in a finer image but it needs the image 
processing
% toolbox and processing time will be longer.
% MapType - ('roadmap') Type of map to return. Any of 
[roadmap, 
% satellite, terrain, hybrid]. See the Google Maps 
API for
% more information. 
% Alpha (1) - (0-1) Transparency level of the map (0 is fully
% transparent). While the map is always moved to 
the
% bottom of the plot (i.e. will not hide previously
% drawn items), this can be useful in order to 
increase
% readability if many colors are plotted 
% (using SCATTER for example).
% ShowLabels (1) - (0/1) Controls whether to display city/street 
textual labels on the map
% Style - (string) A style configuration string. See:
\frac{8}{6}https://developers.google.com/maps/documentation/static-
maps/?csw=1#StyledMaps
% http://instrument.github.io/styled-maps-wizard/
% Language - (string) A 2 letter ISO 639-1 language code for
displaying labels in a 
% local language instead of English (where 
available).
% For example, for Chinese use:
% plot google map('language','zh')
% For the list of codes, see:
```
% http://en.wikipedia.org/wiki/List_of_ISO_639- 1_codes % Marker - The marker argument is a text string with fields % conforming to the Google Maps API. The % following are valid examples: % '43.0738740,-70.713993' (default midsize orange marker) % '43.0738740,-70.713993,blue' (midsize blue marker) % '43.0738740,-70.713993,yellowa' (midsize yellow % marker with label "A") % '43.0738740,-70.713993,tinyredb' (tiny red marker % with label "B") % Refresh (1) - (0/1) defines whether to automatically refresh the % map upon zoom/pan action on the figure. % AutoAxis (1) - (0/1) defines whether to automatically adjust the axis % of the plot to avoid the map being stretched. % This will adjust the span to be correct % according to the shape of the map axes. % FigureResizeUpdate (1) - (0/1) defines whether to automatically refresh the % map upon resizing the figure. This will ensure map % isn't stretched after figure resize. % APIKey - (string) set your own API key which you obtained from Google: \mathbf{Q} http://developers.google.com/maps/documentation/staticmaps/#api_key % This will enable up to 25,000 map requests per day, % compared to a few hundred requests without a key. % To set the key, use: \approx plot_google_map('APIKey','SomeLongStringObtaindFromGoogle') % You need to do this only once to set the key. % To disable the use of a key, use: % plot google map('APIKey','') $\frac{6}{5}$ % OUTPUT: % h - Handle to the plotted map $\frac{8}{6}$ % lonVect - Vector of Longidute coordinates (WGS84) of the image % latVect - Vector of Latidute coordinates (WGS84) of the image % imag - Image matrix (height, width, 3) of the map \approx % EXAMPLE - plot a map showing some capitals in Europe: % lat = $[48.8708 \t 51.5188 \t 41.9260 \t 40.4312 \t 52.523 \t 37.982];$
% lon = $[2.4131 \t -0.1300 \t 12.4951 \t -3.6788 \t 13.415 \t 23.715$ $%$ lon = $[2.4131$ -0.1300 12.4951 -3.6788 13.415 23.715]; % plot(lon,lat,'.r','MarkerSize',20) % plot google map \approx % References: % http://www.mathworks.com/matlabcentral/fileexchange/24113

```
% http://www.maptiler.org/google-maps-coordinates-tile-bounds-
projection/
% http://developers.google.com/maps/documentation/staticmaps/
\approx% Acknowledgements:
% Val Schmidt for his submission of get google map.m
\approx% Author:
% Zohar Bar-Yehuda
\approx% Version 1.8 - 25/04/2016 - By Hannes Diethelm
% - Add resize parameter to resize image using imresize()
% - Fix scale parameter
% Version 1.7 - 14/04/2016
% - Add custom style support
% Version 1.6 - 12/11/2015
% - Use system temp folder for writing image files (with fallback 
to current dir if missing write permissions)
% Version 1.5 - 20/11/2014
% - Support for MATLAB R2014b
% - several fixes for complex layouts: several maps in one 
figure, 
% map inside a panel, specifying axis handle as input (thanks 
to Luke Plausin)
% Version 1.4 - 25/03/2014
% - Added the language parameter for showing labels in a local 
language
% - Display the URL on error to allow easier debugging of API 
errors
% Version 1.3 - 06/10/2013
% - Improved functionality of AutoAxis, which now handles any 
shape of map axes. 
% Now also updates the extent of the map if the figure is 
resized.
% - Added the showLabels parameter which allows hiding the 
textual labels on the map.
% Version 1.2 - 16/06/2012
       - Support use of the "scale=2" parameter by default for finer
rendering (set scale=1 if too slow).
% - Auto-adjust axis extent so the map isn't stretched.
% - Set and use an API key which enables a much higher usage 
volume per day.
