Improving Emergency Response Performance at the City of Rochester Fire Department

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1. Introduction

Emergency response performance is a cornerstone of community safety, particularly in urban environments where populations are dense, and risks are diverse. The Rochester Fire Department (RFD) serves as a critical emergency response entity for a population exceeding 211,000 across 37.17 square miles. As an all-hazards organization, RFD addresses approximately 40,000 service calls annually, deploying over 50,000 unit responses for incidents ranging from fire suppression and hazardous material containment to disaster preparedness and emergency medical services.

RFD operates 15 fire stations, equipped with 13 engines, 6 trucks, and specialized rescue units, strategically positioned to meet community needs. However, increasing call volumes and evolving urban demands challenge the department's ability to maintain optimal response times and equitable service delivery. As a proactive measure, this project explores opportunities to enhance resource allocation and deployment strategies, ensuring RFD's capacity to meet both present and future demands effectively.

This study utilizes advanced geospatial analysis, predictive modeling, and incident response data to identify patterns, optimize personnel and equipment allocation, and assess the potential need for new fire station locations. The analysis includes specific recommendations, such as reallocation of units, adjustments to specialized resources, and consideration of innovative programs like low-acuity response teams, modeled after successful initiatives in other cities.

These recommendations aim to free up critical resources for high-priority incidents, streamline operations, and align with RFD's mission of excellence and equity.

By combining robust data analysis with insights from stakeholders and academic collaborators, this initiative delivers actionable strategies for reducing response times, enhancing operational efficiency, and preparing RFD to address future challenges. This commitment to continuous improvement reflects RFD's dedication to the safety and well-being of Rochester's residents and its firefighters.

2. Datasets

2.1 Dataset Description

The datasets for this project were provided by the Rochester Fire Department (RFD) and contain detailed information to analyze emergency response performance. These datasets are vital for understanding trends, evaluating current response times, and developing optimized deployment strategies. Below is a description of each dataset used:

- **Incident Data**
  Captures details about specific emergency incidents, including the type of incident, the situation found, duration, personnel involved, and actions taken.
- **Station Apparatus Data**
  Contains facility ID details, including unit descriptions and specialty units for each fire station, and provides critical metadata for resource and deployment analysis.
- **Geospatial Data**
  Provides a geographic shapefile for the locations of all RFD fire stations. This data enables geospatial analysis of station coverage, proximity, and response efficiency.

Dataset	**Description**	**Shape**	**Period**
Incident	Tracks incident type, action taken	(650K, 180)	2006–2024
Station Apparatus	Station-specific resources	(16, 6)	-
Geospatial	Fire station location shapefiles	(16, 13)	-

Table 1: Summary of Datasets

2.2 Data Preprocessing

The initial phase of this project involved comprehensive data preprocessing to ensure the dataset was clean and suitable for modeling. The dataset comprised incident reports containing various attributes, such as location, incident type, and personnel data. As a first step, some columns, such as `room_apt_num`, were dropped based on domain knowledge, context, and relevance to streamline the dataset.

For location-based fields, missing values in the `street` and `cross_street` columns were replaced with the placeholder `Unknown`. Missing values in `city` and `state` were imputed using their respective modal values, while missing ZIP codes were also assigned the value `Unknown`. Similarly, for situation-based columns, such as `sitfound` and `incident_type_descr`, shift-related details, such as `schdshiftname_code` and `schdshiftname_descr`, and severity of the incident (`alarmnum`), modal imputation was applied to ensure consistency in data representation.

Certain columns, including `mutual_aid_code`, `mutual_aid_descr`, and those related to secondary and tertiary actions, were removed entirely as they were either redundant or had limited utility for analysis. Apparatus and personnel data fields, which had more than 80% missing values, were also dropped. Similarly, loss-related columns, such as `property_loss` and `contents_loss`, were excluded due to having over 99% missing values. Injury and fatality details were retained, but missing values were filled with zero to reflect the absence of reported incidents.

The dataset underwent additional cleanup to ensure chronological consistency. A particular focus was placed on time-related columns such as `datetimearr` (time of arrival). Missing or invalid values in `datetimearr` were imputed by calculating the median time difference between `datetimealarm` (time of alarm) and valid `datetimearr` entries. Any rows where `datetimearr` was earlier than `datetimealarm` were adjusted by adding this median time difference to the `datetimealarm` value. Further adjustments ensured that outliers exceeding a maximum threshold (25 minutes) were replaced with the 99.5th percentile of valid time-to-arrival values. These changes resolved inconsistencies and improved the reliability of time-related fields.

Finally, latitude and longitude data were merged using an additional dataset provided by the RFD team to enrich the dataset with geographical details. Rows with null geocoordinates were removed to ensure completeness and maintain the integrity of location-based analysis.

2.3 Dataset Preparation and Feature Engineering

Once the data was cleaned, the dataset was prepared for predictive modeling. Feature engineering, which was pivotal in creating an optimized pipeline for forecasting incident counts, began with aggregating the data by month and year for each station. Since one row corresponds to one incident, the aggregation provided monthly incident counts from 2006 to 2024 for each fire station. These monthly counts served as the target variable.

For the independent variables, numerical attributes were summarized using mean or median statistics, depending on their distribution. Categorical attributes were one-hot encoded, and their frequencies were counted per month-year for each station. The aggregated data was then split by fire station, resulting in 16 datasets, each corresponding to one of Rochester's fire stations, with robust feature sets for subsequent modeling.

To identify dependencies and patterns in the time-series data, a detailed analysis was conducted. Since the data represented monthly incident counts, autocorrelation function (ACF) plots were analyzed to determine the most relevant lagged features for inclusion in the models. Lag selection was performed individually for each station to account for station-specific patterns.

3. Exploratory Data Analysis

3.1 Monthly Trends in Incident Records (2006–2024)

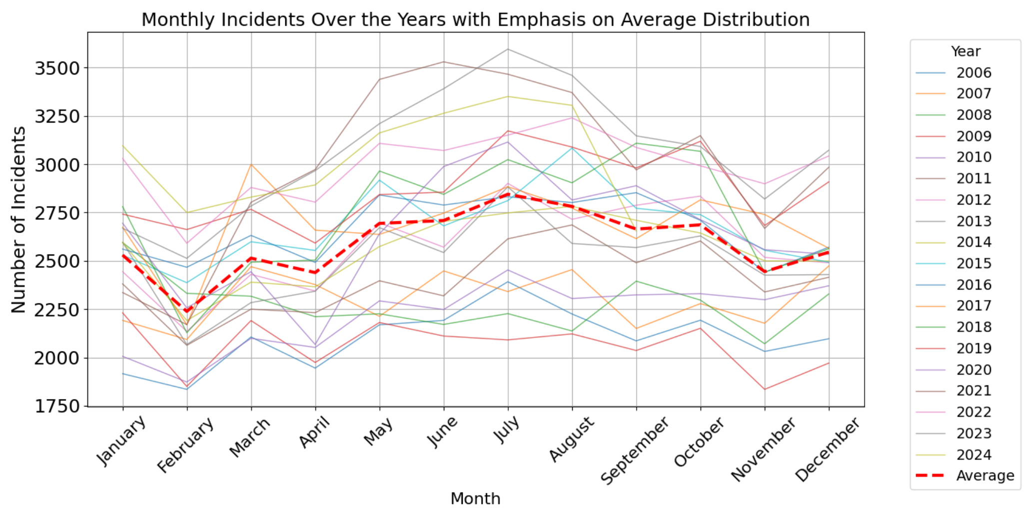


Figure 1: Monthly Incidents Over the Years with Emphasis on Average Distribution

The plot presents the monthly distribution of incident records from January 2006 to August

2024. Each line represents a specific year, while the bold red dashed line highlights the average monthly trend across all years.

