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Using Local Weather Sensors to Improve Airfield Scheduling

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Abstract: Flying operations are significantly affected by weather. The 94th Flying Training Squadron at the United States Air Force Academy currently estimates a 30% weather attrition rate for the year which creates sub-optimal class scheduling and flying operations for their glider aircraft programs. The Air Force Academy has an intensive weather sensor array, called the High Winds Alert System. We take four years of data from the High Winds Alert System's 13 sensors to create descriptive statistics for our client's use in improving scheduling glider classes throughout the year. Our descriptive statistics, combined with the 94th FTS' reported necessary sortie amounts, give us the framework for redoing their scheduling for each year. From our descriptive statistics, one important finding and recommendation is that the 94th Flying Training Squadron should decrease expected operations tempo from November to March, something they have not been taking into account when estimating weather attrition or when scheduling their classes throughout the year.

Keywords: Weather Attrition, Wind, Airfield Operations, Scheduling

1. Introduction

Many flying squarons experience the same issues of wasted time and resources due to ineffective weather predictions. Our client, the 94th Flying Training Squadron (FTS) at the United States Air Force Academy flies and trains in gliders, and has several programs ranging from providing a few flights for every student during their freshman year, to training a select few cadets to become qualified instructor pilots in the glider. The 94th FTS experiences consistent problems due to weather predictions issues. Each flying time slot is roughly 2 hours and no-fly statuses are often decided too late to prevent students from travelling to the airfield unnecessarily. Therefore, our client would like to add to their current weather prediction processes in order to minimize inefficient usage of time for their students and pilots while maintaining safe and efficient airfield operations. Additionally, each flying course is scheduled during specific months of the year that are considered to be the most flying-friendly, however there is no analysis to support the particular decisions for the chosen time-periods.

Our first objective is to provide summary statistics of historical data in order to allow the 94th FTS to better schedule their flying classes throughout the year. Our second objective is to analyze the High Wind Alert System (HWAS) data, provided by the USAFA 306 FTGOSS Weather Operations, in order to create predictions of wind conditions at the airfield. The HWAS is a network of sensors scattered around the airfield at the Air Force Academy, ranging from 1 km away to 12 km. These sensors take many different readings, such as wind data, temperature, humidity, and precipitation. Currently, the 94th FTS Operations Supervisor observes the HWAS data, receives macro-level model predictions from the weather squadron, and acts on their own instinct to make fly/no-fly decisions. We program our prediction methods to a convenient user interface designed to integrate with current processes. This allows the operations supervisors to make more informed decisions on determining the flying status for the next flying time slot.

1.1 Problem Statement

How can we use historical data and local weather sensors to improve airfield operations scheduling?

2. Related Work

In order to understand the difficulties and theory behind our research question, we have done research into existing literature involving weather at airports and predicting such weather based on historical data. Our first question is what weather trends are standard for each airfield in geographical regions similar to ours. As wind speed, and wind gusts in particular, are important to our research, we refer to an article by Tattelman (1975) which concludes that wind gustiness decreases with an increase in average wind speed. This is significant as the gust spread should be less of a factor as wind speed increases. We are also concerned with overall error in our predictions as the mountainous terrain, and find that wind predictions for takeoffs and landings (our primary concerns) generally have at least 10% error due to the inconsistencies with the gusts in such geographical conditions (Wieringa 1980). This sets a baseline for accuracy of our models, and will help in determining if the method we use is a reliable one. Due to the variability in mountainous terrains, we look at studies at Denver International Airport, and found that there is considerable difficulty in predicting short term. There is, however much correlation within seasons, meaning we should definitely factor in these seasonal trends (Rhodes 1992). This result is corroborated by Boldin and Wright (2015) when they conclude that seasonal trends are important in prediction, and outliers can and should be excluded from data.