% Version 1.1 - 25/08/2011
persistent apiKey useTemp
if isnumeric(apiKey)
     % first run, check if API key file exists
     if exist('api_key.mat','file')
       load api \overline{k}ey
     else
       apiKey = ''; end
end
if isempty(useTemp)
     % first run, check if we have wrtie access to the temp folder
```

```
 try
         tempfilename = tempname;
        fid = fopen(tempfilename, 'w');
         if fid > 0
             fclose(fid);
            useTemp = true; delete(tempfilename);
         else
             % Don't have write access to temp folder or it doesn't 
exist, fallback to current dir
             useTemp = false;
         end
     catch
         % in case tempname fails for some reason
         useTemp = false;
     end
end
hold on
% Default parametrs
axHandle = gca;
height = 640;width = 640;scale = 2;
resize = 1;maptype = 'roadmap';
alphaData = 1;
autoRefresh = 1;
figureResizeUpdate = 1;
autoAxis = 1;showLabels = 1;
language = ';
markeridx = 1;
market = \{\};
style = ';
% Handle input arguments
if nargin >= 2for idx = 1:2:length(varargin) switch lower(varargin{idx})
             case 'axis'
                axHandle = varargin{idx+1};
             case 'height'
                height = varargin\{idx+1\};
             case 'width'
                width = varargin\{idx+1\};
             case 'scale'
                 scale = round(varargin\{idx+1\});
                 if scale < 1 || scale > 2 error('Scale must be 1 or 2');
                 end
             case 'resize'
                resize = varargin\{idx+1\}; case 'maptype'
                maptype = varargin\{idx+1\};
```

```
 case 'alpha'
                alphaData = varargin{idx+1};
             case 'refresh'
                autoRefresh = varargin\{idx+1\};
             case 'showlabels'
                showLabels = varargin\{idx+1\};
             case 'figureresizeupdate'
                figureResizeUpdate = varaging_idx+1;
             case 'language'
                language = varargin\{idx+1\}; case 'marker'
                market{market} = varargin{idx+1};markeridx = markeridx + 1;
             case 'autoaxis'
                autoAxis = varargin\{idx+1\}; case 'apikey'
                apiKey = varargin{idx+1}; % set new key
                 % save key to file
                funcFile = which('plot google map.m');
                 pth = fileparts(funcFile);
                keyFile = fullfile(pth, 'api key.math'); save(keyFile,'apiKey')
             case 'style'
                style = varargin\{idx+1\};
             otherwise
                 error(['Unrecognized variable: ' varargin{idx}])
         end
     end
end
if height > 640height = 640;end
if width > 640width = 640;end
% Store paramters in axis handle (for auto refresh callbacks)
ud = get(axHandle, 'UserData');
if isempty(ud)
     % explicitly set as struct to avoid warnings
     ud = struct;
end
ud.gmap params = varargin;
set(axHandle, 'UserData', ud);
curAxis = axis(xHandle);if max(abs(curAxis)) > 500 || curAxis(3) > 90 || curAxis(4) < -90 warning('Axis limits are not reasonable for WGS1984, ignoring. 
Please make sure your plotted data in WGS1984 coordinates,')
     return;
end 
% Enforce Latitude constraints of EPSG:900913 
if curAxis(3) < -85curAxis(3) = -85;end
```

```
if curAxis(4) > 85curAxis(4) = 85;end
% Enforce longitude constrains
if curAxis(1) < -180curAxis(1) = -180;end
if curAxis(1) > 180curAxis(1) = 0;end
if curAxis(2) > 180curAxis(2) = 180;
end
if curAxis(2) <-180curAxis(2) = 0;end
if isequal(curAxis,[0 1 0 1]) % probably an empty figure
     % display world map
    curAxis = [-200 200 -85 85];
     axis(curAxis)
end
if autoAxis
     % adjust current axis limit to avoid strectched maps
     [xExtent,yExtent] = latLonToMeters(curAxis(3:4), curAxis(1:2) );
    xExtent = diff(xExtent); \frac{1}{3} just the size of the span
    yExtent = diff(yExtent);
     % get axes aspect ratio
     drawnow
    org_units = get(axHandle, 'Units');
     set(axHandle,'Units','Pixels')
    ax position = qet(axHandle, 'position');
    set(axHandle, 'Units', org units)
    aspect ratio = ax position(4) / ax position(3);
     if xExtent*aspect_ratio > yExtent 
        centerX = mean(curAxis(1:2));
        centerY = mean(curAxis(3:4));
        spanX = (curAxis(2) - curAxis(1))/2;spanY = (curAxis(4) - curAxis(3))/2; % enlarge the Y extent
        spanY = spanY * xExtent * aspect ratio/yExtent; % new span
        if spanY > 85spanX = spanX * 85 / spanY;
            spanY = spanY * 85 / spanY; end