The analysis reveals a clear seasonal variation in the number of incidents. Incident counts during the summer months (June, July, and August) demonstrate a notable increase, averaging 17.38% higher compared to the winter months. This rise can be attributed to heightened outdoor and community activities facilitated by favorable summer weather. Notable city events, such as the International Jazz Festival and 4th of July celebrations, attract large gatherings, increasing the likelihood of incidents. These incidents are not confined to fires alone but encompass a range of public safety responses, including medical emergencies, disability assistance, and other urgent services.

Additionally, the data indicates an increase in incidents during December and January, coinciding with the holiday season, particularly around Christmas and New Year's celebrations. Conversely, February experiences a decline in incident counts, likely reflecting reduced activity following the holidays.

3.2 Incident Types Contributing to the Summer Increase

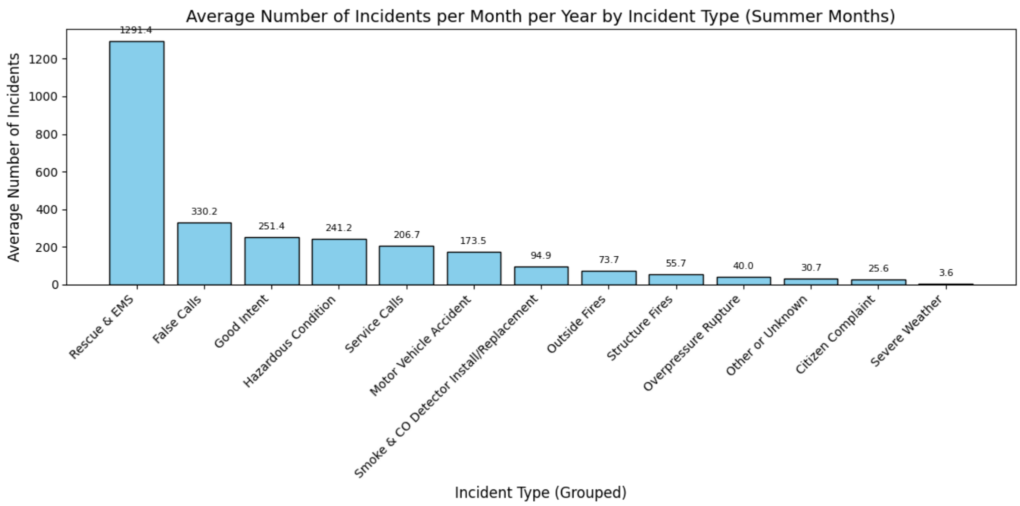


Figure 2: Average Number of Incidents per Month per Year by Incident Type (Summer Months)

The graph above highlights the distribution of incident types contributing to the rise in incident counts during the summer months. It is evident that the 'Rescue & EMS' category accounts for the largest share, averaging 1291.4 incidents per month. This category alone represents the most significant workload for the fire department and aligns with the observed increase in public activities and outdoor events during summer.

Other notable contributors include False Calls (330.2 incidents), Good Intent (251.4 incidents), and Hazardous Conditions (241.2 incidents). These incident types likely reflect increased human activity, miscommunication during emergencies, and elevated environmental hazards such as heat-related conditions.

While Service Calls (206.7 incidents) and Motor Vehicle Accidents (173.5 incidents) also show significant volumes, categories like Severe Weather (3.6 incidents) remain minimal during summer. The data underscores the importance of prioritizing Rescue & EMS services during this period to effectively manage the seasonal surge in incidents.

3.3 Hourly Distribution of Incidents

The graph below illustrates the average number of incidents occurring at each hour of the day across the dataset. A clear trend emerges, with incident counts rising steadily from the early morning hours, reaching a peak at 5 PM (Hour 17). This peak aligns with the end of the standard workday, a time when increased activity—such as commuting, outdoor engagements, and other daily routines—contributes to a higher frequency of incidents. In contrast, the data reveals that the quietest period occurs between 4 AM and 5 AM, corresponding to the hours when most of the city is at rest, with minimal activity and fewer opportunities for incidents to occur.

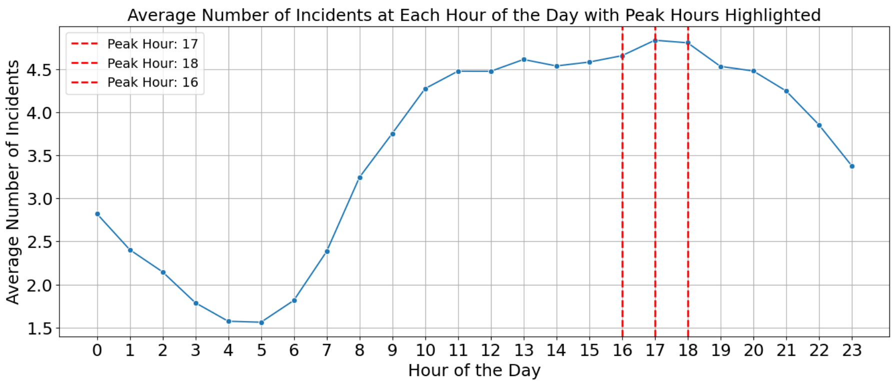


Figure 3: Average Number of Incidents at Each Hour of the Day with Peak Hours Highlighted

3.4 Incident Types During Peak Hours

The graph highlights the distribution of incident types occurring during the identified peak hours (4 PM to 6 PM). The data reveals that 'Rescue & EMS' incidents dominate this period, averaging 6 incidents per day, which further emphasizes the significant workload this category imposes on the fire department.

