Undergraduate Journal
of Service Learning & Community-Based Research

Preparation for Industrial Careers in Mathematics: Analysis of Newport News Fire Department

Kali White, Ashley Christenbury, Jonathon Pilsch, Daniel Sims

Christopher Newport University

Reflection

Over the past two semesters, our group of student researchers has worked closely with the Newport News Fire Department in helping to analyze a large set of structure fire data to solve some questions for the department. Our liaison, Assistant Fire Chief Wesley Rogers, stressed that the following topics were of the utmost importance: characterizing the efficiency and effectiveness of the fire department within the city as well as in individual districts, determining a way to streamline the process of analyzing and compiling the data, examining how response times were affected by the addition of Tech Center in Newport News, and lastly predicting how new developments may impact the response times for the fire department.

Through our experience with working alongside the fire department, we were able to realize the importance of the work that we were completing. In preparation for analyzing the structure fire data that was received from the fire department, we conducted a sizable amount of preliminary research to gather a better understanding of factors relevant to safely fighting fires. For example, we learned that flashover is a term used to describe the period of time when a fire becomes too dangerous for any person to enter a building due to the temperature of said building reaching a point where the air is literally on fire. The data given to us was stratified into several categories such as process time, turnout time, travel ERF time and response ERF time for vehicles on their way to structure fires. The two main categories that we fixated on for our analysis were the travel ERF and response ERF time. By analyzing the average response ERF, the time it takes for an effective response force to arrive at the scene of the fire, for all stations of the Newport News Fire Department from the years 2013-2018, we were able to see just how fast the essential personnel were arriving at the fire. The time that flashover occurs for newer construction is anywhere from 6-10 minutes. The conclusions we drew were very important in helping the fire department see its overall performance and how to find ways to get on the scene faster and better help the Newport News community.

This unique course allowed us to improve our teamwork skills significantly. For this project, we had to communicate within the group every step of the way. During some parts, we would divide up the work individually, though oftentimes we were working in pairs. We soon realized that this is very helpful; for instance, if you get stuck on a problem you can always bounce ideas off of each other to find a solution. Also, if you are unsure of something, it helps to have a second opinion and at the very least, it helps to check over each other’s work to make sure there are no errors. The majority of the calculations were performed for each fire station. Since there are eleven fire stations in

Newport News, it was helpful to divide the work amongst the group. The best part about working in a group is the variety of skill sets. While the majority of us are mathematics majors, we still have different areas we are most proficient in. For example, one of our group members is more knowledgeable than the rest of the group in using "LaTeX", a mathematical document editor required for writing up our results. Therefore, we relied on her for the main formatting of our final paper. Also, one member of our group is a computer science major. Although for a majority of the research project, he was working on his own, he still played an essential part in the overall success of our project. Furthermore, he had taken a very different group of classes than the rest of us allowing for a different thought process when approaching a problem.

Another important lesson this experience taught us was about the importance of failing. For example, sometimes we spent several weeks on a project just to later find a much quicker and easier way to accomplish that same task in an hour. Other times we would do a few calculations to back up one of our main hypotheses only to find that our research actually disproved the point we were hoping to make. We spent a lot of time making graphs and doing linear regressions to compare different parts of our data only to discover that the correlation between these data categories was minimal and at times even zero. While these things were frustrating, we learned from them; it was a lesson that things are not always going to go how we want them to and they are not always going to have a nice or even worthwhile answer. Figuring out how to deal with these setbacks is a skill we are going to need in our future careers and in life. We are grateful for this project because it taught us first-hand how to overcome the plethora of challenges that you must work through to achieve your end goals.

This experience started out as a research-based class in the spring semester of 2019. However, our group decided to continue our research as an independent study in the fall semester of 2019. This experience has been unlike any other. Throughout college, students typically find themselves enrolled in either lecture or lab-based classes. For mathematics majors, we spend a good deal of time learning a variety of theorems, formulas, and proofs. A computer science major is likewise lectured on data structures, algorithms, and critical thinking. However, we do not often have the opportunity to see how the things we are learning can be applied to the real world.

When first signing up for this course, we had no idea what to expect. Our professor, Dr. Kelly, divided us into groups and gave each group a project proposal from a variety of community partners, and we were assigned the Newport News Fire Department. She was there to guide us along the way, and if we got stuck, she could provide us with more ideas for mathematical methods that could help solve our problem. She was also a powerful resource at our disposal when it came to explaining new mathematical methods or helping to find mistakes if our results were not making sense. However, our group took the initiative for the direction of our analysis and research and only relied on Dr. Kelly when we were really stuck on a problem.

This new experience of a completely self-driven research project opened our eyes to what higher-level research is in the industry. One thing we have been trying to figure out is how to apply our math majors to future careers outside the classical path of the classroom. By taking part in this research, we had the chance to see how the things we have learned throughout our college courses can be applied in a way that can be useful to a company or in this case, the fire department. We also learned things that were not taught in other classes. This course gave us a unique approach to learning things in a work environment as opposed to a classroom setting. We got a glimpse of how the things we have been taught can help us with things that are not exactly an in-class example. While some of the material we have learned in our classes was not used directly, these classes still have shaped the way that we think and provided background knowledge to logically approach the questions that were asked of us. By combining our skills, our group was able to take a variety of data and find the big picture of it all. We translated it into a story that the fire department could understand. This combination of using previous knowledge and learning new capabilities helped create some clarity on what work after college could look like.

Recently, our group got a chance to talk to some of the firefighters that work in Newport News. It was very interesting to finally see how the things we had been working on related to everyday operations for the firefighters. It also gave us a better understanding of the meaning of some of our data and how things really work. For example, when doing our research, we found that response times are higher during the midnight hour. While at the fire station, they explained the protocol for when they get a call during the middle of the night. It involves a process of lights and alarms that are meant to gradually wake them up. Since this process is not necessary during the day, it provides an explanation for this increase in response times. Making these connections between the data and the real-life processes was very insightful for our group. It helped us to be more fully aware of the things we were calculating and how much of an impact it has made. Also, when communicating with the chief of the Newport News Fire Department, we were told that the work performed in calculating the 90th percentiles for ERF data and our calculations for the new station 12 location were used in a meeting with the city manager’s office. This was quite exciting to hear, and it showed us that the work we had done was worthwhile.

Overall, this was an experience that we are very grateful for. It helped us see that what we have learned from our majors can help companies and also be something that we enjoy doing. It provided insight into math in the real world. Most importantly, it taught us a lot, not only about ourselves but also about our future career paths by teaching us many skills we will need later in life that you cannot learn in a typical classroom setting. An experience like this is something we would definitely recommend, not only because it is a great thing to put on a resumé, but also because it is a rewarding and eye-opening experience that allows for an abundance of personal and professional growth.

PIC Math Final Paper

Community Partner: Newport News Fire Department

Fire Department Group A - Structure Fires

Kali White, Ashley Christenbury, Jonathan Pilsch, Daniel Sims

Spring and Fall 2019

Contents

1 Project Proposal **37**

2 Significance of Project **37**

3 Research **38**

4 Data **38**

5 Methods **40**

5.1 Use of Descriptive Summary for the Data Analysis 40

5.1.1 90th Percentiles 40

5.1.2 Removing of Outliers 41

5.1.3 95% Confidence Intervals 41

5.1.4 Linear Regressions 41

5.2 Automation Process 42

6 Results **42**

6.1 Sample Percentiles 42

6.2 Linear Regressions 45

6.3 Time of Day 46

7 Conclusions **48**

7.1 Tech Center Effect 48

7.2 Addition of Countdown Clocks 49

7.3 New Station Location 49

7.4 Fire Department Overall Efficiency 54

8 Future Research **54**

9 Acknowledgements **55**

10 References **55**

11 Appendix A **56**

12 Appendix B **69**

12.1 Methods 69

12.1.1 90th Percentile 69

12.1.2 Point-in-Polygon 70

12.2 Computer Code 71

1 Project Proposal

The Newport News Fire Department is 1 of 30 departments in the nation to be both accredited and designated as ISO Class 1. ISO Class 1 is a categorization given by the Insurance Services Office, which evaluates risk in many different areas. The Class 1 certification means that Newport News is a very low risk for insurance agencies due to their extreme efficiency in responding to the various emergencies that arise in the Newport News area. This ISO Class 1 categorization was achieved due to the department's attention to detail and constant efforts to improve their shortcomings.

In efforts to improve their overall efficiency, Chief Rogers, our community liaison with the Newport News Fire Department, challenged us to help his staff find more efficient ways to analyze the data regarding their response times to structure fires around the city. Through our partnership with the fire department our group was tasked with analyzing structure fire data from 2013-2018 in order to find relationships between fire response times and community factors. In particular, our goal was to characterize the efficiency and effectiveness of the Newport News Fire Department as a whole as well as the individual districts or stations; automate the process of compiling and analyzing the data to help the fire department perform calculations more quickly; and analyze how the development of Tech Center has affected response times as well as how new developments in Newport News will potentially impact the Newport News Fire Department.

2 Significance of Project

One of the major factors that plays into how quickly and effectively the firefighters are able to do their job is a phenomenon called flashover. Flashover is the term for the temperature point at which the heat in an area is high enough to ignite all flammable material simultaneously. One of the main factors contributing to how long it takes for a fire to reach its flashover point is the building materials with which the structure was built. In the past 30 years, the average time to reach flashover for a building has decreased from 10-20 minutes to 6-8 minutes. This change corresponds with the shift from using 2x6 inch wooden beams in older buildings to using 2x4 inch wood beams for modern construction, which burn much faster. Another factor that has caused a decrease in the time to reach flashover in newer buildings is the increased use of plastic compounds in household items. During a fire, newer synthetic building materials and plastics burn much more quickly than wood. Newer materials also quickly absorb all of the oxygen in the house causing a huge pressure difference which makes windows explode, further decreasing the time before a fire reaches its flashover point. Due to these changes in construction materials, the Newport News Fire Department is constantly searching for ways to decrease their response times due to the ever-closing window of opportunity once offered by the thicker building materials.

3 Research

Preliminary research on the city of Newport News and on fire departments in general was performed in order to give us a better framework from which to approach the problems our group was tasked with investigating. After investigating flashover, our research expanded into various topics including population density, neighborhood boundaries, and traffic patterns. This research allowed us to get a better idea of which times of day had the most traffic per road. Additionally, research was performed to better understand the fire department accreditation process.

During the researching process, we learned that Tech Center was built in 2016. In hopes of determining the effect Tech Center had on fire response times, we split our original data set, which contained data from 2013-2018, into two groups—pre-2016 and post-2016—so that we could better analyze the changes observed before and after Tech Center's construction.

4 Data

The data provided gave the process, travel, and response times for each fire call. After receiving the data it was necessary to understand these categorizations. Process stands for the amount of time taken by the 911 dispatcher to gather the information and give that information to the individual stations. Travel stands for the time for the first unit to drive to the fire. Travel ERF (Effective Response Force) stands for the time that it takes all units in the ERF to drive from the station to the fire. Response stands for the total time taken to arrive at the scene. Response can be broken into first unit response and Response ERF, which are composed of the process, turnout, and travel times, for the first unit and total ERF respectively. Figure 1 shows how all of the different categories of data were sorted throughout all of the spreadsheets that were used to complete this research.

	A	B	C	D	E	F	G	H	I	J	K	L
1	Incident #	DateTime	Time	Type	Location	Station	Process	Turnout	Travel (1st Unit)	Travel (ERF)	Response (1st Unit)	Response
55	F20131220025	12/20/2013	8:39:54	SRES		3	0:27:00	1:19:00	0:10:00	9:25:00	1:36:00	11:11:(
56	F20130219016	2/19/2013	8:52:52	SRES		9	0:18:00	1:00:00	3:07:00	8:12:00	4:25:00	9:30:0
57	F20130303020	3/3/2013	9:06:44	SCOM		1	0:33:00	0:52:00	4:05:00	7:30:00	5:30:00	8:55:0
58	F20130410025	4/10/2013	9:08:08	SAPT		11	0:08:00	0:20:00	5:37:00	12:13:00	6:05:00	12:41:(

Figure 1: Sample of spreadsheet data

Once received, the data was filtered to remove incomplete data entries. Although the removal of incomplete entries may have some implications on the mathematical analysis, we felt that for our initial analysis, that this was appropriate. Without all the data columns filled in, some calculations would not be possible, and the others would not be as informative. All structure fires that did not have a Response ERF were discarded. Any structure fire data without a Response ERF was either a false alarm or a small enough cooking fire able to be handled by a single firefighter. The data was then reorganized based on various categories that were more convenient for performing mathematical calculations upon. Data was sorted by type of structure fire (i.e. apartment, commercial, residential, trailer, etc.), for each year, and by station number 1-11. By stratifying our data in a variety of ways, we were able to approach the data from a variety of perspectives in an attempt to get the most accurate representation of that data set. Once the statistical tests were decided upon, we were able to go directly to the file that was needed rather than sorting through all of the data at once, which was a very efficient use of time.