        curAxis(1) = centerX-spanX; curAxis(2) = centerX+spanX;
        curAxis(3) = centerY-spanY;curAxis(4) = centerY+spanY; elseif yExtent > xExtent*aspect_ratio
        centerX = mean(curAxis(1:2));
```

```
centerY = mean(curAxis(3:4));
        spanX = (curAxis(2) - curAxis(1))/2;spanY = (curAxis(4) - curAxis(3))/2; % enlarge the X extent
        spanX = spanX*yExtent/(xExtent*aspect ratio); % new span
        if spanX > 180spanY = spanY * 180 / spanX;spanX = spanX * 180 / spanX; end
        curAxis(1) = centerX-spanX;curAxis(2) = centerX+spanX;curAxis(3) = centerY-spanY;curAxis(4) = centerY+spanY; end 
     % Enforce Latitude constraints of EPSG:900913
    if curAxis(3) \lt -85
        curAxis(3:4) = curAxis(3:4) + (-85 - \text{curAxis}(3));
     end
    if curAxis(4) > 85curAxis(3:4) = curAxis(3:4) + (85 - \text{curAxis}(4)); end
     axis(axHandle, curAxis); % update axis as quickly as possible, 
before downloading new image
     drawnow
end
% Delete previous map from plot (if exists)
if nargout \leq 1 % only if in plotting mode
     curChildren = get(axHandle,'children');
    map objs = findobj(curChildren,'tag','gmap');
    bd callback = [];
    for idx = 1: length (map objs)
        if ~isempty(get(map objs(idx), 'ButtonDownFcn'))
             % copy callback properties from current map
             bd_callback = get(map_objs(idx),'ButtonDownFcn');
         end
     end
     delete(map_objs)
end
% Calculate zoom level for current axis limits
[xExtent,yExtent] = latLonToMeters(curAxis(3:4), curAxis(1:2));
minResX = diff(xExternal) / width;minResY = diff(yExtend) / height;minRes = max([minResX minResY]);tileSize = 256:
initialResolution = 2 * pi * 6378137 / tileSize; % 156543.03392804062for tileSize 256 pixels
zoomlevel = floor(log2(initialResolution/minRes));
% Enforce valid zoom levels
if zoomlevel < 0 
    zoomlevel = 0;
end
```

```
if zoomlevel > 19 
    zoomlevel = 19;
end
% Calculate center coordinate in WGS1984
lat = (curAxis(3) + curAxis(4))/2;lon = (curAxis(1) + curAxis(2))/2;% Construct query URL
preamble = 'http://maps.googleapis.com/maps/api/staticmap';
location = ['?center=' num2str(lat,10) ', ' num2str(lon,10)];zoomStr = ['&zoom=' num2str(zoomlevel)];
sizeStr = ['&scale=' num2str(scale) '&size=' num2str(width) 'x'num2str(height)];
maptypeStr = ['&maptype=' maptype ];
if ~isempty(apiKey)
    keyStr = ['&key='apiKey];else
    keyStr = '';end
markers = '&markers=';
for idx = 1: length (markerlist)
     if idx < length(markerlist)
        markers = [\text{marks} \text{ markets} \text{ markets} + \{\text{idx}\} \cdot \text{%} \cdot \text{?}C'];
     else
        markers = [marks markets];
     end
end
if showLabels == 0
     if ~isempty(style)
        style(end+1) = '|'; end
     style = [style 'feature:all|element:labels|visibility:off'];
end
if ~isempty(language)
    languageStr = ['&language=' language];else
    languageStr = ';
end
if ismember(maptype,{'satellite','hybrid'})
     filename = 'tmp.jpg';
    format = '&format =jpq'; convertNeeded = 0;
else
     filename = 'tmp.png';
     format = '&format=png';
     convertNeeded = 1;
end
sensor = '&sensor=false';
if ~isempty(style)
     styleStr = ['&style=' style];
else
```

```
 styleStr = '';
end
url = [preamble location zoomStr sizeStr maptypeStr format markers 
languageStr sensor keyStr styleStr];
% Get the image
if useTemp
     filepath = fullfile(tempdir, filename);
else
     filepath = filename;
end
try
    urlwrite(url, filepath);
catch % error downloading map
     warning(['Unable to download map form Google Servers.\n' ...
        'Matlab error was: %s\n\n' ...
         'Possible reasons: missing write permissions, no network 
connection, quota exceeded, or some other error.\n' ...
        'Consider using an API key if quota problems persist.\n\n' ...
         'To debug, try pasting the following URL in your browser, which 
may result in a more informative error:\n%s'], lasterr, url);
    varargout\{1\} = [];
    varargout\{2\} = [];
    varargout\{3\} = [];
     return
end
[M, Mcolor] = imread(filepath);
Mcolor = uint8 (Mcolor * 255);
M = \text{cast}(M, \text{'double'});delete(filepath); % delete temp file
width = size(M, 2);
height = size(M, 1);
% We now want to convert the image from a colormap image with an uneven
% mesh grid, into an RGB truecolor image with a uniform grid.
% This would enable displaying it with IMAGE, instead of PCOLOR.
% Advantages are:
% 1) faster rendering
% 2) makes it possible to display together with other colormap 
annotations (PCOLOR, SCATTER etc.)