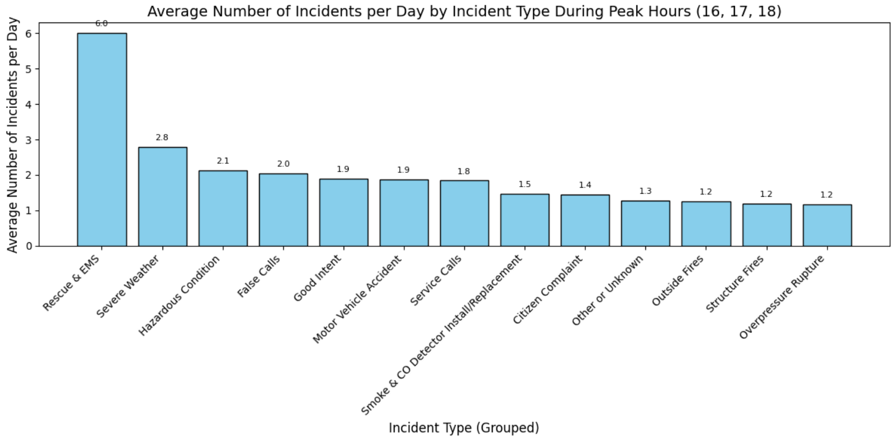


Figure 4: Average Number of Incidents per Day by Incident Type During Peak Hours (16,17,18)

Other notable contributors during peak hours include Severe Weather (2.8 incidents), Hazardous Conditions (2.1 incidents), and False Calls (2 incidents). These incident types are likely influenced by increased public activity and traffic congestion during peak hours. Categories such as Motor Vehicle Accidents and Service Calls also show steady occurrence rates, averaging around 1.9 to 1.8 incidents per day.

The presence of Severe Weather incidents during this time highlights the need for preparedness against unexpected environmental conditions, which can exacerbate traffic and safety issues. The data underscores the importance of focusing resources, particularly on Rescue & EMS responses, during peak hours to efficiently handle the higher frequency of incidents.

3.5 Average Monthly Incidents by Fire Station and Incident Type

The visualization depicts the average number of incidents per month across all fire stations, with the x-axis representing individual fire stations and the y-axis showing the corresponding average monthly incident counts. Each bar is stacked to represent different incident types, as indicated by the color-coded legend on the right.

The analysis identifies the top three busiest fire stations as:

1. Engine 17/Rescue 11
2. Engine 2
3. Engine 13/Truck 10

A significant observation is that nearly half of the total incidents fall under the 'Rescue & EMS' category, as shown by the dominant dark blue segments in the bars. This underscores

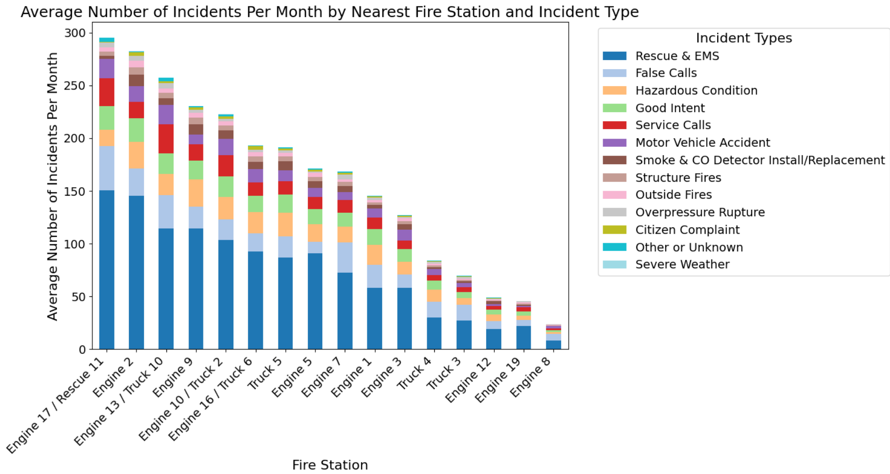


Figure 5: Average Number of Incidents Per Month by Nearest Fire Station and Incident Type

the considerable workload placed on the fire department by Rescue and EMS-related responses. Other notable incident types include False Calls, Service Calls, and Good Intent, but their contributions are comparatively smaller.

This visualization highlights the need for prioritizing resources and personnel for Rescue and EMS incidents, particularly at high-activity stations, to ensure efficient response and operational readiness.

3.6 Interactive Maps

Using the dataset spanning the last six years (2019-2024), two interactive maps were developed utilizing the Folium library to analyze emergency response dynamics and provide actionable insights for resource optimization. Both maps focus on ZIP code-level data, enriched by fire station statistics and incident types.

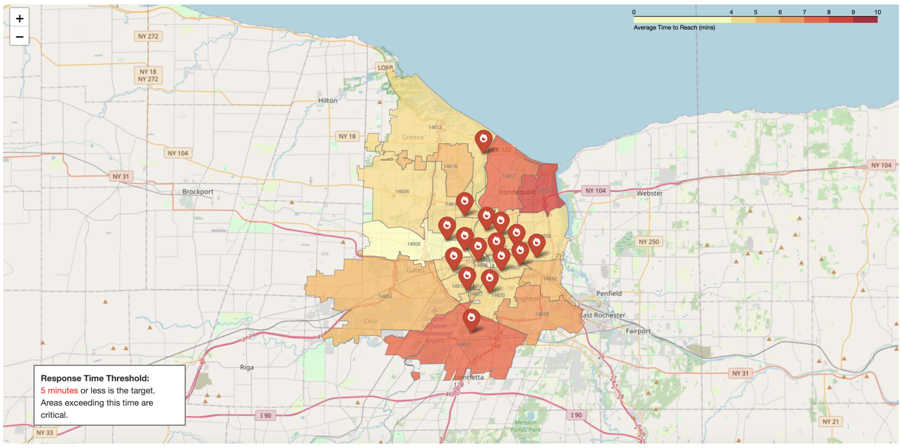


Figure 6: Interactive Map with Average Response Times

The map visualizes average response times by ZIP code, where areas exceeding the Rochester

Fire Department (RFD)'s target of 5 minutes are highlighted in red or orange. Incident types and counts for each fire station are also embedded as interactive markers, enabling detailed station-level analysis. The map reveals that while most coverage areas achieve response times between 4-5 minutes, certain regions with times over 5 minutes lie outside RFD's primary zones and represent less than 1% of incidents. Light yellow zones (ZIPs 14614, 14604, and 14606) outperform with sub-4-minute response times.