To better understand and analyze the data, all of the structure fire data was imported into Google Maps to create a visual representation of the fire distribution. This process took longer than anticipated because there was no easy way to import large data sets into the Google Maps Application Programming Interface or

API without creating an additional program solely for inputting longitude and latitude points into Google Maps. Due to this issue individual addresses had to be entered manually, which was very time consuming. However, this process helped us to be able to visualize our data in many ways. The fires were mapped in regards to individual station as well as a layer on the overall Google Maps for each individual year. The fires were color coded by neighborhood or remote location in order to allow us to see which areas are more prone to fires. This allowed us to step back and look at the distribution and see which stations are covering a larger volume of fires in a larger range. The observations from this process were used to suggest a new station location. This is discussed more in Section 7.3.

5 Methods

5.1 Use of Descriptive Summary for the Data Analysis

5.1.1 90th Percentiles

The measurement of 90th percentiles for response ERF and turnout times are a few of the main metrics used by the fire department for analyzing the data. Compared to the average, the 90th percentile better accounts for outliers. Calculating the 90th percentile means determining the value that 90 percent of the times fall under. For example, if the 90th percentile is 10 minutes, this indicates that in 90 percent of emergencies, the fire department responds within 10 minutes. The percentile command in Excel was used to calculate the 90th percentile for response ERF time and turnout time of each station for each year from 2013-2018. The 90th percentile response ERF and turnout times for all stations from 2013-2017 were also calculated as a whole and compared to the 90th percentile of 2018 for each station in order to see if there was an improvement. Furthermore, the 90th percentile of each station before and after 2016 was also calculated. The 90th percentiles were calculated before and after removing outliers which will be discussed in the next section. The findings will be discussed in Section 5.1.1.

5.1.2 Removing of Outliers

Although the incomplete data entries had been removed in the initial sorting, suspected outliers were still present. An observation is suspected to be an outlier/extreme value observation if it is either > $Q3+1.5*IQR$ or < $Q1-1.5*IQR$. IQR stands for the Interquartile Range and this value is found by subtracting the third quartile by the first quartile (Q3-Q1). The third quartile represents the 75th percentile and the first quartile represents the 25th percentile. By removing these suspected outliers, the calculations and graphs were made more accurate and representative of the data. This process was aided by Excel. There is a function in Excel that will calculate the first quartile and the third quartile values that were used in the calculations. These results will also be discussed in section 5.1.2.

5.1.3 95% Confidence Intervals

Additionally, confidence intervals were calculated to approximate where the average response ERF time in general. This is a highly trusted result; however, this approximate will not be as accurate the farther we move into the future because both the fire department and the city infrastructure will have more changes. Confidence intervals were calculated with a level of significance of $\alpha = 0.05$. An $\alpha = 0.05$ indicates there is a 5% chance that the mean response ERF will fall outside of the calculated interval, allowing us to project the range of times with 95% confidence. In order to calculate this interval we used the following formula to calculate the margin of error:

$$E = z\frac{s}{\sqrt{n}}.$$

To find the 95% confidence interval, we use the mean of our sample $\bar{x}$ and E to calculate $(\bar{x} - E, \bar{x} + E)$.

5.1.4 Linear Regressions

Linear regressions were used to find correlation between different categories within the data. After eliminating outliers in our specific categories, Excel was used to graph the data and find a linear regression. An important component of linear regression is the R^2 value. This value tells us how correlated the data is. The closer the value is to 1 the more correlated.

The following independent and dependent variables are compared using linear regressions in Section 6.2.

x (independent variable)	y (dependent variable)
Process Time	Turnout Time
First Unit Travel Time	Total Response Time
First Unit Travel Time	ERF Travel Time
Turnout Time	Response ERF Time

Figure 2: x and y Variables for Linear Regression

5.2 Automation Process

After calculating the 90th percentile response ERF times for every station from 2013-2018, efforts were made to efficiently automate the 90th percentile calculation process. To automate the process, a User Defined Function (UDF) in Visual Basic for Applications (VBA), the programming language used for creating custom functions and macros in Excel, was used. VBA was used as opposed to another programming language to maximize ease of access of the automation script. The fire department would not need to install any other programs, beyond Excel. Knowing the Fire Department's CAD system can output data in a variety of forms, one of which is Excel, we designed a UDF that will work after being copied into any Excel spreadsheet outputted by the CAD system. See Section 12 for details on automation code and process.

6 Results

6.1 Sample Percentiles

Overall, removing the suspected outliers before running our calculations reduced the 90th percentile of the response ERF times by approximately 9.8%. Removing outliers had a substantial impact on the 90th percentile for the response ERF times for Station 9 before 2016 and for Station 4 after 2016, reducing their response ERF times by 26.3% and 21% respectively. These two stations in particular demonstrate the impact of outliers and how taking the time to remove them from your data set can give you a more representative 90th percentile. For all stations from 2013 to 2018, the 90th Percentile for response ERF time was 13 minutes and 5 seconds with outliers and 11 minutes and 48 seconds without outliers.

After performing the 90th percentile calculations before and after 2016 we noticed that the response ERF times were reduced by 8.7% overall. Furthermore, Station 6's response ERF times were reduced by 20.2%. However, Station 4's response ERF times increased by 5.6% and Station 7's response ERF times increased by 14.8%. In further investigation, we found that the travel ERF times for Station 6 were reduced by 21.5%, but the travel ERF times for Station 7 increased by 30.2% after 2016. Refer to Figures 3,4,5 which highlight Stations 4, 6, and 7. In these stations, we saw the biggest increase or decrease in the response ERF 90th percentile for before and after 2016.

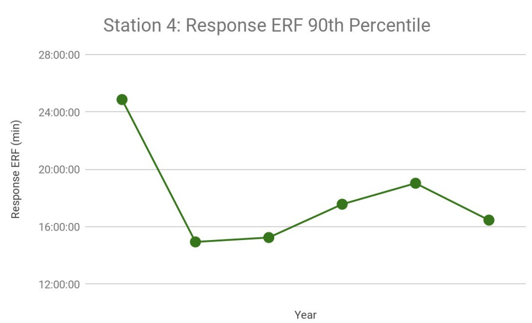

Figure 3: Station 4 (2013-2018)

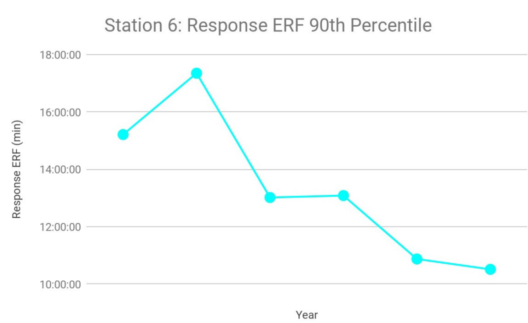

Figure 4: Station 6 (2013-2018)

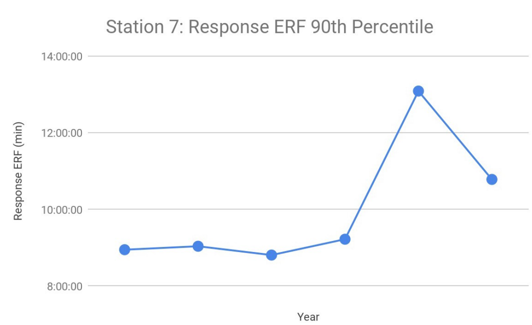

Figure 5: Station 7 (2013-2018)

For an interval with 95% confidence, we needed to use the corresponding z-score, which is 1.96. The sample size of all of the structure fires from 2013-2018 was 1483, which was our n value. We then found that the sample standard deviation was $s = 289$ seconds, thus creating our equation:

$$E = \frac{z \cdot s}{\sqrt{n}} = \frac{1.96 \cdot 289}{\sqrt{1483}}$$

The error value obtained from the equation above was used to create our range of $(\bar{x} - E, \bar{x} + E)$, with $\bar{x}$ being the average response ERF time for the sample. Having a strong idea of where the range will fall can help the individual fire stations adjust to the changing development of the city of Newport News and since our sample was large, the range of our interval was small. See Figure 6 for the confidence intervals of each station.

Station	Range (min)
1	(9:16, 11:94)
2	(8:48, 9:52)
3	(8:02, 8:36)
4	(14:67, 19:83)
5	(12:02, 14:04)
6	(8:55, 10:03)
7	(9:49, 13:11)
8	(8:05, 8:57)
9	(9:28, 10:48)
10	(8:55, 10:53)
11	(9:30, 10:36)

Figure 6: 95% confidence intervals for each station

We can expect the mean of future ERF times to fall within these ranges. Some of the ranges calculated are wider and higher than others. This data can be used as motivation and be set as a goal to beat and show that the changes being made in the fire department are actually improving the response times.

6.2 Linear Regressions

First, we compared process times and turnout times, which showed that there was little or no linear correlation. Next, we tried comparing first unit travel times and total response times. This showed that there was little or no linear correlation between these categories. Furthermore, we compared first unit travel times with ERF travel times. These times also showed very minimal linear correlation. However, we found this interesting because we anticipated to find a decently strong linear regression between these two categories. We believed there would be a strong linear correlation between these because when a car sees one fire truck, they will already be prepared for another and pull over faster. However, Chief Rogers told us that was not the case. Often fire trucks will be needed from different stations, and, as a result, will take different routes to the fire causing the difference between travel times. Another cause for different first unit travel time and ERF travel time is simply that lights and traffic will change causing a different situation for the later trucks than the first truck.

Lastly, we looked into the linear comparison of turnout times and Response ERF times. Finding a strong linear correlation between these categories would have been ideal because turnout times is the only category that the firefighters have decent control over. Unfortunately, these categories also had little linear correlation. This weak linear correlation comes from the amount of variables that go into getting the entire ERF to a fire. Because there are so many things that can change it is hard for such a small amount of time to have a large impact on the overall time for responding to a fire.

Our findings for linear regressions were a bit surprising. The R^2 values for the comparison of first unit travel times and ERF travel time for each year are shown in the table of Figure 7.

We also anticipated a stronger linear relationship between turnout and response ERF. This relationship between turnout times and response ERF times would be the most useful to the fire department. Contrary to the initial intuition, the low linear correlation likely comes from the fact that travel times are so unpredictable. Since the turnout times tend to be small in comparison to these unpredictable travel times, turnout times do not have a big correlation on response ERF times. The following table in Figure 9 displays the R^2 values for the correlation between turnout times and response ERF times.

Year	R^2 Value
2013	.199
2014	.068
2015	.109
2016	.114
2017	.078
2018	.053

Figure 7: R^2 Comparison for first unit travel times and ERF travel time

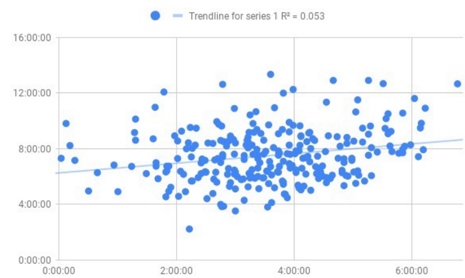

Figure 8: Linear Regression of 1st Unit Travel vs. ERF Travel Times for 2018

Year	R^2 Value
2013	0
2014	.001
2015	0
2016	.005
2017	.001
2018	.053

Figure 9: R^2 Comparison for turnout times and response ERF times

Overall, the linear regression analysis indicates that a linear fit does not describe our data. There are numerous confounding variables as travel times are so unpredictable and rely on many outside factors.

6.3 Time of Day

One additional way that the data was stratified was by time of day. Two types of graphs were made for every station to represent the call volume. One graph for each station was done by splitting the day into four six-hour periods and counting up the number of calls during each. The other type of graph shows how many calls were received within each hour of the day. These graphs help to display what times of the day have a higher call volume. Two graphs were also made in a similar format that represent all the data as a whole instead of being separated by station. These graphs concluded that the number of calls tends to go up later in the day, this can be seen in Figure 10. More specifically, the busiest hour of the day is between six and seven in the evening.

These conclusions led to another question: How does the response ERF time vary during different times of day? To be able to visualize this, more graphs were made. The x-axis was the time of the day and the y-axis was the average response ERF time. This was done for each station. There tends to be a peak in average response ERF time early in the morning. There is also usually a peak a little before noon. In order to compare the busy times of the day with the larger response times, the two graphs were overlaid. In order to do this, the graphs needed to have the same x-axis. To make the x-axis the same, the average response ERF time was calculated for each hour of the day and placed the data into the graph. Using this, conclusions were drawn which showed that although some of the peaks in response ERF times were during peaks in call volume, some of the peaks in response ERF times were during areas of low call volume. After further investigation, this is most likely because the firefighters are not expecting a call during that time of day, they could be sleeping or preparing a meal, or because they may schedule less firefighters during these times knowing that they are not likely to get a high volume of calls.