% Convert image from colormap type to RGB truecolor (if PNG is used)
if convertNeeded
    imag = zeros(height, width, 3, 'uint8');for idx = 1:3cur map = Mcolor(:,idx);imag(:,:,idx) = reshape(curmap(M+1),height,width); end
else
    imag = M;end
% Resize if needed
if resize ~= 1
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```

```
 imag = imresize(imag, resize, 'bilinear');
end
% Calculate a meshgrid of pixel coordinates in EPSG:900913
width = size(imag, 2);
height = size(imag, 1);
centerPixelY = round(height/2);
centerPixelX = round(width/2);
[centerX, centerY] = latLonToMeters(lat, lon ); % center coordinates in
EPSG:900913
curResolution = initialResolution / 2^{\wedge}zoomlevel / scale / resize; %
meters/pixel (EPSG:900913)
xVec = centerX + ((1:width)-centerFixedX) * curResolution; % x vectoryVec = centerY + ((height:-1:1)-centerFixedY) * curResolution; % yvector
[xMesh,yMesh] = meshgrid(xVec,yVec); % construct meshgrid 
% convert meshgrid to WGS1984
[lonMesh, latMesh] = metersTolatLon(xMesh, yMesh);% Next, project the data into a uniform WGS1984 grid
uniHeight = round(height*resize);
uniWidth = round(width*resize);
latVect = linspace(latMesh(1,1), latMesh(end, 1), uniHeight);
lonVect = linspace(lonMesh(1,1),lonMesh(1,end),uniWidth);
[uniLonMesh,uniLatMesh] = meshgrid(lonVect,latVect);
uniImag = zeros(uniHeight, uniWidth, 3);
% Fast Interpolation to uniform grid
uniImag = myTurboInterp2(lonMesh,latMesh,imag,uniLonMesh,uniLatMesh);
if nargout \leq 1 % plot map
     % display image
     hold(axHandle, 'on');
    cax = caxis;h = image(lonVect,latVect,uniImag, 'Parent', axHandle);
     caxis(cax); % Preserve caxis that is sometimes changed by the call 
to image()
     set(axHandle,'YDir','Normal')
     set(h,'tag','gmap')
    set(h, 'AlphaData', alphaData)
     % add a dummy image to allow pan/zoom out to x2 of the image extent
    h tmp = image(lonVect([1 end]), latVect([1
end]),zeros(2),'Visible','off', 'Parent', axHandle);
    set(h tmp, 'tag', 'gmap')
     uistack(h,'bottom') % move map to bottom (so it doesn't hide 
previously drawn annotations)
     axis(axHandle, curAxis) % restore original zoom
    if nargout == 1varargout{1} = h;
     end
     % if auto-refresh mode - override zoom callback to allow autumatic
```

```
 % refresh of map upon zoom actions.
     figHandle = axHandle;
     while ~strcmpi(get(figHandle, 'Type'), 'figure')
         % Recursively search for parent figure in case axes are in a 
panel
         figHandle = get(figHandle, 'Parent');
     end
     zoomHandle = zoom(axHandle); 
     panHandle = pan(figHandle); % This isn't ideal, doesn't work for 
contained axis 
     if autoRefresh 
        set(zoomHandle, 'ActionPostCallback', @update_google_map);
        set(panHandle, 'ActionPostCallback', @update google map);
     else % disable zoom override
        set(zoomHandle,'ActionPostCallback', []);
        set(panHandle, 'ActionPostCallback', []);
     end
     % set callback for figure resize function, to update extents if 
figure
     % is streched.
     if figureResizeUpdate &&isempty(get(figHandle, 'ResizeFcn'))
         % set only if not already set by someone else
        set(figHandle, 'ResizeFcn', @update google map fig);
     end 
     % set callback properties 
    set(h,'ButtonDownFcn',bd callback);
else % don't plot, only return map
    varargout{1} = lonVect;
    varargout{2} = latVect;
    varargout{3} = uniImag;
end
% Coordinate transformation functions
function [lon, lat] = metersTolatLon(x, y)% Converts XY point from Spherical Mercator EPSG:900913 to lat/lon in 
WGS84 Datum
originShift = 2 * pi * 6378137 / 2.0; % 20037508.342789244
lon = (x \cdot / \text{originShift}) * 180;lat = (y \cdot / \text{originShift}) * 180;lat = 180 / pi * (2 * atan( exp( lat * pi / 180)) - pi / 2);
function [x,y] = latLonToMeters(lat, lon)
% Converts given lat/lon in WGS84 Datum to XY in Spherical Mercator 
EPSG:900913"
originShift = 2 * pi * 6378137 / 2.0; % 20037508.342789244
x = lon * originShift / 180;
y = log(tan((90 + lat) * pi / 360)) / (pi / 180);
y = y * originShift / 180;
```

```
function ZI = myTurbofinterp2(X, Y, Z, XI, YI)% An extremely fast nearest neighbour 2D interpolation, assuming both 
input
% and output grids consist only of squares, meaning:
% - uniform X for each column
% - uniform Y for each row
XI = XI(1,:);X = X(1, :);YI = YI(:,1);Y = Y(:,1);xiPos = nan*ones(size(XI));xLen = length(X);yiPos = nan*ones(size(YI));yLen = length(Y);% find x conversion
xPos = 1;for idx = 1: length (xiPos)if XI(idx) \geq X(1) & XI(idx) \leq X(end) while xPos < xLen && X(xPos+1)<XI(idx)
            xPos = xPos + 1; end
        diffs = abs(X(X) <i>Pos</i>: <i>XPos</i>+1) - XI(<i>idx</i>));if diffs(1) < diffs(2)xipos(idx) = xPos; else
            xipos(idx) = xPos + 1; end
     end
end
% find y conversion
yPos = 1;for idx = 1:length(yiPos)if YI(idx) \leq Y(1) && YI(idx) \geq Y(end)
         while yPos < yLen && Y(yPos+1)>YI(idx)
            yPos = yPos + 1; end
        diffs = abs(Y(yPos:yPos+1)-YI(idx));if diffs(1) < diffs(2) yiPos(idx) = yPos;
         else
            yips(idx) = yPos + 1; end
     end
end
ZI = Z(yiPos,xiPos,:);function update_google_map(obj,evd)
% callback function for auto-refresh
drawnow;
try
     axHandle = evd.Axes;
catch ex
     % Event doesn't contain the correct axes. Panic!