The next phase of our literature review aids us in our future work in neural net weather predictions. It includes which models have had success in predicting weather trends using historical weather data. Our first article by McWilliams and Sprevak (1982), which uses the Weibull distribution, looks specifically at wind speed. However, the majority of our findings include an analysis of neural nets. To begin the process, we find a piece by Poli and Jones (1994) that describes using neural nets with time series data. The paper concludes that neural nets are very flexible, and having a sensor array where the exterior sensors start the time series and the sensors at the airfield end the time series is an efficient way to sort data. In order to maintain relevance to our project, we also searched for literature in which researchers attempted to predict weather, but in particular wind speed. After reviewing several articles on the subject, we find that neural nets have had great success in such matters. By using variables such as pressure, temperature, humidity, and rainfall, Sheela and Deepa (2013) were able to create a model that outperformed other models significantly. Maqsood, Khan, and Abraham (2004) concluded the same thing for an area around Saskatchewan, Canada. However, they build their own model by combining several different neural net models, and find they could predict with higher accuracy with this strategy. Finamore et al. (2015) conduct a similar study on an Italian wind farm and find that using a feed-forward neural net model with one hidden layer enables them to predict with a maximum error of 12.5%. Their error is an excellent value considering the unavoidable error of 10% from the study by Wieringa (1980). Finally, we searched for literature with a more specific description of an effective neural net and find that a good baseline for us might be a 5 hidden-layer network with 16 neurons per layer (Abhishek et al. 2012). Overall, this research shows that neural nets might be a good place to start, but we should not ignore other methods that have worked as well.

3. Methodology

Our objective is to provide summary statistics of historical data in order to allow the 94th FTS to better schedule their flying classes throughout the year. The High Wind Alert System, or HWAS, is a network of sensors scattered around the airfield at the Air Force Academy, ranging from 1 km away to 12 km. These sensors take many different readings, such as wind data, temperature, humidity, and temperature to name a few. The first step in our process is to clean and format the data to make it easy to use. Currently, our data has entries every two minutes from 2014 to present containing weather information from thirteen sensors in the local area around the airfield. The data, given to us in a csv format, is now loaded into a Python dataframe for manipulation. The rows in the dataframe are indexed by date and time, while the column labels reference the sensor and the weather reading, such as temperature at the airfield. The problem with the data is missing entries scattered throughout the dataset. In order to handle this problem, we delete all rows with missing data. We mitigate this potential by noting that the data set is extremely large, therefore losing the small amount of data from this method should not significantly affect the outcome. In order to determine the validity of removing the missing values, we also analyze the size of the null gaps in order to decide whether or not it is prudent to remove the nulls. We look for significant numbers of large gaps that would impact our model's accuracy.

Date_Time	Wind_Direct	Wind_Speec	Wind_Gust	max win	Air_Temperi	Relative_Hu	Barometric_	Precipitatio	Precipitatio	Windchill	hr	min	s	
11/16/17 0:00	210	14	0	14	39	30	30.1	0	0	31	0	0	0	12:00 AM
11/16/17 0:02	210	14	0	14	39	30	30.1	0	0	30	0	2	0	12:02 AM
11/16/17 0:04	210	13	19	19	39	30	30.1	0	0	30	0	4	0	12:04 AM
11/16/17 0:06	210	12	0	12	39	30	30.1	0	0	30	0	6	0	12:06 AM
11/16/17 0:08	210	14	0	14	38	30	30.1	0	0	30	0	8	0	12:08 AM
11/16/17 0:10	210	13	0	13	38	30	30.1	0	0	30	0	10	0	12:10 AM
11/16/17 0:12	200	12	19	19	39	30	30.1	0	0	30	0	12	0	12:12 AM
11/16/17 0:14	200	13	0	13	39	30	30.1	0	0	30	0	14	0	12:14 AM
11/16/17 0:16	200	13	0	13	39	29	30.1	0	0	30	0	16	0	12:16 AM
11/16/17 0:18	200	13	0	13	39	29	30.1	0	0	30	0	18	0	12:18 AM
11/16/17 0:20	200	14	0	14	39	29	30.11	0	0	30	0	20	0	12:20 AM
11/16/17 0:22	200	14	0	14	39	29	30.11	0	0	30	0	22	0	12:22 AM
11/16/17 0:24	200	14	0	14	39	29	30.11	0	0	30	0	24	0	12:24 AM
11/16/17 0:26	200	13	0	13	39	29	30.1	0	0	30	0	26	0	12:26 AM
11/16/17 0:28	210	13	0	13	39	30	30.1	0	0	30	0	28	0	12:28 AM
11/16/17 0:30	210	13	0	13	38	30	30.1	0	0	30	0	30	0	12:30 AM
11/16/17 0:32	210	13	0	13	38	30	30.1	0	0	29	0	32	0	12:32 AM