At the beginning of the research, a few hypotheses were created. The average response ERF during rush hour, both in the morning and in the evening, was expected to be higher than other times of the day. However, after analyzing the graphs, this information displays that there was not a significant increase in average response ERF time at these specific time periods. One key observation was that the average response ERF times tend to be highest around midnight. This may be due to the short staffing and additional preparations needed when waking up to a call. For example, in Figure 11 it is observed that Station 3's highest peaks in average response ERF were around midnight and two in the morning. In Appendix A, one can observe that this trend is relatively consistent through each station.

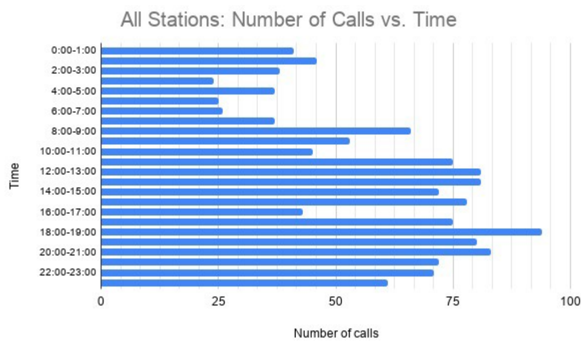

Figure 10: All Stations: Number of Calls vs. Time (per hour)

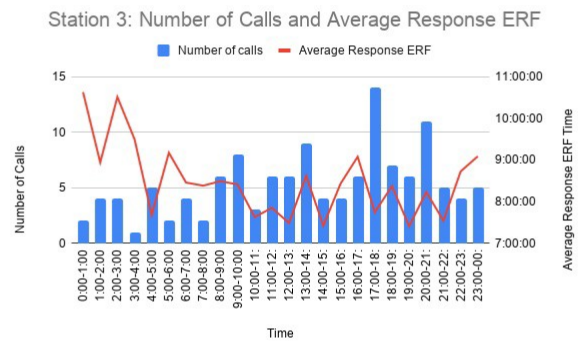

Figure 11: Station 3: Number of Calls and Average Response ERF vs. Time

7 Conclusions

7.1 Tech Center Effect

One focus was the effects that Tech Center had on fire response times. The development was finished in 2016, so we decided to calculate the 90th percentile of response ERF times from before and after 2016. This was decided in order to see the impact that Tech Center and other new developments have had on the response times throughout the city. Our data analysis led us to believe that there was almost no impact on Station 6, where Tech Center is located, the analysis showed that the response time was actually 20.2% faster after 2016.

Although there was not a negative impact on Station 6, there appeared to be a ripple effect into the surrounding stations who experienced a slight bump in their total response times. For example, Station 4 experienced 5.6% higher times after 2016, and Station 7 had a 14.8% increase after 2016. Although the increase in response times happened at the same time as the Tech Center development, the increase in Station 4's district could also be attributed to the construction on Interstate 64. This construction began in November 2015 and continued through 2018. This construction posed a big problem for the affected stations because it was more difficult to maneuver through the heavy traffic associated with I-64. This construction rather than the Tech Center development could have contributed to the changes in response times during

2016-2018.

7.2 Addition of Countdown Clocks

In 2016, countdown clocks were added to each station in hopes of reducing turnout times. The question to be answered was: were the clocks were successful in lowering turnout times? In order to analyze how the clocks impacted the turnout times, the 90th percentile of turnout times was calculated before and after 2016. Overall, the times were reduced by 10.5% after countdown clocks were added. Furthermore, the biggest change in turnout times in Station 9, whose times were reduced by 29.7%.

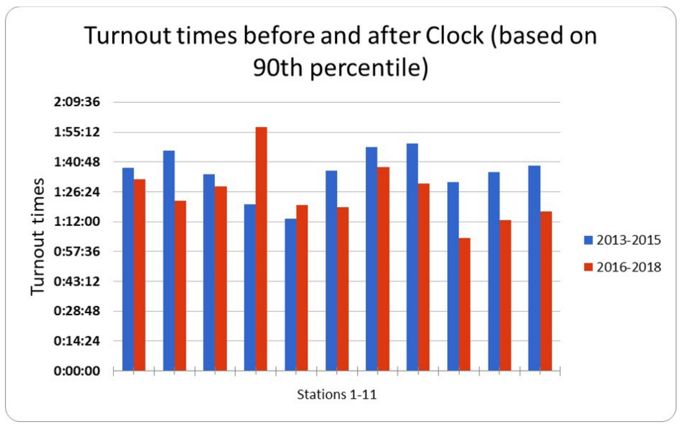

Figure 12: 90th Percentiles Before and After

Countdown Clock Addition

7.3 New Station Location

Although it was not initially part of the project proposal, it was determined that finding potential new locations would be beneficial for the fire department. After carefully mapping out each district the number of fires each district had during 2018 was analyzed, with the goal of reducing the load on Stations 2, 8, and 9. The idea was to try to level out the number of fires that occurred in each district, since Stations 2, 8, and 9 had much higher volume and higher response ERF times than the other eight stations. After analyzing the map it was determined that the most useful places to put a new station would be between Stations 2 and 7, this new station would stretch between 27th Street to 48th Street and from the train tracks to the edge of the city. By placing this station here, based off of the 2018 data, the new station would take 15 fires from Station 2 and 4 from Station 7, which is about 35% of Station 2's calls and 15% of Station 7's calls. The other new station would be placed near Station 9, taking over the area southwest of the train tracks between Deep Creek and Bland Boulevard. By changing Station 6's district there it will allow Station 6 to take over the northern most area of Station 8, which will reduce the call volume in Station 8 as can be seen in Figure 13. This new district would take, from the 2018 data, 15 calls from Station 9 and two calls from Station 6, which is 40% of the volume of Station 9 and 10% of the calls from Station 6. Station 11 will also be moved to cover all the way to I-64 which will remove the westernmost area of Station 6 to lessen its volume in response to the addition of some Station 8's calls. In total, Station 6 will take 11 of the calls from Station 8, which will give Station 8 a nearly 30% decrease in call volume. Although Station 6 will experience a 35% increase in calls, the average number of calls per station from 22 to just under 19. The fires would be more evenly distributed allowing the workload to be shared between each station. These new stations will reduce the chance that any one station receiving more than 30 structure fire calls in a year, which should have an increase in the response rate of those stations since they will not need to be out on calls as often and will decrease the likelihood of having overlapping fires for one station.

Station	# of Fires	# After Recommendation	% Change
2	41	27	-34.1%
6	19	28	36.8%
7	26	21	-19.2%
8	37	26	-29.7%
9	37	22	-40.5%
11	9	11	22.2%

Figure 13: Changes in Fire Calls After Creation of New Station

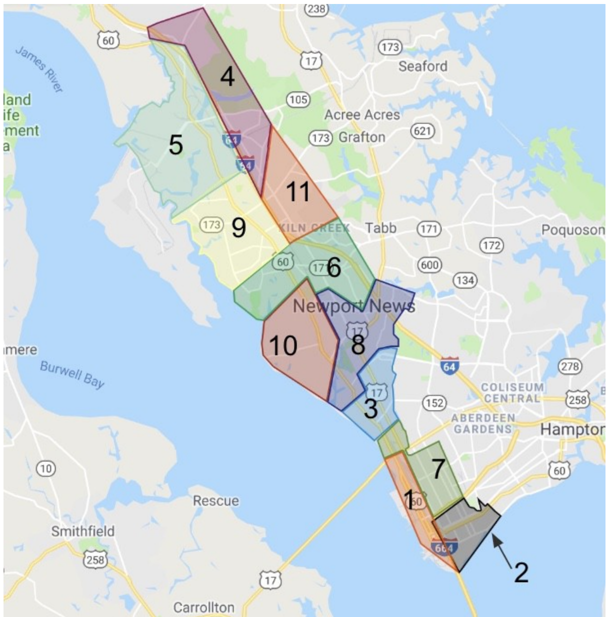

Figure 14: Current Stations

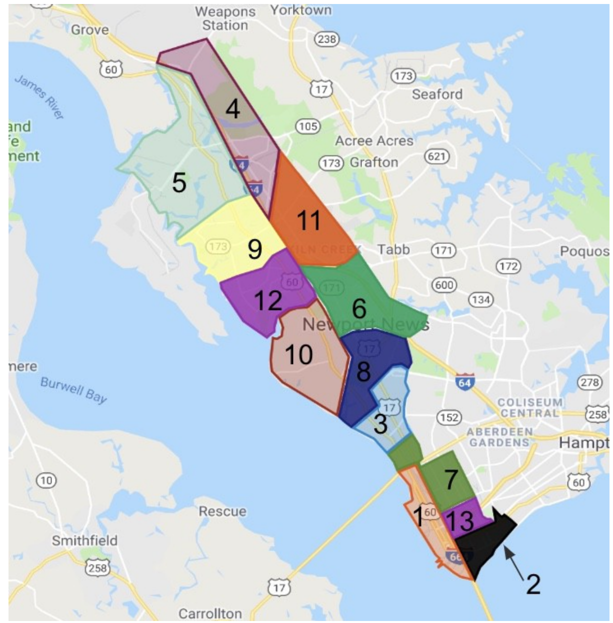

Figure 15: Proposed Stations

After looking at the data showing how the number of fires can be more evenly distributed the fire department wanted the research to be more focused on the new Station 12. The goal was to further determine the ideal area of the new zone as well as to find an acceptable location for the new station itself. The first step in this process was to look at all natural and man-made barriers that could prevent a fire truck from effectively navigating its surroundings, or simply increase the travel time to a particular point on the edge of its region. The main barriers are the railroad tracks that run the length of the city as well as the numerous creeks which flow into the James River. After looking at the locations of Stations 6, 9, 10 it was determined that the borders of the new station should be the James River on the southwest, Deep Creek on the southeast, the railroad tracks on the northeast, and a mixture of colony Road and Lucas Creek on the northwest.

First, a rough estimate of the central point for the proposed region was completed using a simple geometric center calculation. To do this diagonal lines were drawn across the roughly square region from each of the four corners. Where the two lines intersected was our rough estimate for the center. After determining the center, two concentric circles were drawn around the calculated central point with radii of .25 miles and .5 miles, respectively, as can be seen in Figure 16.

After calculating the approximate center of the district, the map of all fires that took place from 2013-2018 was overlaid onto the map of Station 12. As each individual structure fire is shown as a point on the map, a heat map of the concentrated areas where most of the fires occur was made. This heat map was then used to show the two areas with the highest concentration of fires. Since both of the areas with the highest concentration were in the northwest area of our zone they were placed into a rectangle and the center between the two high concentration areas was calculated using the same method as before.

After this rough location for a center point was calculated, a programmatic approach was used to tackle the problem. The aim was to calculate which points lie within the boundaries of Station 12's district, then taking the average of those points to create a weighted center based off of all the fires that occurred within Station 12's district. First a foray was made into parsing the KML file outputted by the Google Maps custom map that contained the potential new district for Station 12 (see Figure 17).

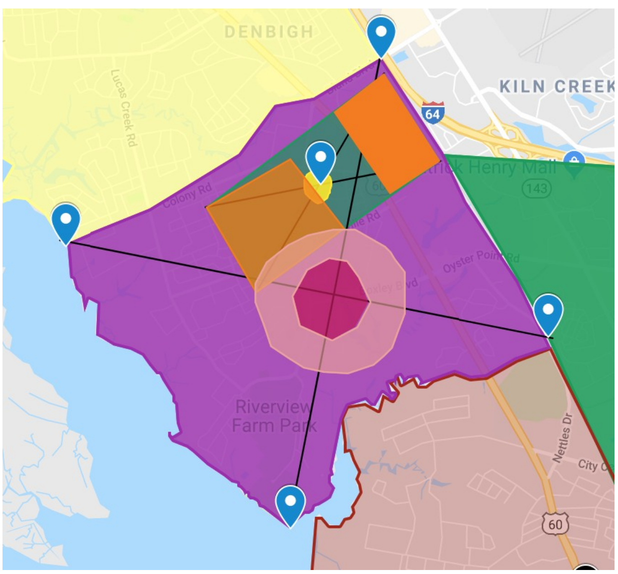

Figure 16: Calculation of center

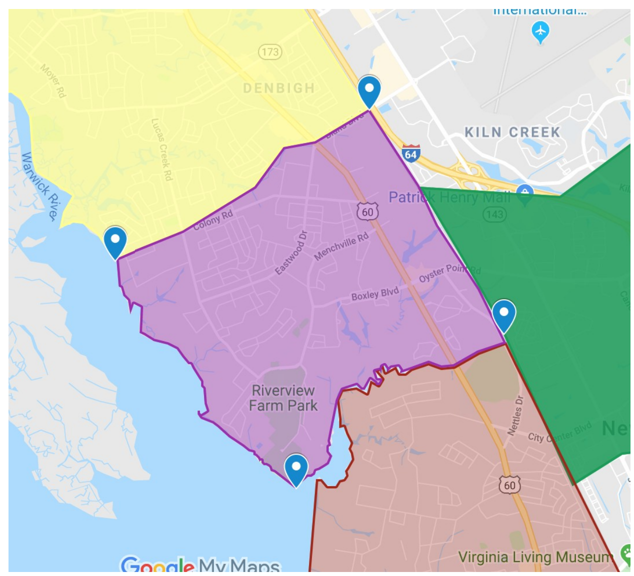

Figure 17: Map of District 12

After successfully parsing the KML data extracted from all the points on the new district map (see Figure 18), the find Point-in-Polygon algorithm was used to determine which points were within the boundaries of the proposed station district. To see a detailed description of the Point-in-Polygon algorithm, see Appendix B. The weighted center point calculated by averaging the latitude and longitude values of the points within Station 12's district for Station 12's district lies at longitude and latitude (-75.5204, 37.1107), or approximately the intersection of Smucker Road and Caldroney Drive.

