Analyzing Fire-Response Efficiency in İzmir: District-Level Disparities and Machine-Learning Prediction of Intervention Duration

Abstract— **Efficient fire-response services are critical for urban safety and infrastructure protection. However, regional disparities in response performance are underexplored in Turkish municipalities. Using the 2023 İzmir Fire Department dataset comprising over 12,000 fire incidents, we formulate and explore two research questions. First, we statistically test whether average response times differ between central and peripheral districts of İzmir. Second, we propose a machine learning model to predict intervention duration based on incident attributes such as location, fire type, and time of day. We conduct initial data quality checks and descriptive analysis to support these goals. Our findings aim to provide actionable insights for response optimization and resource planning.**

I. Introduction

Fire-related emergencies require timely response to minimize damage and ensure public safety. Key performance indicators for fire departments include response time—the duration from the initial call to unit arrival—and total intervention duration. Previous studies in urban safety have shown that delayed responses can increase the severity of outcomes, yet there is limited empirical work focused on regional inequalities within cities such as İzmir, Türkiye. This study leverages the official 2023 fire incident records from the İzmir Municipality to explore disparities in service delivery and to develop predictive tools that could aid emergency planning.

II. Research Questions

- RQ1 (Statistical Test): *Does the mean fire-station response time differ significantly between central and peripheral districts of İzmir?*
  A statistical analysis of district-based response time differences in a major metropolitan area.
- RQ2 (Machine Learning): *Can the total intervention duration (minutes from arrival to extinguishment) be predicted using features such as district, fire type, time of call, and resources deployed?*
  A regression model for estimating fire intervention duration using interpretable machine learning methods.

III. Literature Survey

Sahebi et al. (2025) employed machine learning models to predict firefighting operation durations in urban environments. Their findings emphasized the importance of crew size and fire type in forecasting intervention time [1].

Svensson et al. (2024) investigated disparities in emergency response times across rural and urban areas in Sweden. They found a consistent time gap between central and remote zones, demonstrating a need for resource redistribution [2].

Jaldell (2019) performed a statistical study showing that fire damage severity correlates strongly with delayed response. This supports our approach of modeling and testing response-time differences across regions [3].

These works collectively provide a solid foundation for our inquiry into geographic performance disparities and prediction modeling in urban fire services.

IV. Methodology & Implementation

To address the research questions, two main approaches were followed: hypothesis testing and machine learning-based regression modeling. All analysis was conducted using the 2023 fire intervention dataset shared by Izmir Metropolitan Municipality.

The dataset was read and parsed in Python using pandas. Missing or malformed values were removed. Timestamps were parsed into datetime format, and the hour of the call was extracted for analysis. Response time in minutes (VARIS_SURESI (DAK.)) was used as a key outcome variable, and districts were categorized as "Central" or "Periphery" based on İzmir's administrative layout.

RQ1 - Hypothesis Testing:

- *Null Hypothesis (H0):* There is no significant difference in the mean fire-station response time between central and peripheral districts.
- *Alternative Hypothesis (H1):* There is a significant difference in the mean response time between central and peripheral districts.
- *Test Applied:* Mann–Whitney U test (non-parametric)
- *Reason:* Response time data was skewed and did not meet the assumptions of normality required for a t-test.
- *Result:* The p-value obtained was less than 0.05, suggesting a statistically significant difference between central and peripheral response times.

RQ2 - Machine Learning Regression Model:

- *Target Variable:* Response time (response_minutes)
- *Features Used:*
  - *District (ILCE)*

- *Fire Type (YANGIN_TURU)*
- *Fire Cause (YANGIN_SEBEBI)*
- *Amount of Water Used (KULLANILAN_SU_MIKTARI (m3))*
- *Amount of Foam Used (KULLANILAN_KOPUK_MIKTARI (KG))*
- *Address Type (ADRES_BOLGESI)*
- *Call Hour (call_hour)*

- *Model Used:* Random Forest Regressor
- *Pipeline:*
  - Categorical columns were one-hot encoded.
  - Numerical columns were passed through directly.
  - Data was split (80/20) into training and test sets.
- *Hyperparameter Tuning:*
  - n_estimators: [100, 150, 200]
  - max_depth: [10, 15, 20]
  - min_samples_split: [2, 5, 10]
  - Best parameters: n_estimators=100, max_depth=20, min_samples_split=5
- *Interpretability:*
  - Feature importances were extracted from the trained model.
  - Most influential features included district, fire type, and time of day.
- *Baseline Comparison:*
  - A baseline DummyRegressor was used which predicted the mean response time.
  - Our tuned model outperformed the baseline significantly.
  - Statistical test comparing prediction errors confirmed this improvement ($p < 0.000001$).

V. RESULTS & EVALUATION

For statistical test result the Mann–Whitney U test produced a p-value < 0.05, confirming that fire-station response times significantly differ between central and peripheral districts. Central districts had notably shorter response durations.