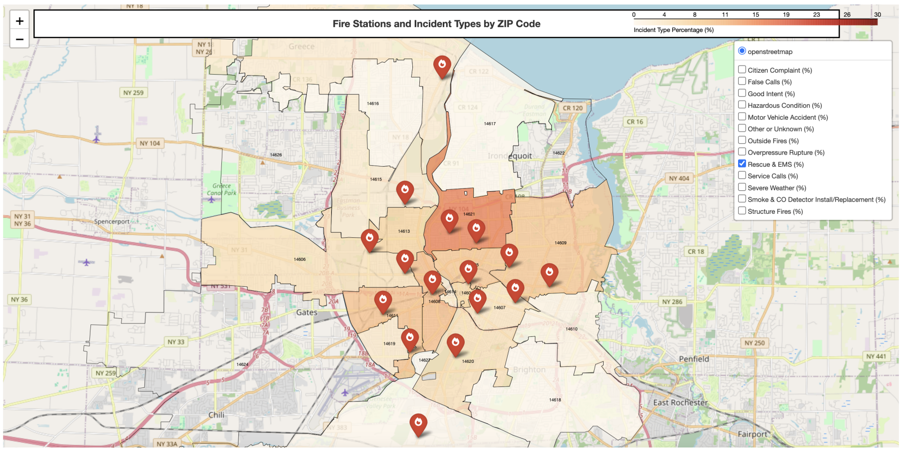


Figure 7: Interactive Map with Incident Distribution by Type

The map above delves into incident distribution by type, providing layered visualizations where each incident category (e.g., Rescue & EMS, Motor Vehicle Accident, or False Calls) can be toggled individually. This map integrates incident type percentages within each ZIP code, creating a heatmap that highlights patterns such as clusters of incidents. Each fire station marker includes detailed statistics on incident counts and type-specific percentages, offering granular insight into station workload and specialization.

These maps serve as interactive tools for identifying high-risk areas, understanding incident trends, and planning strategic deployment of resources. By coupling these visualizations with further data analyses, we propose targeted strategies for enhancing RFD's operational efficiency and response effectiveness, to be discussed in subsequent sections.

3.7 Resource Allocation and Suggested Changes

3.7.1 Unit E17: Handling Hazardous Conditions

Engine 17 is a specialized unit tasked with responding to Hazardous Conditions and is currently stationed at Fire Station Engine 17/Rescue 11. However, analysis of the interactive map (Figure 1) reveals that the highest concentration of Hazardous Conditions incidents occurs near Fire Station Engine 2.

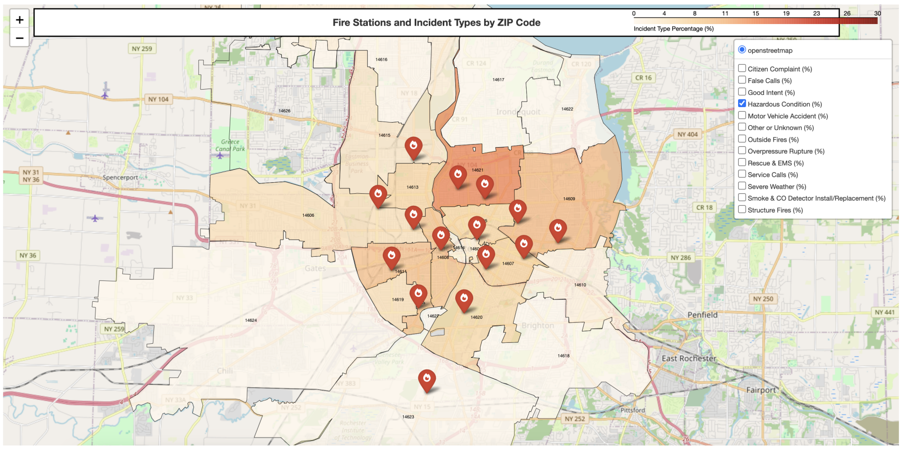


Figure 8: Interactive Map Highlighting Hazardous Conditions

To optimize response times and resource efficiency, we recommend the following adjustments:

- Relocate Unit E17 to Fire Station Engine 2
- Move Unit E2 to Fire Station Engine 17/Rescue 11

This reallocation will allow for improved coverage of hazardous incidents and better utilization of specialized resources.

3.7.2 Fire Investigation Vehicles (CAR91–CAR98)

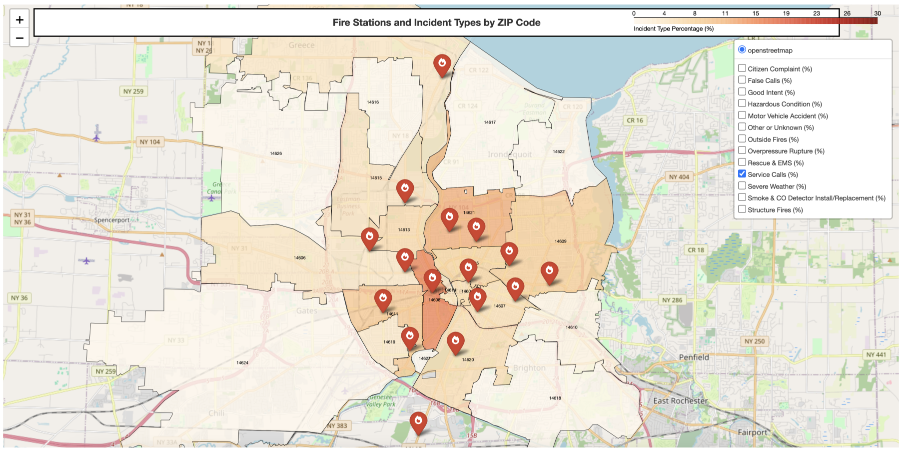


Figure 9: Interactive Map Highlighting Service Calls

Currently, all five Fire Investigation Vehicles (CAR91–CAR98) are stationed at Engine 10/Truck 2. As shown in the heat map (Figure 3), Service Calls account for approximately 80% of their workload. Furthermore, the interactive map (Figure 2) highlights that a significant number of Service Calls occur near Engine 13/Truck 10.

To balance workload and reduce response times, we recommend:

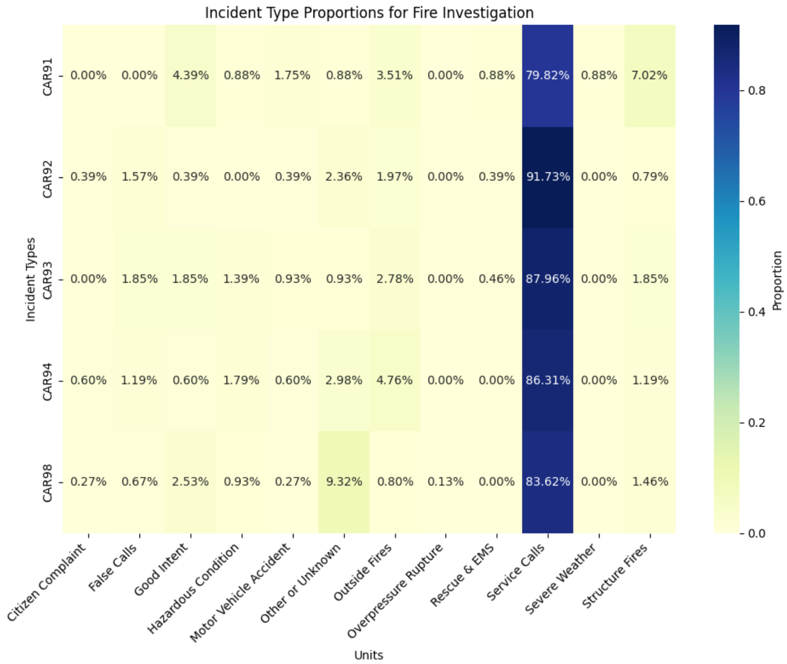


Figure 10: Heat Map of Incident Type Proportion for Fire Investigation Units

- Relocating 2 out of the 5 vehicles to Fire Station Engine 13/Truck 10.