    axHandle = qca;
```

```
end
ud = get(axHandle, 'UserData');
if isfield(ud, 'gmap_params')
     params = ud.gmap_params;
    plot google map(params{:});
end
function update google map fig(obj, evd)
% callback function for auto-refresh
drawnow;
axes_objs = findobj(get(gcf,'children'),'type','axes');
for idx = 1: length (axes objs)
     if ~isempty(findobj(get(axes_objs(idx),'children'),'tag','gmap'));
         ud = get(axes_objs(idx), 'UserData');
        if isfield(ud, 'gmap params')
             params = ud.gmap_params;
         else
            params = \{\};
         end
         % Add axes to inputs if needed
         if ~sum(strcmpi(params, 'Axis'))
            params = [params, {'Axis', axes objs(idx)}];
         end
         plot_google_map(params{:});
     end
end
```
Draw Ellipse

```
function h=ellipse(ra,rb,ang,x0,y0,C,Nb)
% Ellipse adds ellipses to the current plot
\mathbf{Q}% ELLIPSE(ra,rb,ang,x0,y0) adds an ellipse with semimajor axis of ra,
% a semimajor axis of radius rb, a semimajor axis of ang, centered at
% the point x0,y0.
\approx% The length of ra, rb, and ang should be the same. 
% If ra is a vector of length L and x0,y0 scalars, L ellipses
% are added at point x0,y0.
% If ra is a scalar and x0,y0 vectors of length M, M ellipse are with 
the same 
% radii are added at the points x0,y0.
% If ra, x0, y0 are vectors of the same length L=M, M ellipses are 
added.
% If ra is a vector of length L and x0, y0 are vectors of length
% M~=L, L*M ellipses are added, at each point x0,y0, L ellipses of 
radius ra.
\frac{6}{2}% ELLIPSE(ra,rb,ang,x0,y0,C)
% adds ellipses of color C. C may be a string ('r','b',...) or the RGB 
value. 
% If no color is specified, it makes automatic use of the colors 
specified by 
% the axes ColorOrder property. For several circles C may be a vector.
\mathbf{R}% ELLIPSE(ra,rb,ang,x0,y0,C,Nb), Nb specifies the number of points
% used to draw the ellipse. The default value is 300. Nb may be used
% for each ellipse individually.
\mathbf{Q}% h=ELLIPSE(...) returns the handles to the ellipses.
\approx% as a sample of how ellipse works, the following produces a red 
ellipse
% tipped up at a 45 deg axis from the x axis
% ellipse(1, 2, pi/8, 1, 1, 'r')\approx% note that if ra=rb, ELLIPSE plots a circle
\approx% written by D.G. Long, Brigham Young University, based on the
% CIRCLES.m original 
% written by Peter Blattner, Institute of Microtechnology, University 
of 
% Neuchatel, Switzerland, blattner@imt.unine.ch
% Check the number of input arguments 
if nargin<1,
  ra=[];
end;
if nargin<2,
```

```
rb=[];
end;
if nargin<3,
  ang=[];
end;
%if nargin==1,
% error('Not enough arguments');
%end;
if nargin<5,
 x0=[;;y0=[;;end;
if nargin<6,
 C=[] ;
end
if nargin<7,
  Nb=[];
end
% set up the default values
if isempty(ra), ra=1; end;
if isempty(rb), rb=1; end;
if isempty(ang),ang=0;end;
if isempty(x0),x0=0;end;
if isempty(y0),y0=0;end;
if isempty(Nb), Nb=300; end;
if isempty(C),C=get(gca,'colororder');end;
% work on the variable sizes
x0=x0 (:);
y0=y0 (:);
ra=ra(:);
rb=rb(:);
ang=ang(:);
Nb=Nb(:);if isstr(C), C=C(:); end;
if length(ra)~=length(rb),
 error('length(ra)~=length(rb)');
end;
if length(x0) \sim =length(y0),
  error('length(x0)~=length(y0)');
end;
% how many inscribed elllipses are plotted
if length(ra) \sim =length(x0)
```

```
 maxk=length(ra)*length(x0);
else
   maxk=length(ra);
end;
% drawing loop
for k=1:maxk
  if length(x0) == 1 xpos=x0;
     ypos=y0;
     radm=ra(k);
     radn=rb(k);
     if length(ang)==1
       an=ang;
     else
      an=ang(k);
     end;
   elseif length(ra)==1
    xpos=x0(k); ypos=y0(k);
     radm=ra;
     radn=rb;
     an=ang;
   elseif length(x0)==length(ra)
     xpos=x0(k);
     ypos=y0(k);
     radm=ra(k);
     radn=rb(k);
     an=ang(k)
   else
    rada=ra(fix((k-1)/size(x0,1))+1);radb=rb(fix((k-1)/size(x0,1))+1);an=ang(fix((k-1)/size(x0,1))+1);
    xpos=x0(rem(k-1,size(x0,1))+1);ypos=y0 (rem(k-1, size(y0, 1))+1);
   end;
   co=cos(an);
   si=sin(an);
 the=linspace(0,2*pi, Nb(rem(k-1, size(Nb, 1))+1,:)+1);
% x=radm*cos(the)*co-si*radn*sin(the)+xpos;
% y=radm*cos(the)*si+co*radn*sin(the)+ypos;
   h(k)=line(radm*cos(the)*co-
si*radn*sin(the)+xpos,radm*cos(the)*si+co*radn*sin(the)+ypos);
  set(h(k),'color',C(rem(k-1,size(C,1))+1,:));
```

```
end;
```
Overlapping Analysis

```
clear all