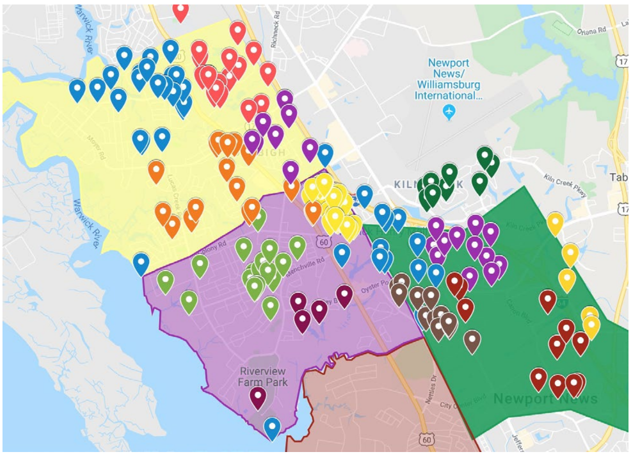

Figure 18: All Fires Within Station 12

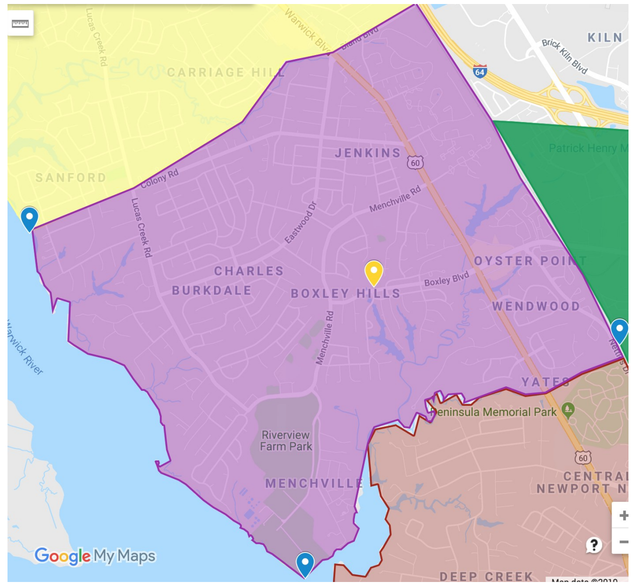

Figure 19: Recommended location of Station 12

Once the two general areas were determined, an arbitrary point within the geographic center and within the high-concentration center were used to determine travel times within the entire district. Both points were used to calculate the travel time at 11:30am as well as 5:00pm to ensure that there was not a large difference at rush hour. The times were calculated using Google Maps and do not show the time that may be saved by using a siren to clear traffic.

Time of Day	High Concentration Center	Geographic Center
Middle of Day	3:31.2	3:56.4
Rush Hour	5:00.9	3:58.08

Although the times are lower during the day for the high concentration center the overall average is much lower for the geographic center and because it is closer to the entire district it guarantees that the time will be lower for every single section of the district.

After looking at the entire district to find a suitable location for the new station, two locations looked promising. The first potential location for the new Station 12 would be 13128 Warwick Blvd. This 3.86 acre, two parcel lot is currently listed on loopnet.com for rent and is a mere 1190 feet from the weighted center of Station 12's district. This location is preferable because it is under a minute drive from the weighted center of this district and is directly on Warwick Boulevard, one of the busiest streets in Newport News and a main thoroughfare through the city. The second location is on Boxley Boulevard across from the intersection of Pine Bluff Drive. This location would be the preferable because it is within the .25 mile range of the geographic center of the district as well as being on one of the main roads of the district which will allow faster response times. Another advantage of this is that the lot is already owned by the city as it is a small section of the woods surrounding Yoder pond (Figure 19).

7.4 Fire Department Overall Efficiency

Through various calculations, it was found that the 90th percentile of response ERF was higher than the ideal range. However, after computing linear regressions it was observed that turnout times do not have a major linear impact on response ERF times. Thus, the parts of the process that firefighters have the most control over have a minimal effect on the overall time. The best way to improve this would be to somehow reduce travel times. This could be improved by adding another station or changing some of the rules and regulations when it comes to fire trucks on the roads.

8 Future Research

Moving forward with the connections made at the Newport News Fire Department, it could prove beneficial to gain some additional insight into how the individual firefighters are being affected by the problems we began to investigate in our research. It would be interesting to conduct a study on how well informed the firefighters are on the impact of new housing developments and the difference in calls the various fire stations receive over the course of the day. We could also measure the firefighters' overall happiness with their current compensation package with a scale from very unhappy to very happy and relate that to the overall strain on their fire station and see if there is any correlation.

The fire department uses the 95th-percentile measure as its standard for accreditation reports. This metric is also important to use because it sets a high standard for every member of the department to ensure fast response times and maintain high levels of public safety. Mathematically, it could be more interesting to compare the median and quartile measurements because these values are less sensitive to outliers. Although the overall results may differ, this may provide a clearer picture of the fire department's response time.

While conducting our research we found little linear correlations in our data when performing linear regressions. Since there were minimal linear correlations, it would be interesting to use non-linear regressions to analyze our data and see if a different type of regression would better fit our data set. In the future, more time could be devoted to this particular subset of our problem, ideally concluding in the use of a non-linear regression curve which may provide a curve which better fits and represents our data.

9 Acknowledgements

Thank you to the Newport News Fire Department for the allowing us to assist you in the process of analyzing the data you provided us with and to Dr. Jessica Kelly for providing us with guidance throughout the semester.

Our work was supported through the Preparation for Industrial Careers in Mathematics (PIC Math) program. PIC Math is a program of the Mathematical Association of America (MAA) and the Society for Industrial and Applied Mathematics (SIAM). Support is provided by the National Science Foundation (NSF grant DMS-1722275).

10 References

Rogers, Wesley. "Overview of Newport News Fire Department." Luter Hall. Newport News. Jan. 8, 2019. PowerPoint Presentation.

Triola, Mario F. *Elementary Statistics*. Boston: Pearson Education, Inc., 2014. Print.