Figure 1. Data Format

Figure 1 above is a sample of the HWAS dataset. The first column is date and time and the rest of the columns indicate a specific sensor and a specific weather reading.

We add a column to the data that is a binary variable indicating whether the wind was within flyable limits or not based on wind speeds and directions in the preceding columns. We visualize the data by creating a time series graph of the daily average, by year, of the proportion of time the weather was within limits, shown in Figure 2

. This initially allows us to determine which time periods tend to have weather that is not flyable, and which time periods might be better for flying. We choose to incorporate seasonality since weather trends will definitely be different at different times of the year. We visualize in Figure 2 that for the vast majority of the year, the 94th FTS is not hitting their number of sorties scheduled.

4. Analysis and Results

As stated before, removing missing values is the first step in providing summary graphs. However, we must first determine the validity of removing entire rows of data and ensure that creating these gaps will not negatively affect our analysis. We remove all time stamps that contain missing data, and then load all of the remaining dates and times into Excel. This leaves approximately 930,000 observations. We then count the number of instances where there is a greater than 2 minute gap, and find there to be 4,392 gaps of this size. However, we also find that 99.9% of these gaps in data were less than 10 minutes, showing that the removal of the missing entries will not adversely affect the creation of summary graphs.

Armed with a clean dataset, an analysis of the weather is possible. However, it is necessary to determine what weather is permissible for flying and record in the data this information. For this, we write a function with arguments of wind speed, wind direction, and wind gust speed, and an output of whether the winds were in limits or not. We then average the result of this function for each time stamp over three years in order to get a more representative value for each time period. Finally, we determine the percentage of time each day that there was a fly status. With this new data, we are able to create graphs summarizing a year at USAFA airfield. As shown below, we create two graphs, one with a broader view with each data point consisting of a monthly average and one with a data point for each day of the year. The results of these graphs show that when just considering winds, we are expected to fly less during the months of November to April, while obtaining a positive fly status much more often during the summer and fall months.