close all
clc
counter=0;
all data overlap=[];
%% Read in data
addpath('mat Files')
for ii=1:4
     for kk=1:7
         if 3*ii<10
             Date= ['2015.0', num2str(3*ii), '.0', num2str(kk)]
         else
             Date= ['2015.', num2str(3*ii), '.0', num2str(kk)]
         end
Fargo_data=load(['Short_Merged_', Date,'_', 'Fargo.mat']);
Finley data=load(['Short Merged ', Date, ' ', 'Finley.mat']);
%% Drop Outs
%Load Data
Fargo do=Fargo data.data do;
Finley do=Finley data.data do;
%Find all the ID numbers that experienced drop outs 
Finley unique do=unique(Finley do(:,2), 'rows', 'sorted');
Fargo unique do=unique(Fargo do(:,2),'rows','sorted');
%Compare Finley to Fargo data
do logical same ID Fargo=ismember(Fargo do(:,2), Finley unique do);
do Fargo same ID=Fargo do(do logical same ID Fargo==1,:);
Fargo do size=size(do Fargo same ID);
%Compare Fargo to Finley data
do logical same ID Finley=ismember(Finley do(:,2),Fargo unique do);
do Finley same ID=Finley do(do logical same ID Finley==1,:);
Finley do size=size(do Finley same ID);
%Check for overlap at same time instance => transponder failure
do_overlap_summary=[];
for aa=1:Finley_do_size(1)
     for bb=1:Fargo_do_size(1)
        if do Finley same ID(aa, 2) ==do Fargo same ID(bb, 2)
             if (abs(do_Finley_same_ID(aa,4)-
do Fargo same ID(bb, 4))) <17
                 do_overlap_summary=[do_overlap_summary; 
do Fargo same ID(bb,:),0000000000000000000, do Finley same ID(aa,:)];
             end
         end
     end
end
```

```
%Summary of results for drop outs
instances transponder do=size(do overlap summary);
instances_transponder_do=instances_transponder_do(1); %transponder 
failure instances
if length(do overlap summary) >=1
    planes transponder do=length(unique(do overlap summary(:,2)));
%number of planes with transponder failures
else
   planes transponder do=0;
end
planes Finley radar do=length(unique(do Finley same ID(:,2))); %number
of planes with radar failures at Finley
planes Fargo radar do=length(unique(do Fargo same ID(:,2))); %number of
planes with radar failures at Fargo
percentage radar do=((planes Finley radar do(1)-
planes transponder do(1))/planes Finley radar do(1)); & percentage of
radar failures 
percentage_transponder_do=((planes_transponder_do(1))/planes_Finley_rad
ar do(1)); %percentage of transponder failures
%% Outliers
%Load data
Fargo out=Fargo data.outliers;
Finley out=Finley data.outliers;
%Find all the ID numbers that experienced outliers
Finley_unique_out=unique(Finley_out(:,2),'rows','sorted');
Fargo_unique_out=unique(Fargo_out(:,2),'rows','sorted');
%Compare Finley to Fargo data
out logical same ID Fargo=ismember(Fargo out(:,2), Finley unique out);
out Fargo same ID=Fargo out (out logical same ID Fargo==1,:);
Fargo out size=size(out Fargo same ID);
%Compare Fargo to Finley data
out logical same ID Finley=ismember(Finley out(:,2), Fargo unique out);
out Finley same ID=Finley out (out logical same ID Finley==1,:);
Finley out size=size(out Finley same ID);
%Check for overlap at same time instance => transponder failure
out overlap summary=[];
for aa=1: Finley out size(1)
    for bb=1:Fargo out size(1)
        if out Finley same ID(aa, 2) == out Fargo same ID(bb, 2)
             if (abs(out_Finley_same_ID(aa,4)-
out_Fargo_same_ID(bb,4)))<17
               out overlap summary=[out overlap summary;
out Fargo same ID(bb,:),0000000000000000000, out Finley same ID(aa,:)];
             end
         end
     end
end
```

```
111
```

```
%Summary of results for outliers
instances transponder out=size(out overlap summary);
instances_transponder_out=instances_transponder_out(1); %transponder 
failure instances
if length(out overlap summary) >=1
   planes transponder out=length(unique(out overlap summary(:,2)));
%number of planes with transponder failures
else
   planes transponder out=0;
end
planes Finley radar out=length(unique(out Finley same ID(:,2))); %number
of planes with radar failures at Finley
planes Fargo radar out=length(unique(out Fargo same ID(:,2))); %number
of planes with radar failures at Fargo
percentage radar out=((planes Finley radar out(1)-
planes transponder out(1))/planes Finley radar out(1)); &percentage of
radar failures 
percentage_transponder_out=((planes_transponder_out(1))/planes_Finley_r
adar out(1)); %percentage of transponder failures