11 Appendix A

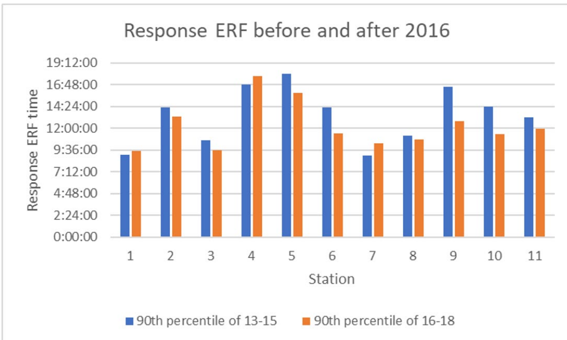

Figure 20: Response ERF before and after 2016

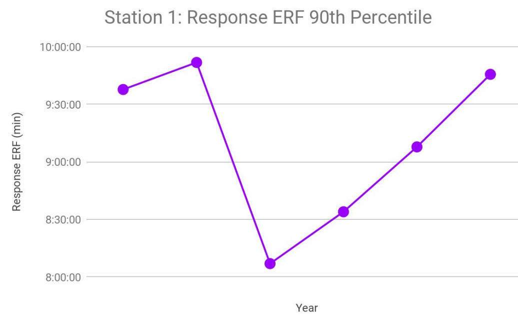

Figure 21: Station 1

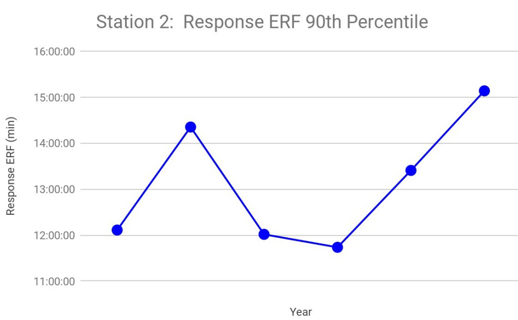

Figure 22: Station 2

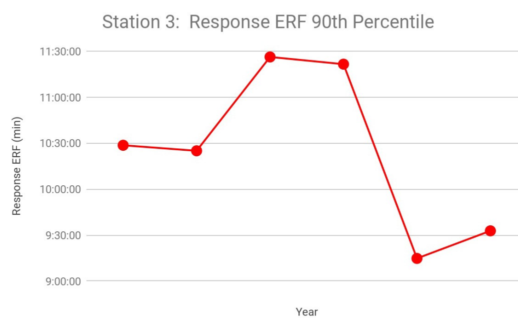

Figure 23: Station 3

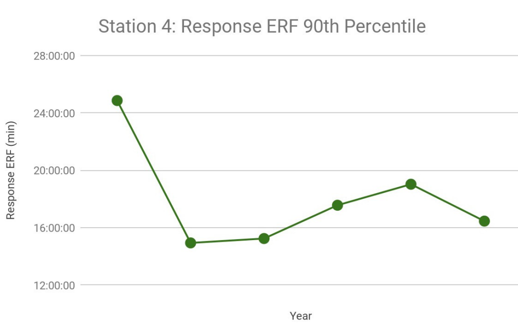

Figure 24: Station 4

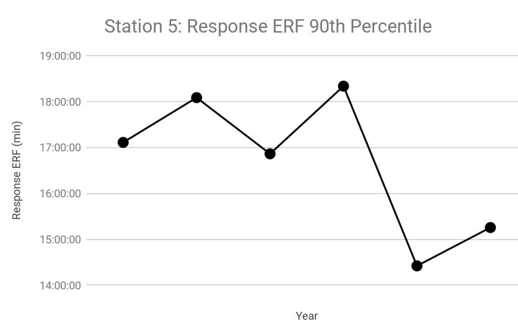

Figure 25: Station 5

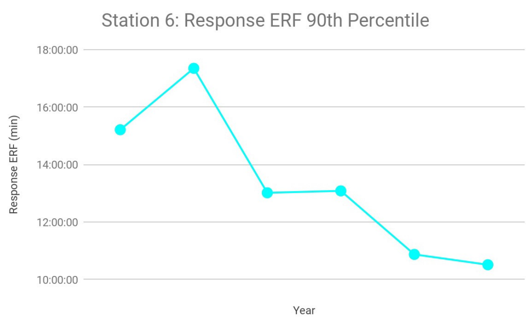

Figure 26: Station 6

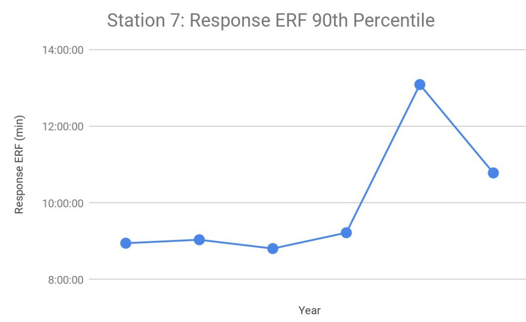

Figure 27: Station 7

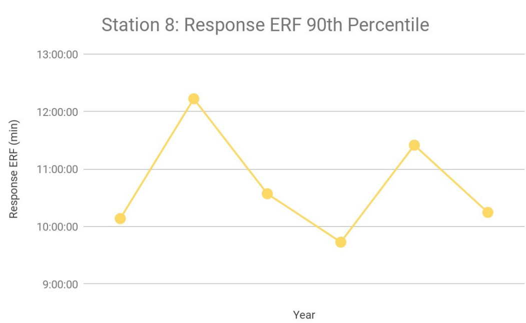

Figure 28: Station 8

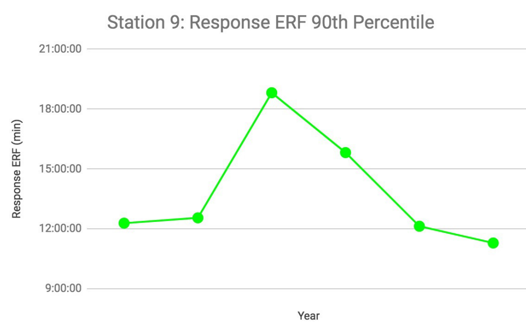

Figure 29: Station 9

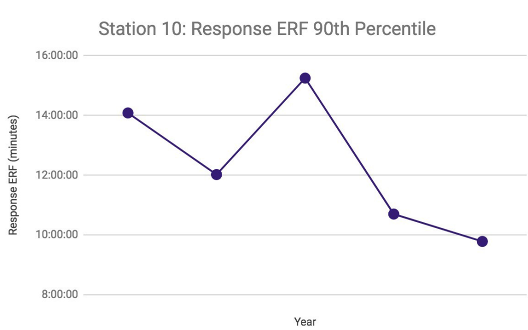

Figure 30: Station 10

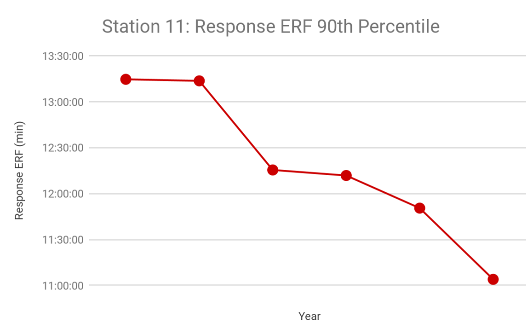

Figure 31: Station 11

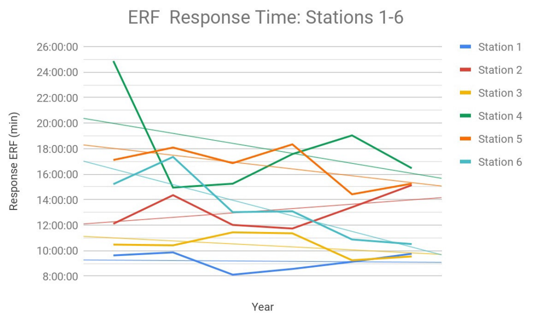

Figure 32: Stations 1-6: 90th Percentile

Response ERF

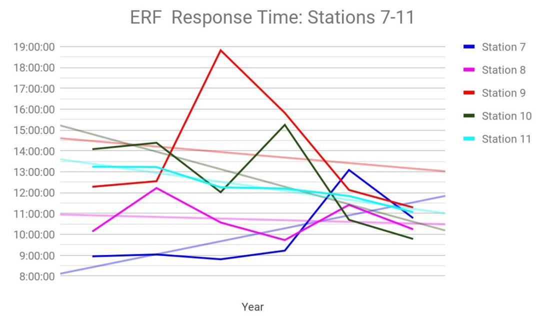

Figure 33: Stations 7-11: 90th Percentile

Response ERF

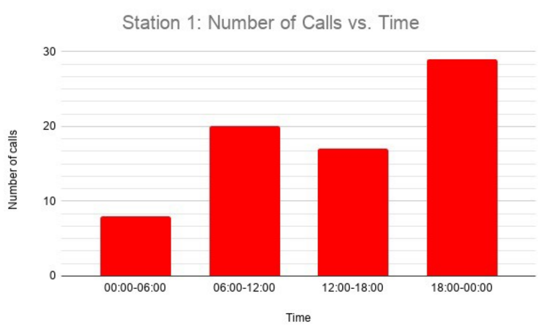

Figure 34: Station 1: Number of Calls vs. Time

(6 hour time frames)

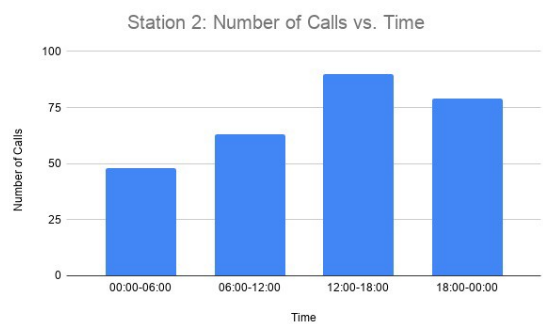

Figure 35: Station 2: Number of Calls vs. Time

(6 hour time frames)

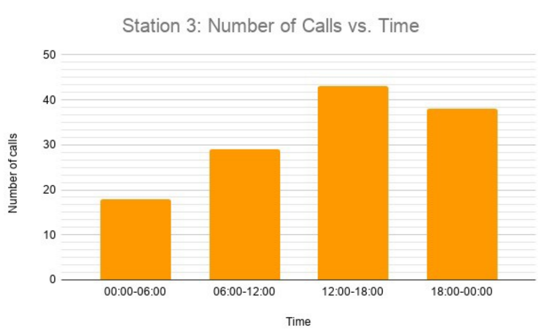

Figure 36: Station 3: Number of Calls vs. Time

(6 hour time frames)

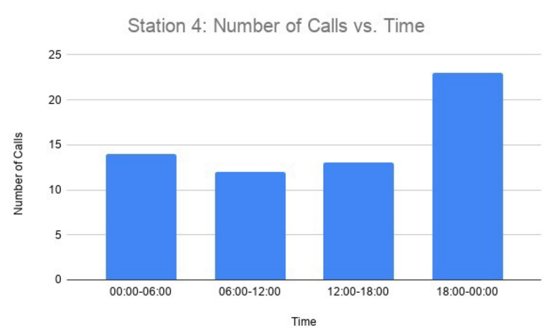

Figure 37: Station 4: Number of Calls vs. Time

(6 hour time frames)

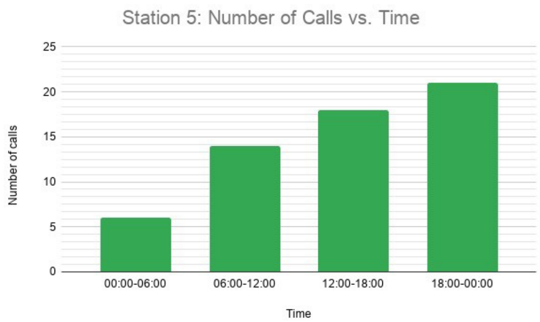

Figure 38: Station 5: Number of Calls vs. Time

(6 hour time frames)

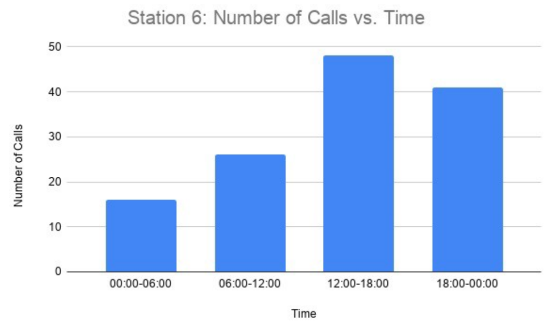

Figure 39: Station 6: Number of Calls vs. Time

(6 hour time frames)

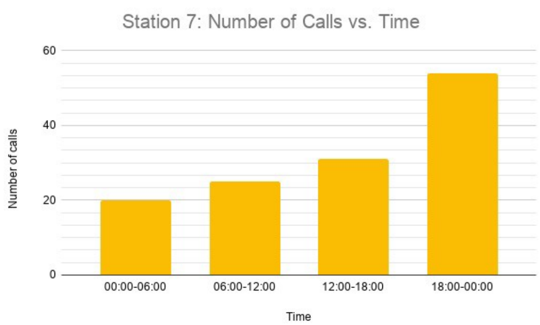

Figure 40: Station 7: Number of Calls vs. Time

(6 hour time frames)

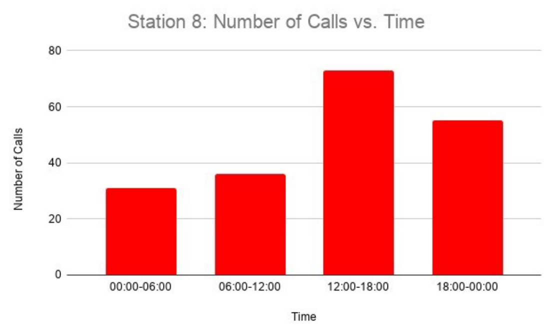

Figure 41: Station 8: Number of Calls vs. Time

(6 hour time frames)

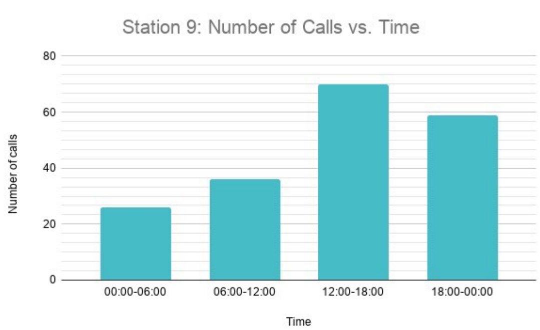

Figure 42: Station 9: Number of Calls vs. Time

(6 hour time frames)

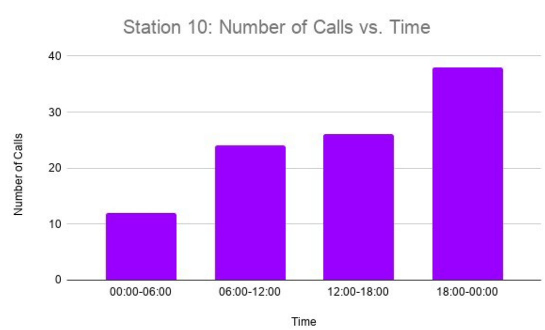

Figure 43: Station 10: Number of Calls vs. Time (6 hour time frames)

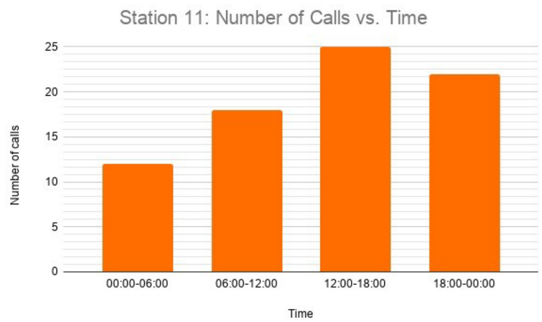

Figure 44: Station 11: Number of Calls vs. Time (6 hour time frames)

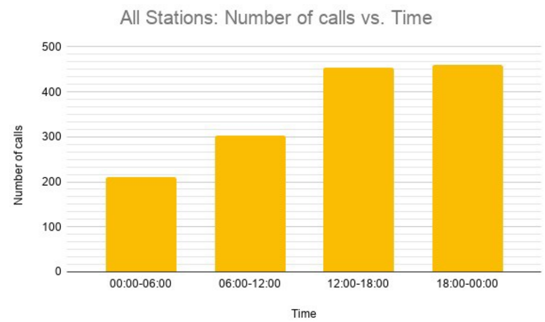

Figure 45: All stations: Number of Calls vs. Time (6 hour time frames)

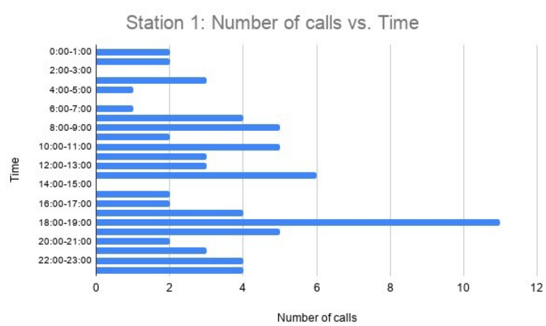

Figure 46: Station 1: Number of Calls vs. Time (per hour)

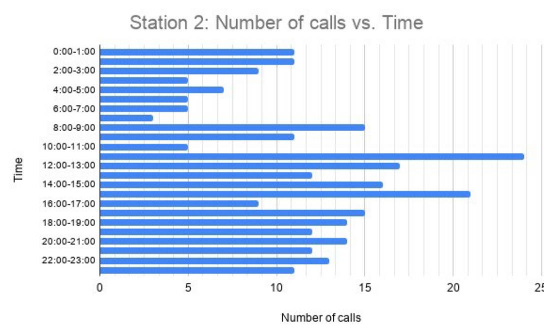

Figure 47: Station 2: Number of Calls vs. Time (per hour)

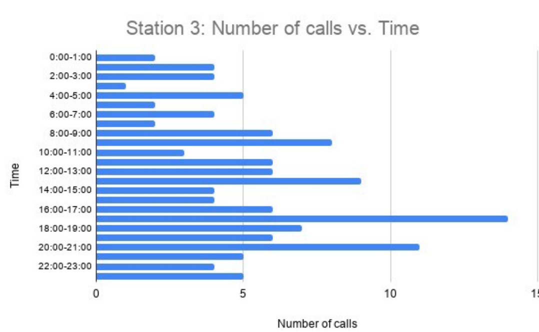

Figure 48: Station 3: Number of Calls vs. Time (per hour)

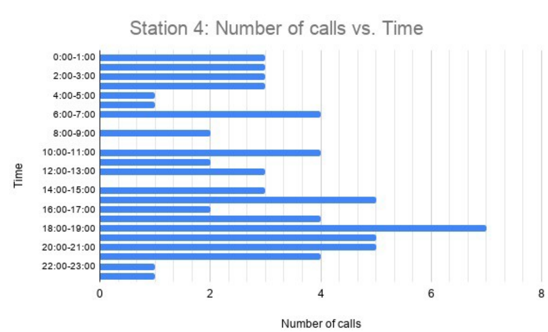

Figure 49: Station 4: Number of Calls vs. Time (per hour)