This adjustment ensures better resource distribution and aligns vehicle placement with demand hotspots.

3.7.3 Comments on Specific Trucks and Engines

1. **Unit R11 (Rescue Truck)**

   Unit R11 is the city's only rescue truck and is currently stationed at Engine 17/Rescue 11, a centrally located fire station. This location ensures optimal response times for rescue operations across the city. Therefore, no changes are recommended for this unit.

2. **Units E1 and E10 (Equipped with Jaws of Life)**

   Engines E1 and E10 are equipped with the Jaws of Life tool, which is critical for vehicle rescue operations. Their current locations—Engine 1 and Engine 10/Truck 2—are strategically positioned on opposite sides of the city, ensuring city-wide coverage.

   Given that vehicle rescue operations can occur anywhere in the city, their current placements are deemed effective. Both units primarily handle Rescue & EMS calls, along with other incident types, ensuring flexibility and responsiveness.

3.7.4 Overall Observations

Most units primarily respond to incidents near their respective fire stations. Analysis of incident patterns did not reveal significant inefficiencies that would warrant further relocation at this time. The current resource allocation remains effective overall, with minor adjustments suggested to enhance performance in specific areas.

3.8 Proposed Low-Acuity Program

To address the growing burden of non-emergency calls, particularly in Rochester's densely populated and disadvantaged areas, we propose a pilot low-acuity response program modeled after Seattle's *Health One* initiative. Low-acuity calls, such as those involving substance abuse, minor injuries, or crises affecting vulnerable populations like the homeless, represent a significant portion of Rochester Fire Department's (RFD) call volume. These calls, often referred to as "ridiculous calls," strain resources intended for emergencies and detract from the core training and responsibilities of firefighters and police.

Based on qualitative research, including 20 interviews with experienced firefighters, we identified a national crisis in handling low-acuity EMS cases, especially in cities like Rochester, which face high rates of poverty and homelessness. We propose deploying a team of two firefighters and one social worker to respond to non-emergency EMS calls during peak hours, operating four days a week. This $400,000 program could be proposed as an enhancement to the current Nurse Navigation Program and aims to divert patients to appropriate therapeutic destinations, reduce reliance on emergency departments, and free up first responders for high-priority emergencies.

While examples from other cities demonstrate the potential impact of such initiatives, Rochester faces unique regulatory and logistical challenges. Additionally, we found that existing data does not classify low-acuity incidents, limiting our ability to analyze trends and make data-driven recommendations. We suggest adding this classification as a data label to improve future assessments. However, implementing this program without expanding backend social services could overwhelm providers and limit its effectiveness. Despite these challenges, this initiative could significantly improve resource allocation, alleviate the strain on emergency responders, and provide critical support to Rochester's most vulnerable populations.

3.9 Summary

The exploratory data analysis highlights seasonal, hourly, and station-level trends in incident patterns, with Rescue & EMS incidents consistently dominating across all dimensions. Key insights include a summer peak in incidents driven by increased outdoor activities and a notable hourly spike during late afternoons (4-6 PM). These findings underscore the need for targeted resource allocation and strategic adjustments to enhance the Rochester Fire Department's operational efficiency.

4. Model Development

4.1 Feature Selection

4.1.1 Identifying Multicollinearity

Purpose: Multicollinearity occurs when independent variables are highly correlated with one another, leading to redundancy and instability in the model. Addressing multicollinearity ensures that the model performs optimally, reduces overfitting risks, and makes feature importance and predictions more interpretable and reliable.

Approach: Multicollinearity among features was addressed through correlation analysis. Highly correlated pairs of variables were identified using a correlation threshold (e.g., $r > 0.7$). Variables in these pairs were flagged for further evaluation to determine which feature to retain and which to drop.

Decisions: For each pair of highly correlated variables, decisions on feature retention were based on:

1. **Domain Knowledge**: Features with greater relevance to the problem were retained
2. **Target Correlation**: The feature with a stronger correlation to the target variable (monthly incident counts) was kept

By following these principles, redundancy in the dataset was reduced without compromising predictive power.

4.1.2 Creating Interaction Terms

Purpose: Interaction terms capture relationships between features that, when combined, reveal patterns not evident in individual variables. This enhances the model's ability to identify complex dependencies and improves predictive performance.

Approach: Interaction terms were created based on domain knowledge, focusing on features that naturally interact or frequently occur together. For example, geographical data such as `'latitude'` and `'longitude'` were combined to account for spatial relationships. Additionally, combinations that reflect severity, such as `'civilian_deaths'` and `'alarmnum_5'` (indicating severe incidents), were considered.

Examples:

1. **Spatial Interactions**: `'latitude'` × `'longitude'` to represent location-based relationships.
2. **Severity Indicators**: `'civilian_deaths'` × `'alarmnum_5'` to highlight high-severity incidents where even one civilian death qualifies as severe.
3. **Custom Domain Features**: Other combinations were explored based on expert input and problem-specific insights, ensuring that all interaction terms had meaningful interpretations.

4.1.3 Feature Importance Analysis

Purpose: Identifying the most predictive features ensures that the model focuses on the most critical variables while reducing dimensionality. This step also improves computational efficiency and interpretability.

Approach: Feature importance was evaluated using a combination of machine learning models and interpretability techniques:

1. **Random Forest**: A Random Forest model was trained on the dataset to calculate the importance scores of individual features.
2. **SHAP Values**: SHAP (SHapley Additive exPlanations) values were computed to identify the top 10 features contributing to the predictions.
3. **Consensus**: A consensus approach was used to select features that overlapped between the top Random Forest and SHAP-ranked features.

4.1.4 Model Validation

Purpose: Model validation ensures that the selected features and models generalize well to unseen data and that the predictions are reliable across different time periods.

Approach: Time-series cross-validation was used to evaluate the model's performance. Five folds were created based on chronological splits of the dataset to mimic real-world forecasting scenarios. The models were trained on earlier data and validated on later time periods.

Results: The models achieved an average R^2 of approximately 85.28% across folds and stations. This robust performance validated the selection of features and the overall modeling approach, ensuring the models were well-suited for forecasting monthly incident counts.

4.2 Model Building

4.2.1 Handling COVID-19 Effects

Purpose: The COVID-19 pandemic introduced unique circumstances that could significantly distort feature trends. It was essential to determine whether features were impacted during the COVID-19 period (March 2020 to June 2021) and account for these effects in the modeling process to improve forecasting reliability.