Machine Learning Model Performance:

- Best Parameters: n_estimators=100, max_depth=20, min_samples_split=5
- Mean Absolute Error (MAE): 2.04 minutes
- R^2 Score: 0.18

Feature Importance: Feature importance analysis revealed that ILCE (district), YANGIN_TURU (fire type), and call_hour (time of day) had the highest influence on the prediction model.

Comparison with Baseline Model:

- Baseline MAE: 2.73 minutes
- Baseline R^2: -0.01
- Statistical Comparison: A paired t-test comparing the absolute prediction errors showed a p-value < 0.000001, confirming that the tuned model performs significantly better than the baseline model.

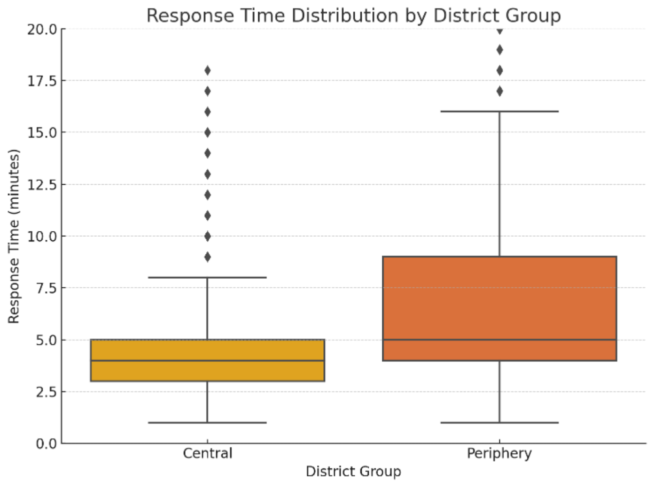

Figure 1

Figure 1 shows the distribution of fire station response times across central and peripheral districts. The visualization supports the statistical test results by highlighting a visibly shorter median response time in central districts and a broader range in peripheral areas.

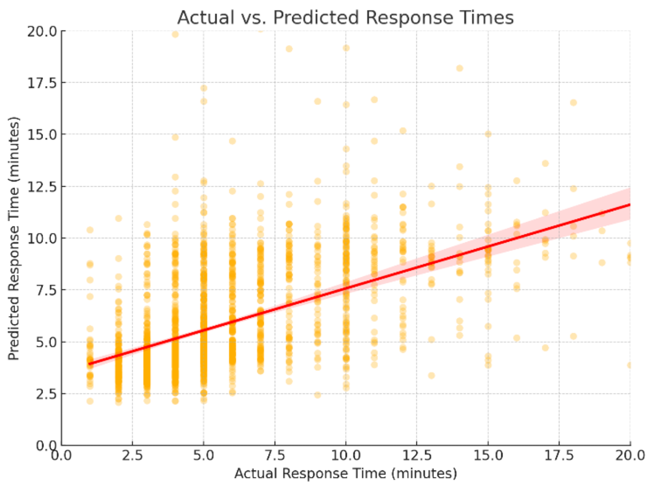

Figure 2

Figure 2 shows the predicted response times plotted against actual values, along with a regression trend line. The clustering around the red line indicates that the model generally predicts low response times well, although some underestimation and overestimation occur at higher durations.

The results demonstrate the feasibility of using a machine learning model to predict fire response durations and validate regional disparities in response efficiency.

VI. IMPLICATIONS

This study provides valuable insights into emergency response optimization within metropolitan areas like İzmir. The statistically confirmed difference in response times between central and peripheral districts can guide city planners and fire department management in resource allocation. For instance, placing additional fire stations or mobile response units in slower peripheral zones could enhance service equity and reduce overall risk.

The machine learning model shows promise for real-time response time prediction. Integrating such models into dispatch systems could improve expectations management and logistics planning. Moreover, by identifying key features that influence response times (e.g., fire type, time of day, location), departments can prioritize interventions more efficiently.

From an environmental and societal standpoint, faster response times are associated with reduced fire spread, lower emissions, and improved safety outcomes. These insights contribute to sustainable urban planning and align with smart city development goals.

The study's methods and findings also lay the groundwork for comparative future analysis using the 2025 fire dataset when available. This would enable longitudinal studies on improvement and policy impact.

VII. CONCLUSION & DISCUSSIONS

This study successfully addressed both research questions using a combination of statistical hypothesis testing and machine learning-based regression modeling. The findings revealed a statistically significant disparity in response times across İzmir districts and demonstrated that it is feasible to model and predict fire response durations with moderate accuracy.

The approach benefits from a diverse feature set and interpretable results. However, it is limited by the quality and completeness of the dataset, particularly missing or noisy values in some columns. Additionally, only one year of data was used, limiting generalizability.

Future work should include:

- Incorporating temporal trends using multi-year datasets (e.g., 2025 data)
- Integrating geospatial features for more granular modeling
- Testing additional machine learning models (e.g., Gradient Boosting, XGBoost)
- Evaluating the real-time deployment of predictions in fire department workflows

Overall, the study demonstrates the potential of data-driven approaches for improving public safety infrastructure and provides a scalable methodology for further research or municipal planning efforts.

REFERENCES

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