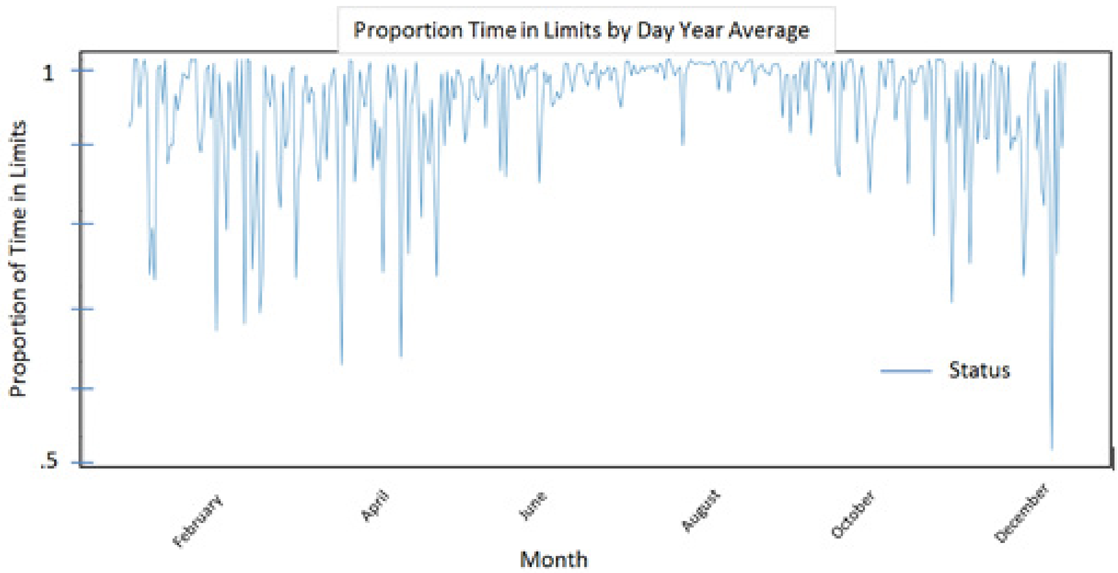

Figure 2. Daily Average Proportion of Time Within Flying Limits

Figure 2 shows a three-year average of the proportion of time by day that they have a positive fly status. This graph shows similar information as Figure 3, but in a more specific manner. However, this level of specificity includes outliers and can be difficult to interpret in general, so the monthly graph is a much more useful visualization of the summary statistics.

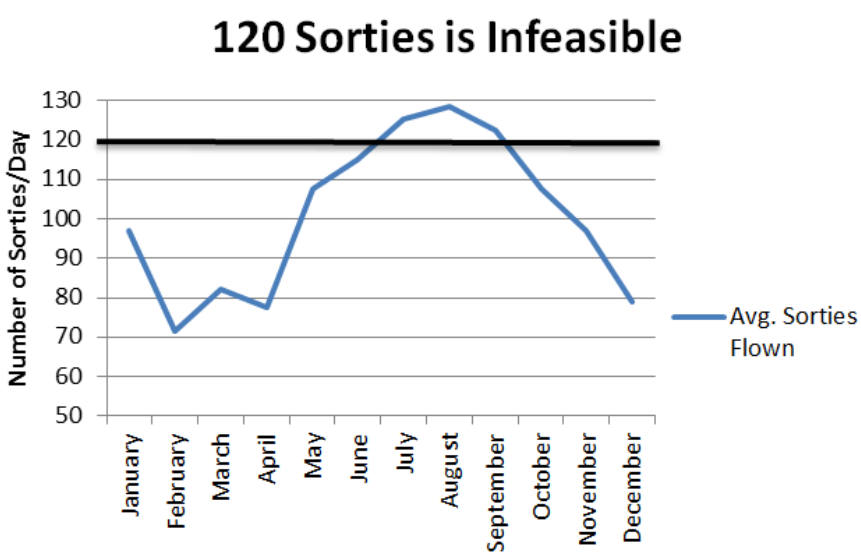

Figure 3. Average Number of Sorties Flown

In Figure 3, we took the average proportion of time in limits and converted it to number of sorties flown. The data of number of sorties flown is not available, but we do know that optimally 15 sorties can be flown per hour. Therefore, we created a formula that converted the proportion of time into hours, converted that into number of sorties then subtracted 20. The 20 is an estimate of sorties that could not be flown due to other factors like maintenance issues or other weather conditions. We came

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up with this value through discussion with the 94th FTS commander and instructor pilots in the program, therefore it can be assumed to be a realistic estimate.

Our client can use Figure 3 to explain to their supervisors the need for more travel opportunities in order to complete necessary sorties in more weather-restricted months. We are given a required number of sorties to be completed each year which is 15,320. We are able to articulate the infeasibility of the current scheduling method that calls for 120 sorties a day. This graph is used to edit the expected number of sorties which, as of now, is the same for every day no matter what season or month. Using this information, we create a new goal for each month's duty days.