Content: A binary indicator variable, `is_covid`, was created to distinguish incidents occurring during the pandemic period (`is_covid = 1`) from those outside it (`is_covid = 0`). The dataset was split into two groups based on this variable, and statistical tests were conducted to evaluate whether the means of the two groups were significantly different. Depending on the distribution and variance, either a t-test (for normal distribution and equal variance) or a Mann-Whitney U test (for non-normal distribution or unequal variance) was used. The null hypothesis (H_0) stated that the means of the two groups were equal, indicating no significant impact of COVID-19. Features for which H_0 was rejected were deemed affected by COVID-19, and `is_covid` was added as an exogenous variable during the modeling of those features. This approach ensured that future forecasts accurately accounted for COVID-related anomalies.

4.2.2 Feature Forecasting

Purpose: Independent features must be forecasted before using them as regressors in the final model. Accurate feature forecasting prevents static regressors and enhances the reliability of long-term predictions.

Content: Each selected feature was forecasted individually for each fire station. SARIMAX models, tailored with hyperparameter tuning, were the primary method used for forecasting. Hyperparameters optimized for SARIMAX included the following:

- **p, d, q:** Parameters for the non-seasonal ARIMA component:
  - **p:** The order of the autoregressive (AR) term.
  - **d:** The degree of differencing.
  - **q:** The order of the moving average (MA) term.
- **P, D, Q:** Parameters for the seasonal component:
  - **P:** The order of the seasonal autoregressive term.
  - **D:** The degree of seasonal differencing.
  - **Q:** The order of the seasonal moving average term.

For hyperparameter tuning in SARIMAX, grid search was used. This was done for every selected feature for every station, totaling 124 SARIMAX models with hyperparameter tuning.

For features where SARIMAX performed poorly (mean absolute percentage error (MAPE) ¿ 0.4), alternative models, such as Poisson regression or Holt-Winters exponential smoothing, were explored. The model yielding the lowest MAPE was chosen to ensure the most accurate forecasts for each feature. These forecasted values were prepared for use as inputs to the final model, ensuring dynamic and meaningful contributions to the monthly incident count predictions.

4.2.3 Final Prophet Model

Purpose: The Prophet model was employed to predict monthly incident counts for the next ten years. It leveraged the forecasted features as regressors and incorporated seasonal trends and holiday effects for robust long-term forecasting.

Content: Using the forecasted values of independent features as regressors, the Prophet model was trained to predict monthly incident counts for each fire station. This approach avoided static predictions by dynamically incorporating the evolving trends of the regressors. Prophet's ability to handle seasonality, holidays, and trend changes made it particularly suitable for this task. The model was validated on historical data and showed strong predictive performance, enabling actionable insights for future resource allocation and operational planning for the fire department.

5. Performance and Results

5.1 Performance

This section evaluates the forecasting models' accuracy and efficiency across stations using computational metrics that capture trends while balancing complexity and fit, ensuring reliable time series forecasting.

5.1.1 Performance Metrics Across Stations for Forecasting Independent Features

To evaluate the accuracy and efficiency of the forecasting independent features across stations, the following performance metrics were used:

- **Root Mean Square Error (RMSE):** RMSE measures the square root of the average squared differences between predicted and actual values. It penalizes large errors more heavily, making it a sensitive measure of model performance. Lower RMSE values indicate better predictive accuracy.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

- **Mean Absolute Error (MAE):** MAE calculates the average of the absolute differences between predicted and actual values. It provides a straightforward interpretation of prediction errors in the same units as the data. Lower MAE values indicate better performance.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

- **Mean Absolute Percentage Error (MAPE):** MAPE represents the mean absolute error as a percentage of the actual values. It provides insight into the relative magnitude of prediction errors, making it particularly useful for comparing across different datasets or scales. Lower MAPE values indicate better performance.

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100$$

- **Akaike Information Criterion (AIC):** AIC evaluates the model's goodness of fit while penalizing model complexity to prevent overfitting. Lower AIC values indicate a better balance between accuracy and simplicity.

  $$\text{AIC} = 2k - 2\ln(\hat{L})$$

  where k is the number of parameters and $\hat{L}$ is the maximum likelihood.

- **Bayesian Information Criterion (BIC):** Similar to AIC, BIC penalizes model complexity but applies a stronger penalty for the number of parameters. Lower BIC values indicate a model that balances accuracy and parsimony.

  $$\text{BIC} = k\ln(n) - 2\ln(\hat{L})$$

  where n is the number of observations.

These metrics were chosen to evaluate the model from multiple perspectives:

- RMSE and MAE provide absolute error measures to assess overall prediction quality.
- MAPE offers a percentage-based error evaluation for easy interpretability across stations.
- AIC and BIC ensure the model remains efficient by balancing complexity and fit, preventing overfitting.

The combination of these metrics provides a comprehensive view of the model's performance, ensuring robust and reliable predictions for forecasting independent features across stations.

Metric	**Value**
RMSE (Root Mean Square Error)	5.835
MAE (Mean Absolute Error)	4.740
MAPE (Mean Absolute Percentage Error)	18.945
AIC (Akaike Information Criterion)	743.375
BIC (Bayesian Information Criterion)	766.315

Table 2: Performance Metrics Across Stations for Forecasting Independent Features

Forecasting Accuracy: The model demonstrated reasonable forecasting performance, with low errors and deviations across stations. The RMSE and MAE values indicate that the model captures trends effectively, while the MAPE reflects the relative prediction error across stations.

Model Efficiency: The low AIC (743.375) and BIC (766.315) values highlight a balance between model accuracy and simplicity, ensuring that the model avoids overfitting while maintaining predictive power.

These metrics validate the model's ability to predict independent features for time series forecasting effectively, enabling better allocation of resources based on future incident trends.

5.1.2 Model Performance

The evaluation of the Prophet model for forecasting demonstrated strong predictive accuracy across all stations. Key performance metrics are summarized below:

- **Mean Absolute Error (MAE):** The model achieved an average MAE of 0.34, indicating that the average magnitude of prediction errors across stations was minimal.
- **Mean Absolute Percentage Error (MAPE):** With an average MAPE of 19.2%, the model exhibited good predictive accuracy relative to actual values.
- **Root Mean Square Error (RMSE):** The model achieved an average RMSE of 0.43, reflecting its ability to effectively capture trends while maintaining relatively low prediction errors.

Station Name	**MAE**	**RMSE**	**MAPE**
Engine 1	0.292	0.460	0.142
Engine 2	0.782	0.821	0.202
Engine 3	0.140	0.190	0.078
Engine 5	0.474	0.489	0.261
Engine 7	0.184	0.209	0.092
Engine 8	0.014	0.017	0.036
Engine 9	0.295	0.402	0.108
Engine 10/Truck 2	0.643	0.671	0.223
Engine 12	0.345	0.752	0.535
Engine 13/Truck 10	0.391	0.471	0.159
Engine 16/Truck 6	0.373	0.471	0.166
Engine 17/Rescue 11	0.488	0.570	0.175
Engine 19	0.037	0.050	0.053
Truck 3	0.133	0.150	0.145
Truck 4	0.408	0.528	0.472
Truck 5	0.436	0.621	0.218

Table 3: Station-wise Performance Metrics

The station-wise results highlight variability in predictive performance, with some stations, such as Engine 8 and Engine 19, achieving significantly lower errors compared to others. These differences underscore the need for station-specific analysis to enhance overall performance.