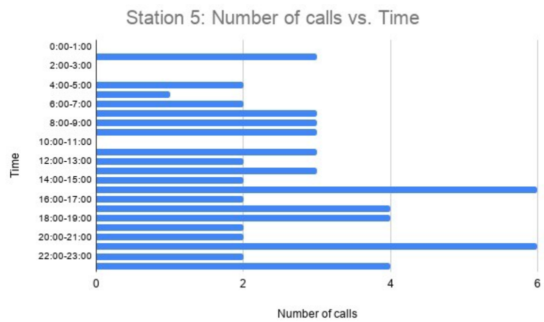

Figure 50: Station 5: Number of Calls vs. Time (per hour)

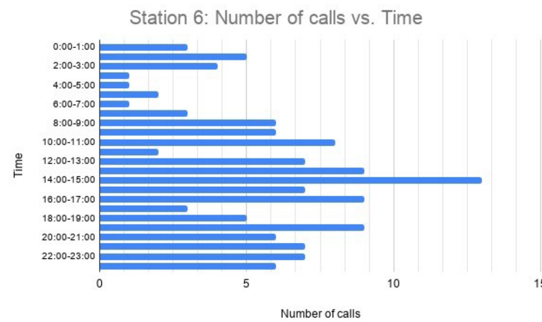

Figure 51: Station 6: Number of Calls vs. Time (per hour)

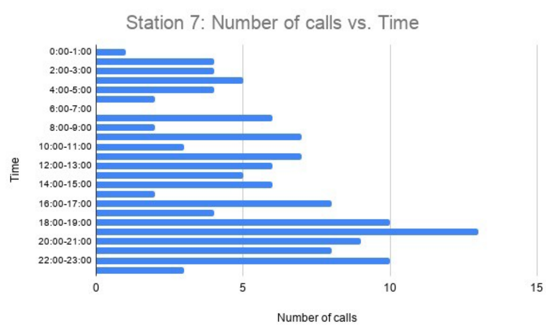

Figure 52: Station 7: Number of Calls vs. Time (per hour)

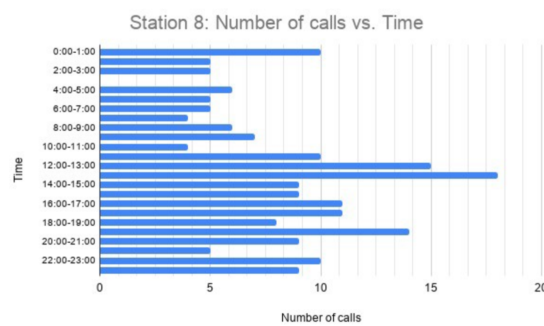

Figure 53: Station 8: Number of Calls vs. Time (per hour)

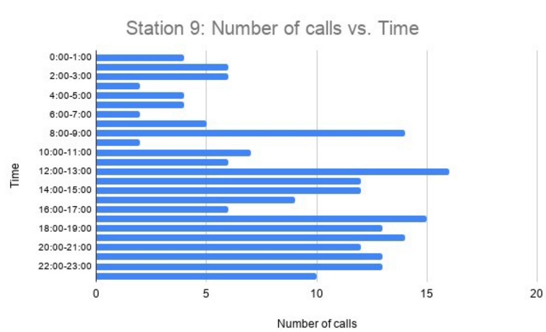

Figure 54: Station 9: Number of Calls vs. Time (per hour)

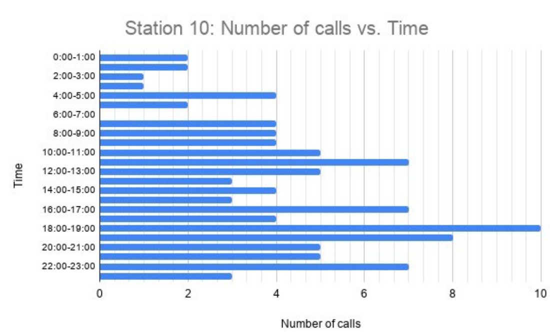

Figure 55: Station 10: Number of Calls vs. Time (per hour)

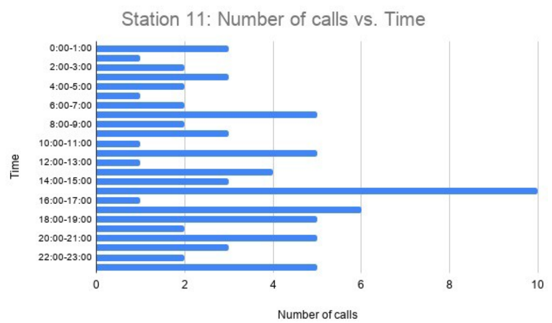

Figure 56: Station 11: Number of Calls vs. Time (per hour)

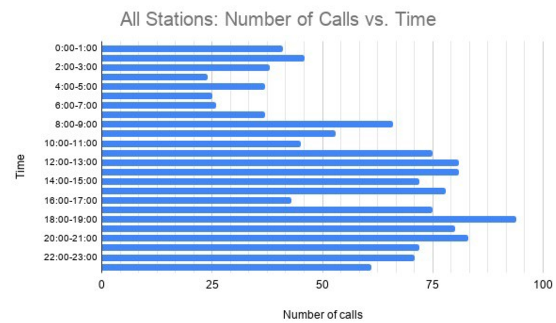

Figure 57: All Stations: Number of Calls vs. Time (per hour)