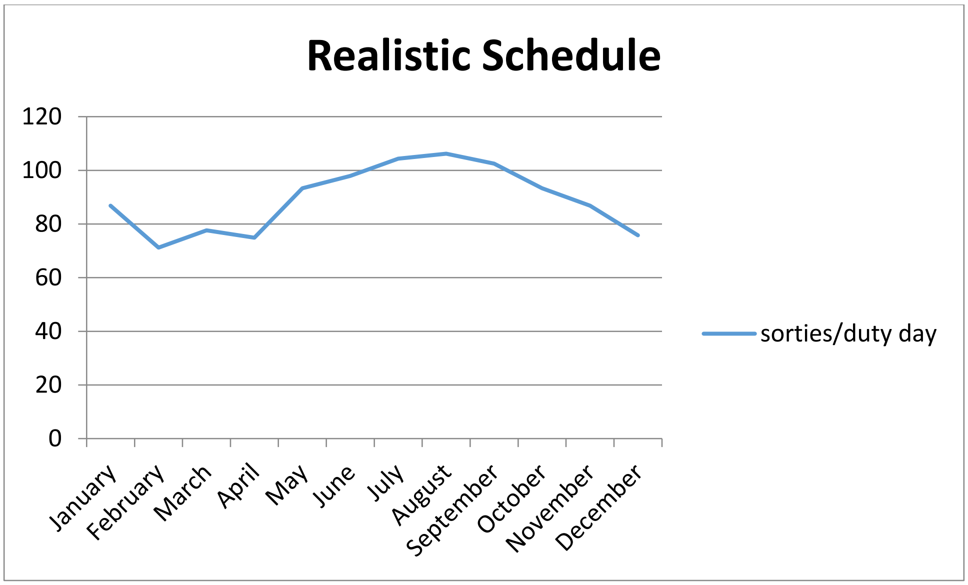

Figure 4. Realistic schedule of number of sorties scheduled per day in each month

Above, we have created a new schedule of the number of sorties scheduled per month that will still give us the necessary goal of 15,320 sorties per year. To create this, we first take the proportion of time in limits in a given month and multiply by the number of duty days in that month. This gives us the total time per month that the 94th FTS is operating in good conditions. We then take the necessary number of sorties, 15,320, and divide it by the total time in good conditions. We take that number and multiply it by each individual month's time in limits in order to distribute the number of sorties per day in each month in accordance with the seasonal weather trends. We then add 15 sorties to each month's daily scheduled amount in order to allow for getting more work done when possible and allow for other issues to happen without detracting from hitting the 15,320 sortie goal. This new schedule will accomplish the mission in a much more effective and realistic way.

5. Conclusion

The 94th Flying Training squadron at the United States Air Force Academy has been scheduling their airfield operations in an ineffective and unrealistic way. They have been scheduling 120 sorties per day for every day throughout the year despite seasonal weather trends. We analyzed three years of wind data taken every two minutes from USAFA's High Winds Alert System Data in order to improve their scheduling. We compiled the data and created a new variable that indicates whether or not the weather is within limits or not at the specific time stamp. We used that variable to find monthly averages of the proportion of time that the weather was within flying limits. We then converted that into number of sorties actually able to be flown on average in each month. This showed us that the goal of 120 per day was not being met nine months out of the year. We then were able to use the necessary amount of sorties, number of duty days in each month, and proportion of time in limits per month to create a new schedule for the 94th FTS. This will optimize their time usage, enable them to schedule students more effectively in each class throughout the year, and enable them to decide when they should be going out of town to complete their mission elsewhere in order to get the greatest amount of sorties they can in more weather-restricted months.

6. Future Work

Although summary statistics are useful to the 94th FTS, another prediction method will also help them make flying decisions. Given the current HWAS data, a machine learning algorithm, such as a neural net, could be used to help better predict the winds. If the operational supervisors could have access to such an algorithm, they could have another tool to determine if they should keep the status on standby, or cancel all together.

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