Overall, the Prophet model has proven to be a reliable forecasting tool, capturing temporal trends effectively while maintaining reasonable error margins across stations.

5.2 Results

5.2.1 Monthly Incident Counts Forecast Across RFD Stations (2024 - 2034)

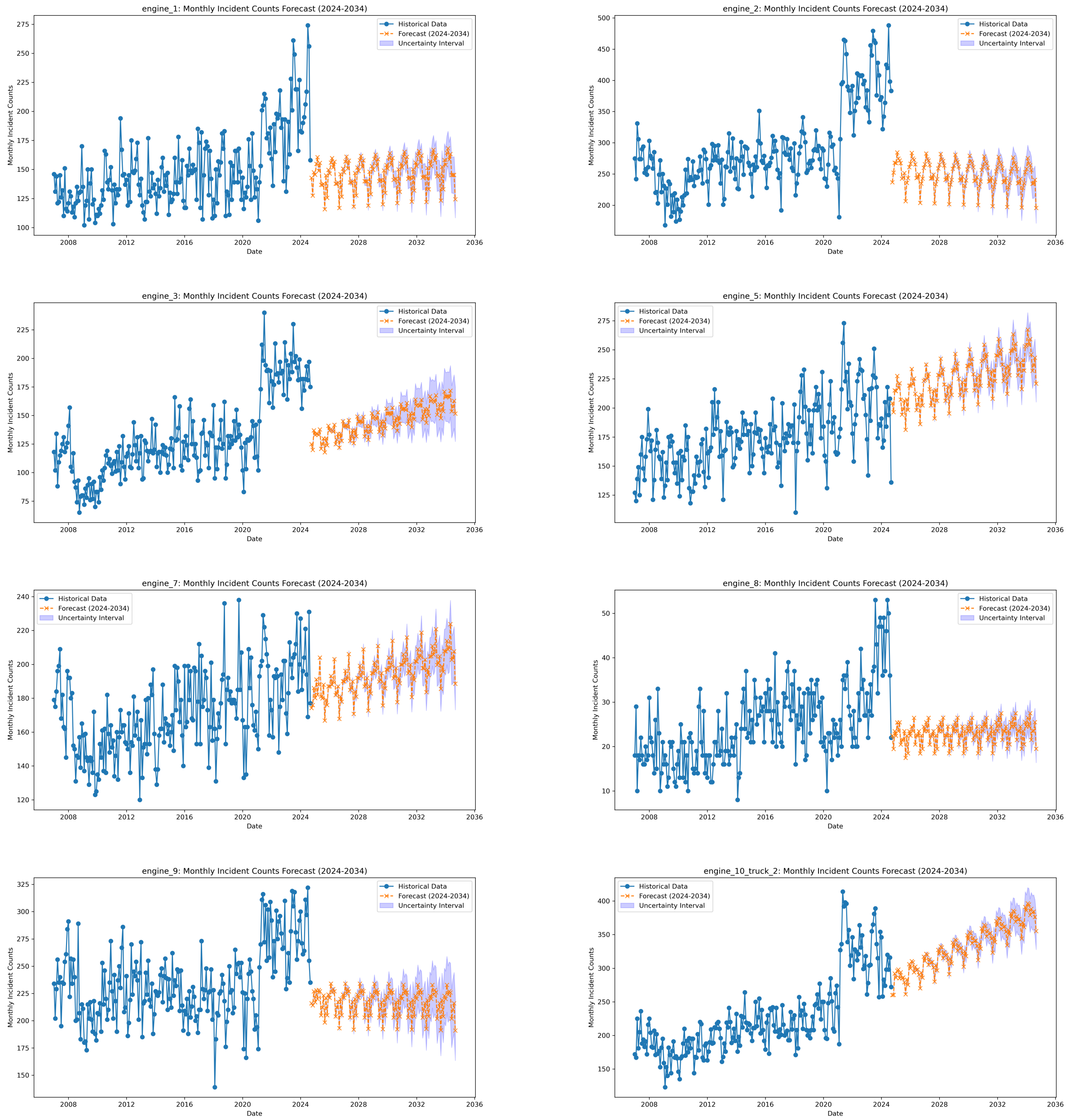


Figure 11: Monthly Incident Counts Forecast (Engine 1 - Engine 10/Truck 2)