%% Prolonged Altitude Failure
if length(Fargo data.p alt failure)<1
    instances transponder paf=0;
    planes transponder paf=0;
    planes Finley radar paf=0;
   planes Fargo radar paf=0;
   percentage radar paf=0;
    percentage transponder paf=0;
else
%Load data
Fargo paf=cell2mat(Fargo data.p alt failure);
Finley paf=cell2mat(Finley data.p alt failure);
%Find all the ID numbers that experienced prolonged altitude failures
Finley unique paf=unique(Finley paf(:,2), 'rows', 'sorted');
Fargo_unique_paf=unique(Fargo_paf(:,2),'rows','sorted');
%Compare Finley to Fargo data
paf logical same ID Fargo=ismember(Fargo paf(:,2),Finley unique paf);
paf Fargo same ID=Fargo paf(paf logical same ID Fargo==1,:);
Fargo paf size=size(paf Fargo same ID);
%Compare Fargo to Finley data
paf logical same ID Finley=ismember(Finley paf(:,2),Fargo unique paf);
paf_Finley_same_ID=Finley_paf(paf_logical_same_ID_Finley==1,:);
Finley paf size=size(paf Finley same ID);
%Check for overlap at same time instance => transponder failure
paf overlap summary=[];
for aa=1:Finley_paf_size(1)
    for bb=1:Fargo paf size(1)
```

```
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```

```
if paf Finley same ID(aa, 2) ==paf Fargo same ID(bb, 2)
            if (abs(paf Finley same ID(aa, 4)-
paf_Fargo_same_ID(bb,4)))<17
                paf overlap summary=[paf overlap summary;
paf Fargo same ID(bb,:),0000000000000000000, paf Finley same ID(aa,:)];
             end
         end
     end
end
%Summary of results for prolonged alititude failure
instances transponder paf=size(paf overlap summary);
instances transponder paf=instances transponder paf(1); %transponder
failure instances
if length(paf overlap summary) >=1
    planes transponder paf=length(unique(paf overlap summary(:,2)));
%number of planes with transponder failures
else
    planes_transponder_paf=0;
end
planes_Finley_radar_paf=length(unique(paf_Finley_same_ID(:,2)));%number 
of planes with radar failures at Finley
planes Fargo radar paf=length(unique(paf Fargo same ID(:,2))); %number
of planes with radar failures at Fargo
percentage_radar_paf=((planes_Finley_radar_paf(1)-
planes transponder paf(1))/planes Finley radar paf(1)); & percentage of
radar failures 
percentage_transponder_paf=((planes_transponder_paf(1))/planes_Finley_r
adar paf(1)); \sqrt[8]{2} percentage of transponder failures
end
%% Repeated Data
%Load Data
Fargo rd=Fargo data.repeated data;
Finley rd=Finley data.repeated data;
%Find all the ID numbers that experienced repeated data
Finley unique rd=unique(Finley rd(:,2),'rows','sorted');
Fargo unique rd=unique(Fargo rd(:,2),'rows','sorted');
%Compare Finley to Fargo data
rd logical same ID Fargo=ismember(Fargo rd(:,2),Finley unique rd);
rd Fargo same ID=Fargo rd(rd logical same ID Fargo==1,:);
Fargo rd size=size(rd Fargo same ID);
%Compare Fargo to Finley data
rd logical same ID Finley=ismember(Finley rd(:,2),Fargo unique rd);
rd_Finley_same_ID=Finley rd(rd logical same ID Finley==\overline{1},:);
Finley rd size=size(rd Finley same ID);
%Check for overlap at same time instance => transponder failure
rd_overlap_summary=[];
for aa=1: Finley rd size(1)
     for bb=1:Fargo_rd_size(1)
```

```
if rd Finley same ID(aa, 2) ==rd Fargo same ID(bb, 2)
            if (abs(rd Finley same ID(aa, 4)-
rd_Fargo_same_ID(bb,4)))<17
                rd overlap summary=[rd overlap summary;
rd Fargo same ID(bb,:),0000000000000000000, rd Finley same ID(aa,:)];
             end
         end
     end
end
%Summary of results for repeated data
instances transponder rd=size(rd_overlap_summary);
instances transponder rd=instances transponder rd(1); %transponder
failure instances
if length(rd overlap summary) >=1
    planes transponder rd=length(unique(rdoverlap summary(:,2)));
%number of planes with transponder failures
else
    planes transponder rd=0;
end
planes_Finley_radar_rd=length(unique(rd_Finley_same_ID(:,2)));%number 
of planes with radar failures at Finley
planes Fargo radar rd=length(unique(rd Fargo same ID(:,2))); %number of
planes with radar failures at Fargo
percentage radar rd=((planes Finley radar rd(1)-
planes transponder rd(1))/planes Finley radar rd(1)); & percentage of
radar failures 
percentage_transponder_rd=((planes_transponder_rd(1))/planes_Finley_rad
ar rd(1)); %percentage of transponder failures
%% Multiple Aircraft
%Load Data