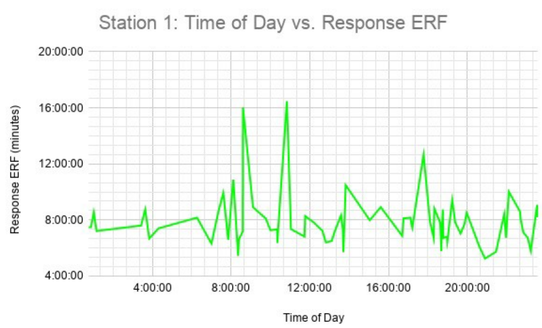

Figure 58: Station 1: Time of Day vs. Response ERF

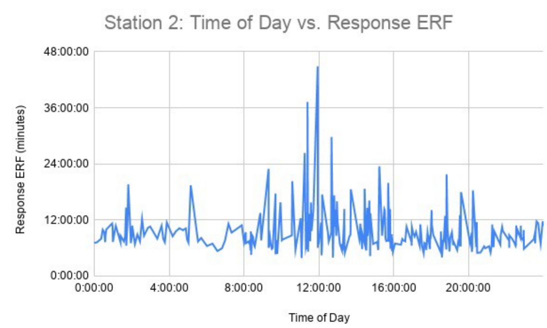

Figure 59: Station 2: Time of Day vs. Response ERF

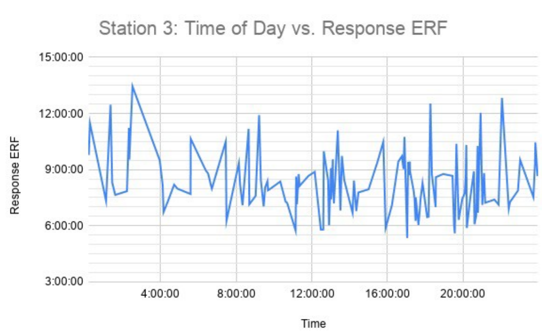

Figure 60: Station 3: Time of Day vs. Response ERF

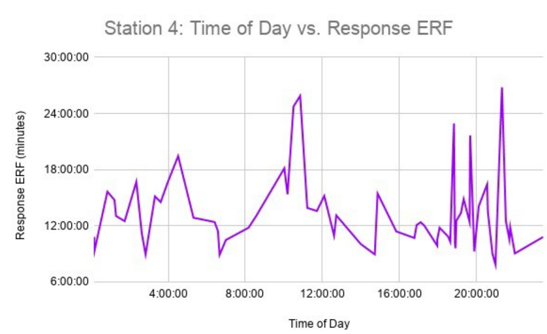

Figure 61: Station 4: Time of Day vs. Response ERF

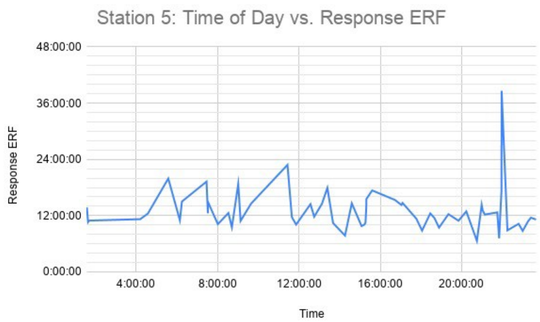

Figure 62: Station 5: Time of Day vs. Response ERF

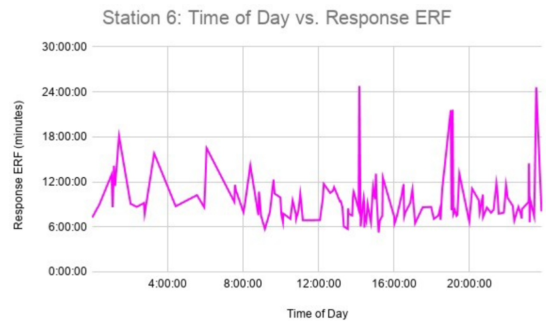

Figure 63: Station 6: Time of Day vs. Response ERF

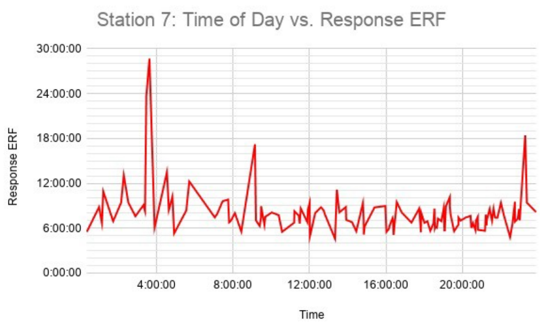

Figure 64: Station 7: Time of Day vs. Response ERF

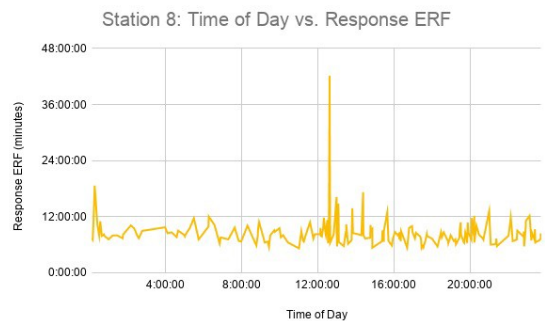

Figure 65: Station 8: Time of Day vs. Response ERF

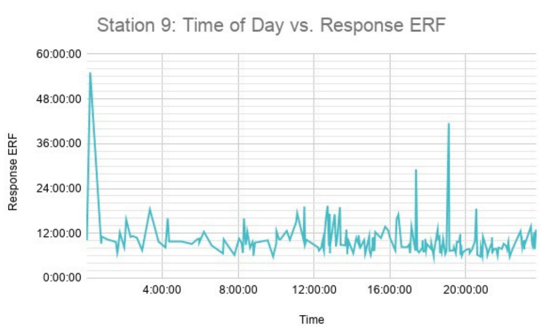

Figure 66: Station 5: Time of Day vs. Response ERF

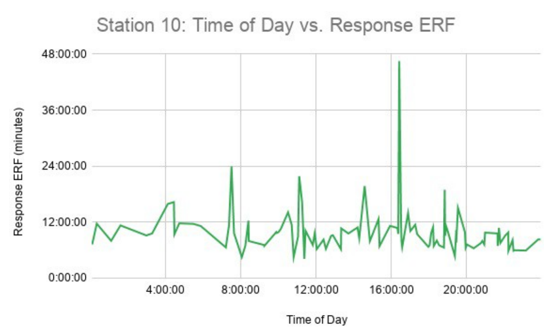

Figure 67: Station 10: Time of Day vs. Response ERF

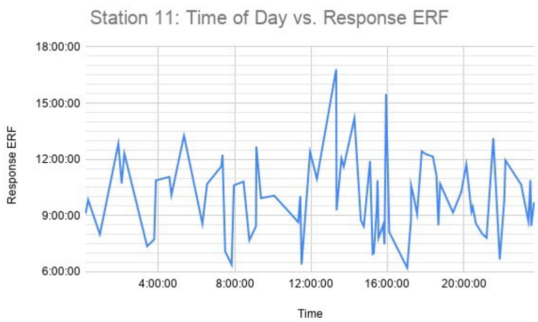

Figure 68: Station 11: Time of Day vs. Response ERF

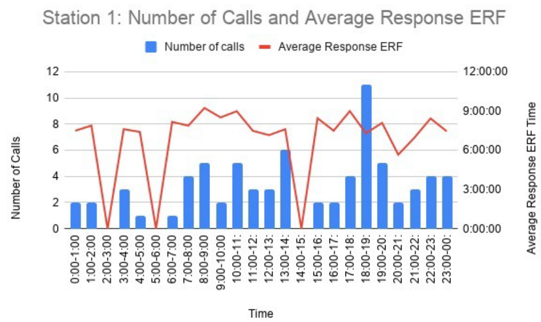

Figure 69: Station 1: Number of Calls and Average Response ERF vs. Time

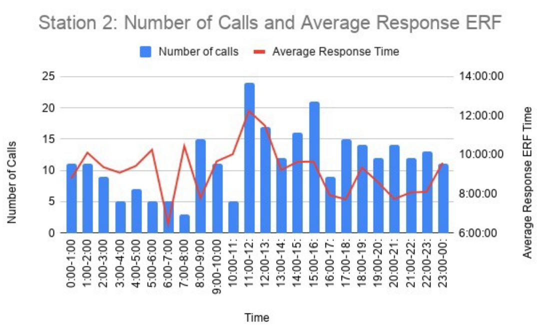

Figure 70: Station 2: Number of Calls and Average Response ERF vs. Time

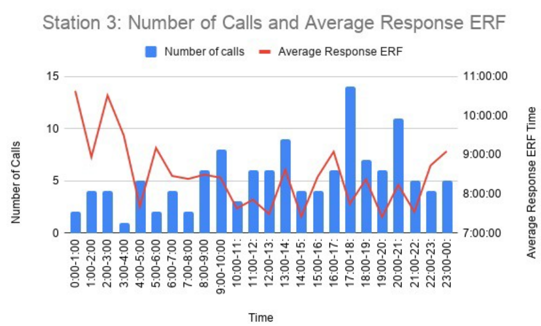

Figure 71: Station 3: Number of Calls and Average Response ERF vs. Time

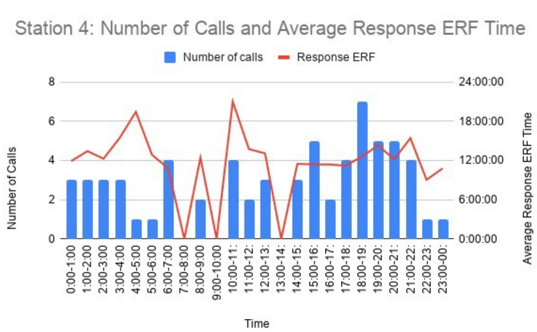

Figure 72: Station 4: Number of Calls and Average Response ERF vs. Time

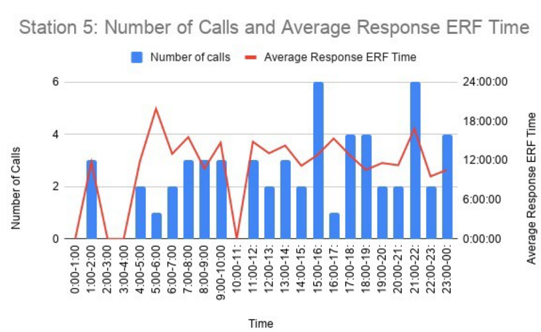

Figure 73: Station 5: Number of Calls and Average Response ERF vs. Time

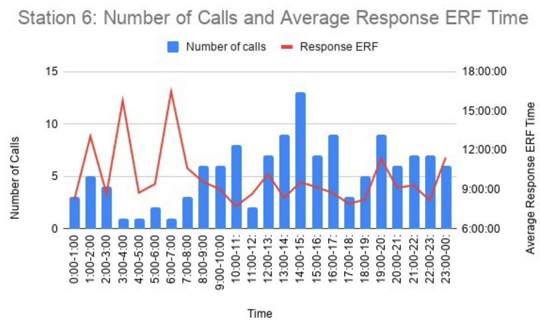

Figure 74: Station 6: Number of Calls and Average Response ERF vs. Time

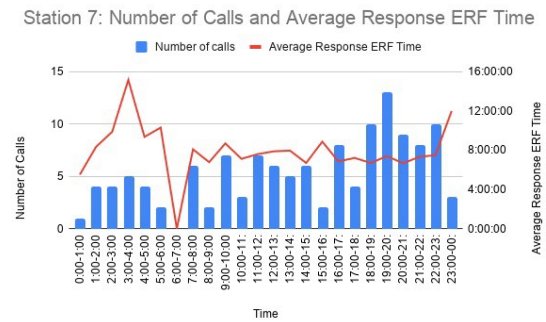

Figure 75: Station 7: Number of Calls and Average Response ERF vs. Time

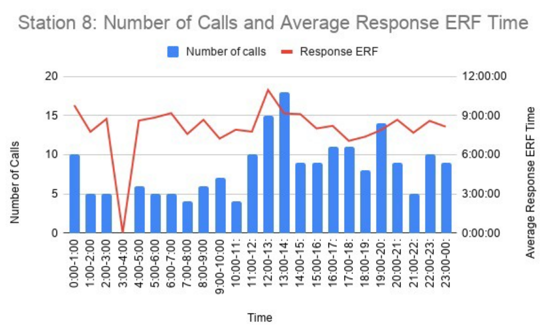

Figure 76: Station 8: Number of Calls and Average Response ERF vs. Time

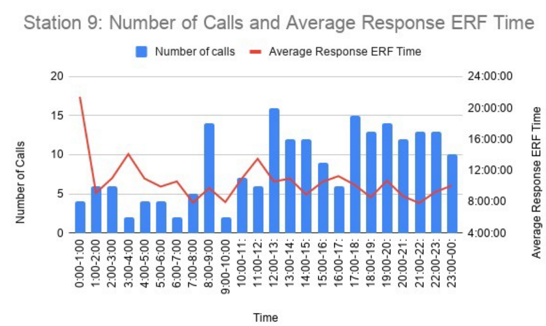

Figure 77: Station 9: Number of Calls and Average Response ERF vs. Time

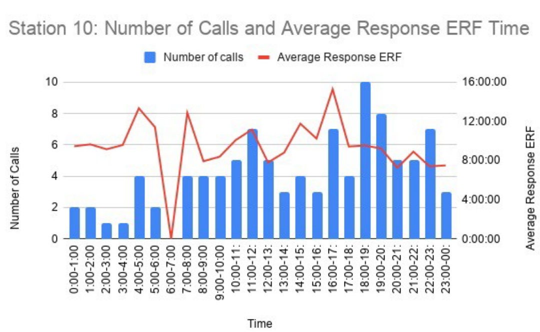

Figure 78: Station 10: Number of Calls and Average Response ERF vs. Time

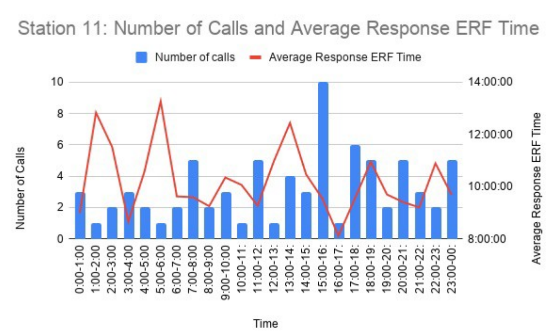

Figure 79: Station 11: Number of Calls and Average Response ERF vs. Time

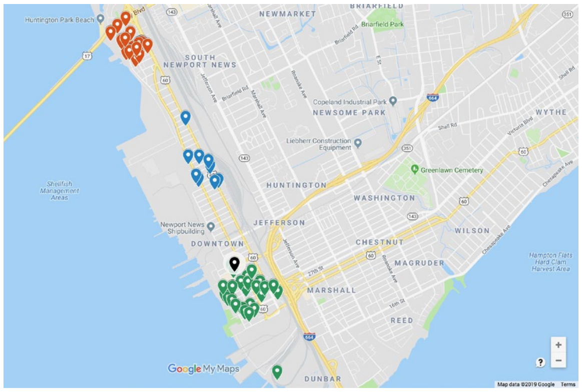

Figure 80: Station 1 Fires (2013-2018)

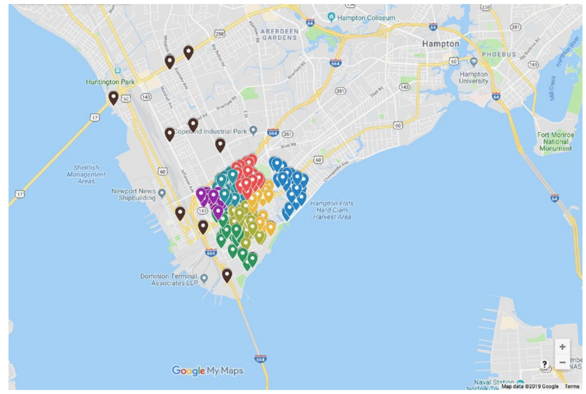

Figure 81: Station 2 Fires (2013-2018)

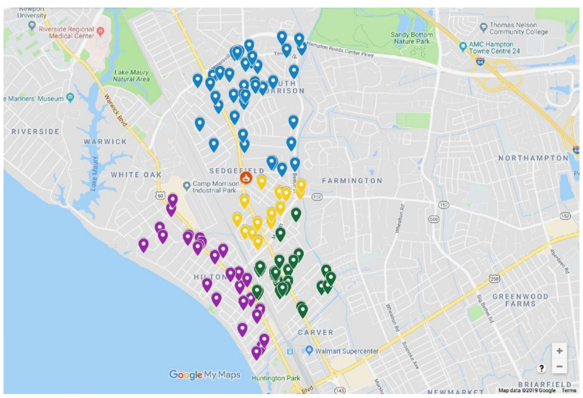

Figure 82: Station 3 Fires (2013-2018)

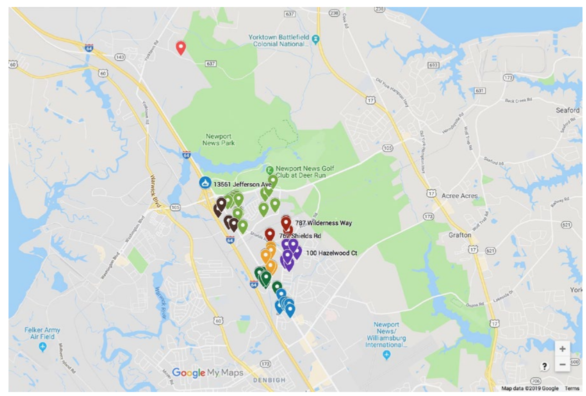

Figure 83: Station 4 Fires (2013-2018)

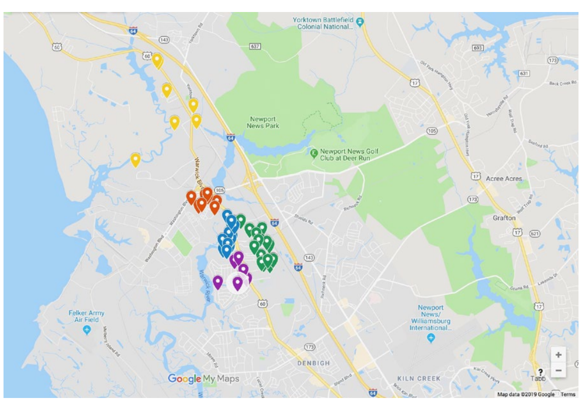

Figure 84: Station 5 Fires (2013-2018)

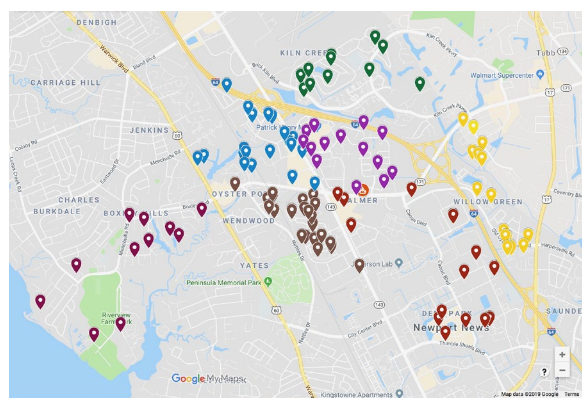

Figure 85: Station 6 Fires (2013-2018)

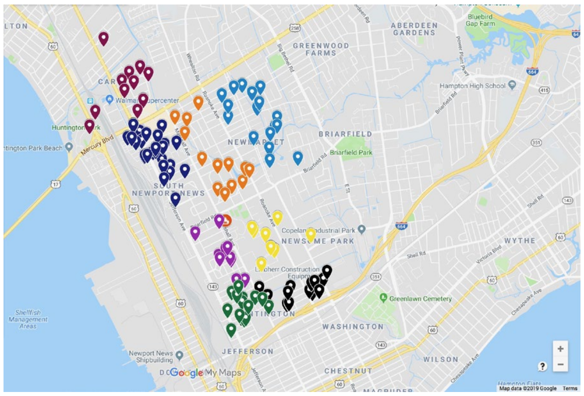

Figure 86: Station 7 Fires (2013-2018)