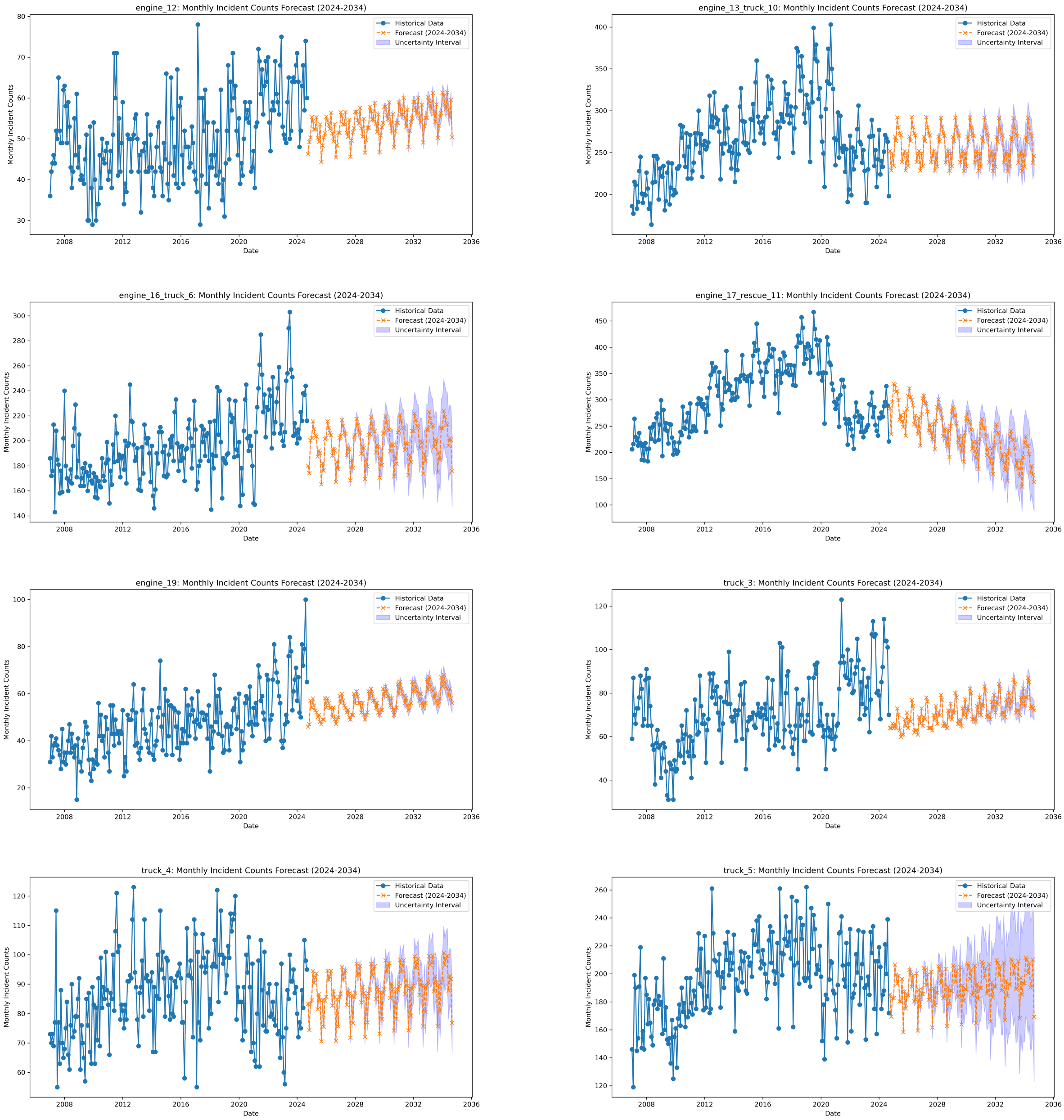
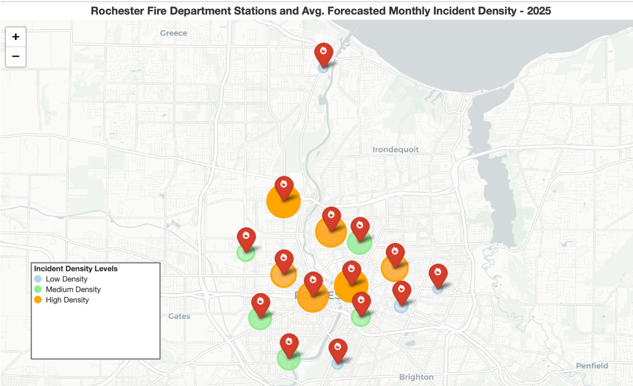


Figure 12: Monthly Incident Counts Forecast (Engine 12 - Truck 5)

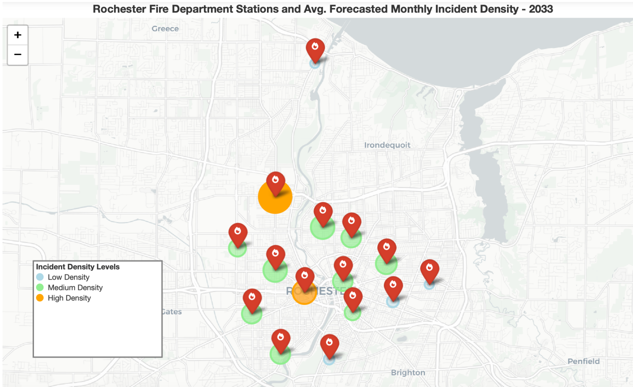
The Prophet forecasts show monthly incident trends for each fire station (Engine 1 through Truck 5) from 2024 to 2034. Historical data (blue) highlights rising demands, while forecasts (orange) suggest continued growth, with confidence intervals (purple) marking uncertainties.

Stations like Engine 10/Truck 2 and Engine 13/Truck 10 handle significantly higher volumes, making them activity hotspots. In contrast, stations like Engine 8 show lower volumes, suggesting potential opportunities to redistribute resources. These insights stress the need for strategic planning to meet growing demands.

5.2.2 Average Forecasted Monthly Incident Densities



(a) Predicted Counts Density - 2025



(b) Predicted Counts Density - 2033

Nearest Station Name	2025 Incidents	2033 Incidents
Engine 1	142.70	150.27
Engine 10/Truck 2	286.30	372.19
Engine 12	51.42	56.68
Engine 13/Truck 10	258.25	257.51
Engine 16/Truck 6	194.13	202.60
Engine 17/Rescue 11	285.39	193.42
Engine 19	52.03	60.72
Engine 2	254.32	246.04
Engine 3	129.99	159.66
Engine 5	207.80	241.91
Engine 7	183.61	203.58
Engine 8	22.13	23.75
Engine 9	217.37	216.40
Truck 3	65.42	76.38
Truck 4	85.28	90.97
Truck 5	186.99	195.87

Table 4: Predictions for 2025 and 2033: Monthly Incidents per Nearest Fire Station

6. Conclusion & Future Works

This project aimed to enhance the operational efficiency of the Rochester Fire Department (RFD) by analyzing historical incident data, optimizing resource allocation, and assessing potential improvements in deployment strategies. Through the application of geospatial analysis and predictive modeling, we successfully identified key trends in incident patterns and proposed actionable recommendations to optimize the department's resources and reduce response times.

The project's key accomplishments include:

- Development of interactive maps showcasing incident types and response times across different fire stations.
- Recommendations for resource reallocation, such as relocating specific units (e.g., hazardous condition response units) to better align with incident hotspots.
- Insights into the deployment of a proposed low-acuity response program to address non-emergency EMS calls, potentially reducing the load on critical emergency resources.

Our predictive modeling efforts achieved promising accuracy metrics, particularly with the Prophet model used for forecasting monthly incident counts. This model provides RFD with a robust tool to anticipate and prepare for future demands, ensuring preparedness and operational excellence.

Despite these achievements, there are areas for further exploration and enhancement:

1. **Improved Predictive Modeling for Response Times**
   Existing models demonstrated limited accuracy in predicting response times due to insufficient external data. Incorporating additional datasets, such as traffic flow or road conditions, could significantly improve model performance.
2. **Exploration of Alternative Similarity Measures**
   Beyond conventional distance-based approaches, employing techniques like Jaccard similarity or Pearson correlation could provide new insights into unit and resource allocation.
3. **Implementation of the Low-Acuity Program**
   Establishing this program requires feasibility analysis, pilot testing, and stakeholder engagement to ensure alignment with RFD's strategic goals.
4. **Interactive Reporting and Visualization**
   Expanding current visualizations into a user-friendly dashboard could support decision-making and improve accessibility for stakeholders.
5. **Collaboration with External Partners**
   Engaging with urban planners and traffic management agencies could enrich the data ecosystem and enhance future modeling efforts.

This project demonstrates the potential of data-driven strategies in public safety management, providing RFD with tools and insights to better serve the Rochester community. By addressing the identified gaps and continuing to integrate innovative practices, RFD can further advance its mission of safeguarding lives and property.

References

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