Fargo ma pre=Fargo data.multiple aircraft;
Finley ma pre=Finley data.multiple aircraft;
%Eliminate ID numbers of 0 and 1200 
Fargo ma=[];
for mm=1:length(Fargo_ma_pre)
    if Fargo_ma_pre(mm, 2) ~=0
        if Fargo ma pre(mm,2) ~=1200
            Fargo ma=[Fargo ma;Fargo ma pre(mm,:)];
         end
     end
end
Finley ma=[];
for mm=1: length (Finley ma pre)
    if Finley ma pre(mm, 2) \sim=0if Finley ma pre(mm,2) ~=1200
            Finley ma=[Finley ma;Finley ma pre(mm,:)];
         end
     end
end
if length(Fargo_ma)>=1
```

```
 if length(Finley_ma)>=1
         %Find all the ID numbers that experienced multiple aircraft 
        Finley unique ma=unique(Finley ma(:,2),'rows','sorted');
        Fargo unique ma=unique(Fargo ma(:,2),'rows','sorted');
         %Compare Finley to Fargo data
ma logical same ID Fargo=ismember(Fargo ma(:,2), Finley unique ma);
        ma Fargo same ID=Fargo ma(ma logical same ID Fargo==1,:);
        Fargo ma size=size(ma Fargo same ID);
         %Compare Fargo to Finley data
ma logical same ID Finley=ismember(Finley ma(:,2), Fargo unique ma);
        ma Finley same ID=Finley ma(ma logical same ID Finley==1,:);
        Finley ma size=size(ma Finley same ID);
         %Check for overlap at same time instance => transponder failure
         ma_overlap_summary=[];
        for aa=1:Findey ma size(1)
             for bb=1: Fargo ma size(1)
                  if ma_Finley_same_ID(aa,2)==ma_Fargo_same_ID(bb,2)
                      if (abs(ma_Finley_same_ID(aa,4)-
ma Fargo same ID(bb, 4)))<17
                          ma overlap summary=[ma_overlap_summary;
ma Fargo same ID(bb, :),0000000000000000000, ma Finley same ID(aa, :)];
end and the control of the control o
                  end
              end
         end
         %Summary of results for multiple aircraft
        instances transponder ma=size(ma overlap summary);
        instances transponder ma=instances transponder ma(1);
%transponder failure instances
        if length(ma overlap summary) >=1
planes transponder ma=length(unique(ma_overlap_summary(:,2))); \frac{1}{2} mumber
of planes with transponder failures
         else
            planes transponder ma=0;
         end
planes Finley radar ma=length (unique (ma_Finley_same_ID(:,2))); %number
of planes with radar failures at Finley
planes Fargo radar ma=length(unique(ma Fargo same ID(:,2))); %number of
planes with radar failures at Fargo
        percentage radar ma=((planes Finley radar ma(1)-
planes transponder ma(1))/planes Finley radar ma(1)); &percentage of
radar failures 
percentage_transponder_ma=((planes_transponder_ma(1))/planes_Finley_rad
ar ma(1)); %percentage of transponder failures
```

```
 end
else
    instances transponder ma=0;
    planes_transponder_ma=0;
    planes Finley radar ma=0;
    planes Fargo radar ma=0;
    percentage radar m\bar{a}=0;
    percentage_transponder_ma=0;
end
 %% Store all data
 counter=counter+1;
 all data overlap=[all data overlap; planes Finley radar do,
planes Fargo radar do, planes transponder do, instances transponder do,
percentage radar do, percentage transponder do,
planes Finley radar out, planes Fargo radar out,
planes_transponder_out, instances_transponder_out, 
percentage radar out, percentage transponder out,
planes Finley radar paf, planes Fargo radar paf,
planes transponder paf, instances transponder paf,
percentage radar paf, percentage transponder paf,
planes Finley radar rd, planes Fargo radar rd, planes transponder rd,
instances transponder rd, percentage radar rd,
percentage transponder rd, planes Finley radar ma,
planes Fargo radar ma, planes transponder ma, instances transponder ma,
percentage radar ma, percentage transponder ma];
 if counter==28
      xlswrite('Overlapping Analysis.xlsx', all_data_overlap)
 end
 %% Save .mat file
 matFileDir= 'C:\Users\nicholas.allen\OneDrive - North Dakota 
University System\UAS Research\Radar Analysis\Overlapping Mat Files\';
 save([matFileDir, Date, '.mat'])
 disp('done data write')
     end
end
```

```
116
```
APPENDIX C: RADAR DATA ANOMALIES SUMMARY

Aircraft Count/Location Summary

Drop Outs

Altitude Outliers

Multiple Aircraft & Repeated Data

APPENDIX D: OVERLAPPING ANALYSIS RESULTS

Drop Outs

Altitude Outliers

APPENDIX E: CLIMATE EFFECTS SUMMARY

Fargo

Finley

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