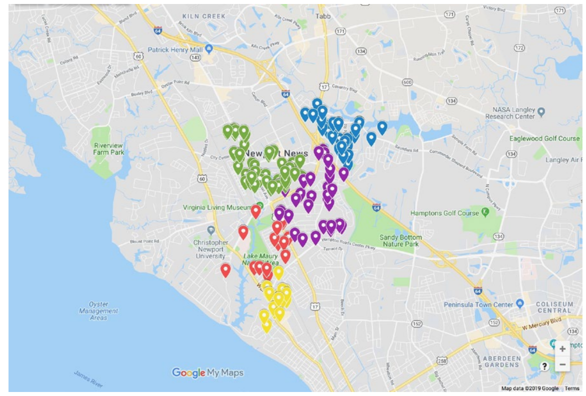

Figure 87: Station 8 Fires (2013-2018)

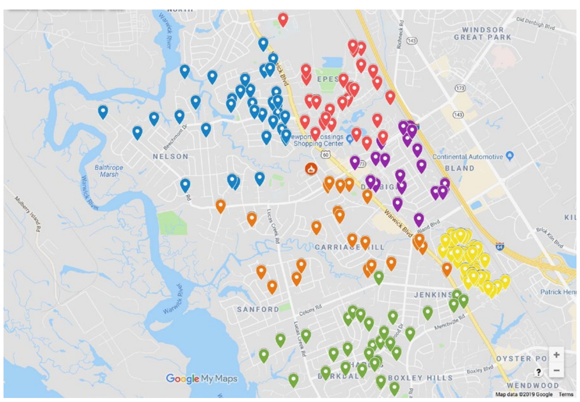

Figure 88: Station 9 Fires (2013-2018)

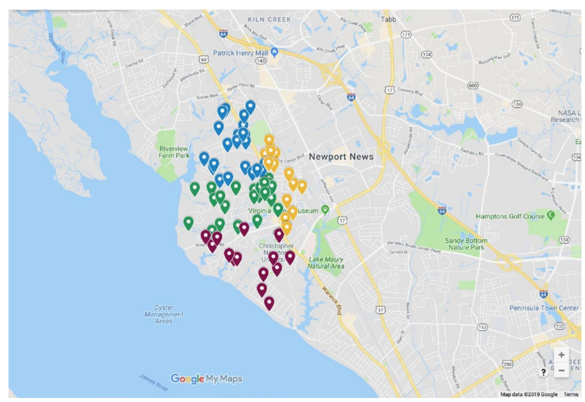

Figure 89: Station 10 Fires (2013-2018)

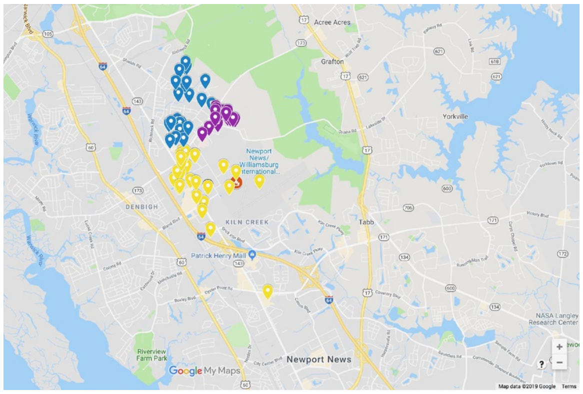

Figure 90: Station 11 Fires (2013-2018)

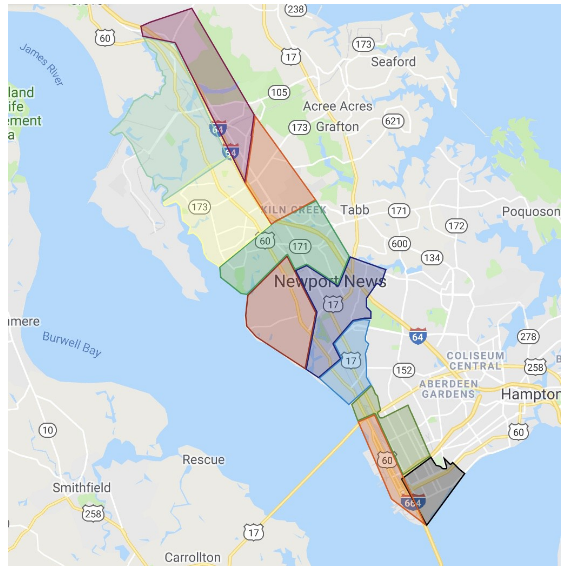

Figure 91: Current Station Layout

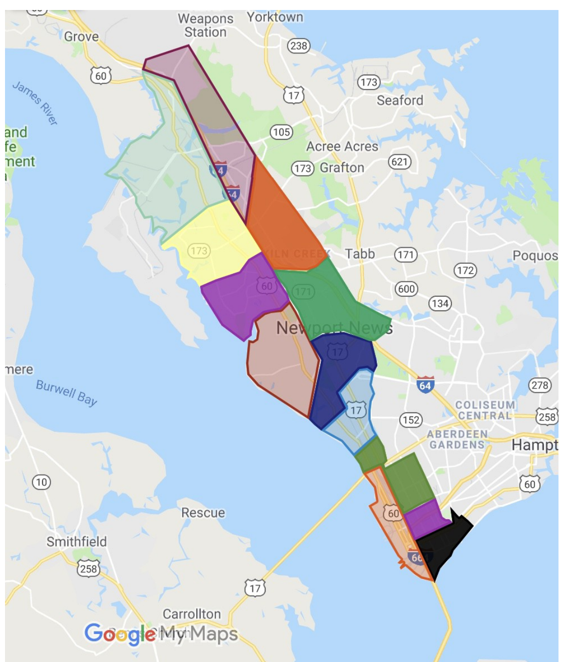

Figure 92: Suggested Station Layout

12 Appendix B

12.1 Methods

12.1.1 90th Percentile

The User Defined Function used to calculate the 90th percentile ERF data is called *ERFPercentile()*. It requires only one parameter, that of the station whose 90th percentile ERF data you want. For example, if you wanted to calculate the 90th percentile Response ERF time for Station 2, you would click the cell you want the output to be in, then type *=ERFPercentile(2)*; press enter and the 90th percentile Response ERF time for Station 2 will be displayed in the cell you previously selected.

The UDF works by first sorting through the data corresponding to the station number entered as a parameter and collects all pieces of Response ERF data that are valid numbers. After collecting all pieces of numerical data, it calculates and removes all outliers from the data set using the previously mentioned in Section 4.2.

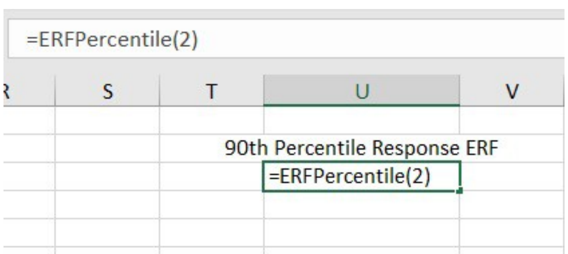

Figure 93: Step 1: Automation Process

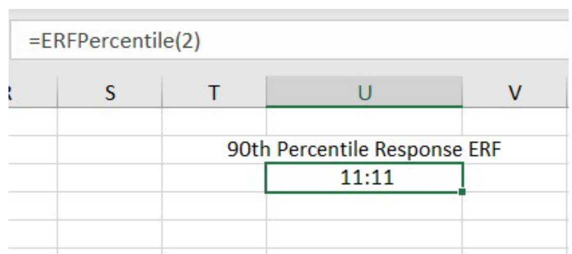

Figure 94: Step 2: Automation Process

To get the ERFPercentile() function to work on all Excel documents on your machine, you will first need to download the attached excel add-on file, "*FireFunctions.xlam*". After downloading the Excel add-on, open a new Excel spreadsheet. At the top of the Excel document click on the search bar and type in "Add-Ins". Press Enter, then click "Browse...", then browse for and select "*FireFunctions.xlam*". Click the check box that says "Fire Department Add-In", then OK, and the function is ready to use.

12.1.2 Point-in-Polygon

First attempts were made to use the python library 'fastkml' to parse the KML file, but halfway through the creation of the kml-processing code, massive breaking changes were pushed to the 'fastkml' github repository which rendered all work on the python kml-parsing code defunct. During the downtime of the 'fastkml' repository, the target language of the processing code was switched to C++ due to the availability of other easier-to-use libraries for the parsing of KML-formatted data.

The find Point-in-Polygon algorithm (Figure 96) functions by drawing a line on the same two dimensional plane as the polygon extending out to infinity from any particular point and checking the number of intersections the line has with the bounding polygon in question. If there are an odd number of collisions, then one can conclude that the point being checked lies within the bounding polygon. If it intersects an even number, including zero, of times, then one can conclude that the point lies outside of the polygon.

This point-checking process was facilitated by a vector of points to check, with each point storing a latitude, and longitude (x, y), and a Polygon object, which stored the coordinates of the vertices of the bounding polygon and the lines connecting them. After iterating through the collection of points to find, the points which satisfied the algorithm were written to a new .csv file so that they could easily be ported back into google maps for viewing on the map. This .csv file of the points inside the proposed Station 12's district was then used to calculate the weighted center point, and thus the ideal station location within Station 12's district.

12.2 Computer Code

```
Public Function ERFPercentile(StationNumber As String)
    Dim LastRow As Long
    Dim finalMins, finalSecs As Integer
    Dim element, finalString As String
    Dim numMins, numSecs, totalSecs, timeVal, IQR, OutlierBoundry As Double
    Dim goodItems As Variant
    Dim arrList, arrList2 As Object

    Set arrList = CreateObject("System.Collections.ArrayList") 'Create the ArrayList
    Set arrList2 = CreateObject("System.Collections.ArrayList")
    'Calculating the number of rows with data in them
    LastRow = ActiveSheet.Range("K" & ActiveSheet.Rows.Count).End(xlUp).Row

    'Searching each row that is filled with data
    For i = 2 To LastRow
    element = Trim(Range("K" & i).Value)
        If (element <> "--:--" And StationNumber = Trim(Range("E" & i).Value)) Then 'If correctly formatted time of Station X
            'Converting mm:ss to total in seconds
            numMins = Hour(element)
            numSecs = Hour(element)
            totalSecs = numMins * 60 + numSecs
            arrList.Add (totalSecs) 'Adding total to list
        End If
    Next

    goodItems = arrList.ToArray

    'Calculating Inter-Quartile Range
    IQR = Application.WorksheetFunction.Quartile(goodItems, 3) - Application.WorksheetFunction.Quartile(goodItems, 1)
    OutlierBoundry = Application.WorksheetFunction.Quartile(goodItems, 3) + IQR * 1.5

    'Removing Outliers
    For Each Item In arrList
        If (Item <= OutlierBoundry) Then
            arrList2.Add (Item)
        End If
    Next Item

    Dim arr As Variant
    arr = arrList2.ToArray
    'Getting 90th percentile
    timeVal = Application.WorksheetFunction.Percentile(arr, 0.9)
    finalMins = timeVal / 60
    finalSecs = Int(timeVal) Mod 60

    'Making sure time is mm:ss instead of mm:s
    finalString = (Str(Int(finalMins)) & ":")
    If (Int(finalSecs) < 10) Then
        finalString = finalString & "0" & Trim(Str(Int(finalSecs)))
    Else
        finalString = finalString & Trim(Str(Int(finalSecs)))
    End If

    ERFPercentile = finalString
End Function
```

Figure 95: Automation Process Code

```cpp

using namespace std;
// Define Infinite (Using INT_MAX caused overflow problems)
#define INF 10000
struct Point
{
    float x;
    float y;
};
bool pointInPolygon(float x, float y){
    float polyX[] = {-76.51821, -76.49827, -76.62896, -76.55585};
    float polyY[] = {37.12461, 37.09811, 37.07994, 37.10682};
    int i, j= 3;
    bool oddNodes= false;

    for (i = 0; i < 4; i++) {
        if ((polyY[i] < y && polyY[j] >= y || polyY[j] < y && polyY[i] >= y)
        &&  (polyX[i] <= x || polyX[j] <= x))
        {
        oddNodes ^= (polyX[i]+(y-polyY[i]) / (polyY[j]-polyY[i]) * (polyX[j]-polyX[i])<x);
    }
    j=i;
}
return oddNodes;
}
int main()
{
    fstream in, good, bad;
    string line, word;
    vector<string> row;
    in.open("new_station_points_csv.csv",ios::in);
    good.open("trimmed_points.csv",ios::out);
    bad.open("outside_points.csv",ios::out);
    getline(in,line);
    good << line << endl;
    bad << line << endl;
    // parse x, y and print to new file
    while(!in.eof()){
        row.clear();
        getline(in,line);
        stringstream ss(line);
        while (getline(ss, word, ',')){
            row.push_back(word);
        }
        float x = stof(row[0]);
        float y = stof(row[1]);
        if(pointInPolygon(x,y)){
            good << x << "," << y << endl;
            cout << x << "," << y << " is in" << endl;
        }
        else{
            bad << x << "," << y << endl;
            cout << x << "," << y << " is out" << endl;
        }
    }
    in.close();
    good.close();
    bad.close();
```

Figure 96: Point-in-Polygon Algorithm