

Analysis of Vance County EMS Ambulance Distribution

1 Background

The Vance County Emergency Medical Services system currently operates four ambulances and two stations with one located in the Southern district and one in the Central district. This configuration led to the residents in the Northern district being under-served with higher average response times than the other two districts. Such delays can lead to critical differences in patient outcomes especially in life threatening emergencies.

In response to this issue and demand for EMS coverage in the North region, Vance county is evaluating the potential of adding a new station in one of the two northern locations: near north or far north station. We use historical EMS call data to make a decision. Each record in the dataset represents one individual emergency trip which includes information like dispatch station, patient location coordinates, and time logs for dispatch, arrival, hospital transport, and clearance.

The main motivation of this analysis is to assess how travel times and system load vary across different station allocation scenarios which are listed in table 1 of the appendix and in particular we aim to answer three central questions: 1) which of the two possible Northern station locations would better serve the community through faster response time 2) which relocation (South or Central) would yield to improved response time and 3) how should the four available ambulances be allocated across stations to optimize service coverage and response times.

2 Exploratory Data Analysis

We modeled the distribution of best-guess travel time and from the histogram shown in figure 1 we can see that south station has a shorter median travel time and both the near north and far north stations have a longer travel time with a wider variability. We can see that the far north has the widest spread and the most outliers which implies more inconsistent travel times possibly stemming from it being so far up north by itself.

Talk about load conflict
mixed model thing

3 Model Assumptions & Assessment

Before the modeling, we set a “dispatch rule” on how we will dispatch the ambulances. For scenario 0 which is our baseline where we just have 3 ambulances in central and 1 in the south station, we will assume that all north and central calls are taken by the central station and the south calls are taken by the south station ambulances. For scenarios 1 and 2 which are still 3 ambulances in the central but we move the south station to either the near north or far north station respectively, we assume that north calls are taken only by the North station and the central and south calls are only taken by the central station ambulances. Finally for scenarios 3 and 4 which are the ones where we keep the 1 south ambulance in the south station but move one of the central stations to either the near north or far north station respectively, we just assume all calls are taken by the same region station ambulance. The only exception to our modeling assumptions is if there are 3+ load conflicts at a assigned station, we make the available ambulance from the next closest station to be dispatched to take the call.

Under the assumption of a hierarchical approach where we condition on the calls where there is a total change in time, we fit a couple of models. The covariates are _____. They are both linear mixed models where utilize a random effect for a call since there is within group variation for each call. One takes into account heteroscedasticity concern and varies potential errors by longitude and latitude. (EXPLAIN RESIDUAL PLOT ETC HERE)

Based on these assessments, our final model is the following linear mixed model: $\text{ResponseTime} \sim \text{Scenario} + \text{Distance} + \text{RushHour} + (1 \mid \text{CallID}) +$

For fixed effects, we include scenarios as a categorical variable, with S0 as baseline and S1~S4 as changes. Distance from the station to the call location is set as a continuous variable. We also include rush hour as binary variable to account for traffic level, by categorizing the time of day into non-rush vs rush hour. We define rush hour to be 7:30-9:30AM and 4:00-6:30PM for each day, as per observation of average traffic levels. The model’s random effects accounts for variation by call group, and residual error models day-to-day variance.

For model assumptions, we first let residual error follow a normal distribution, We also assume traffic level to be consistent within and outside rush hours, to simplify traffic levels on a binary level rather than continuous. Based on our residual plot, we do not model for heteroscedasticity for random effects as it leads to a better model fit. Finally, we assume that if distance is the same, the actual latitude and longitude coordinates would not affect response time differently.

4 Results

We note that there are different residuals for the aforementioned fits. We find that when examining the normality condition, that the model without the error variations seems to be a better fit for the data as seen in (ref the Q-Q plots), and consequently we analyze the results under the fit without the additional variation.

Our final model is the following linear mixed model: $\text{ResponseTime} \sim \text{Scenario} + \text{Distance} + \text{RushHour} + (1 \mid \text{CallID}) + \epsilon$

For fixed effects, we included scenarios as a categorical variable, with S0 as baseline and S1~S4 as changes. Distance from the station to the call location was set as a continuous variable. We also decided to include rush hour as binary variable to account for traffic level, by categorizing the time of day into non-rush vs rush hour. We defined rush hour to be 7:30-9:30AM and 4:00-6:30PM for each day, as per observation of average traffic levels. The model's random effects accounted for variation by call group, and residual error modeled day-to-day variance.

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Linked below (ADD THE TABLE NUMBER) is our coefficient summary for the better fit model. We find that none of the scenarios are significant

Question 1

If relocate to north: faster response time – near north vs far north?

Question 2

If relocate to north: faster response time – south vs central?

Question 3

Overall: does relocation to north yield significant benefit?

5 Conclusion and Future Work

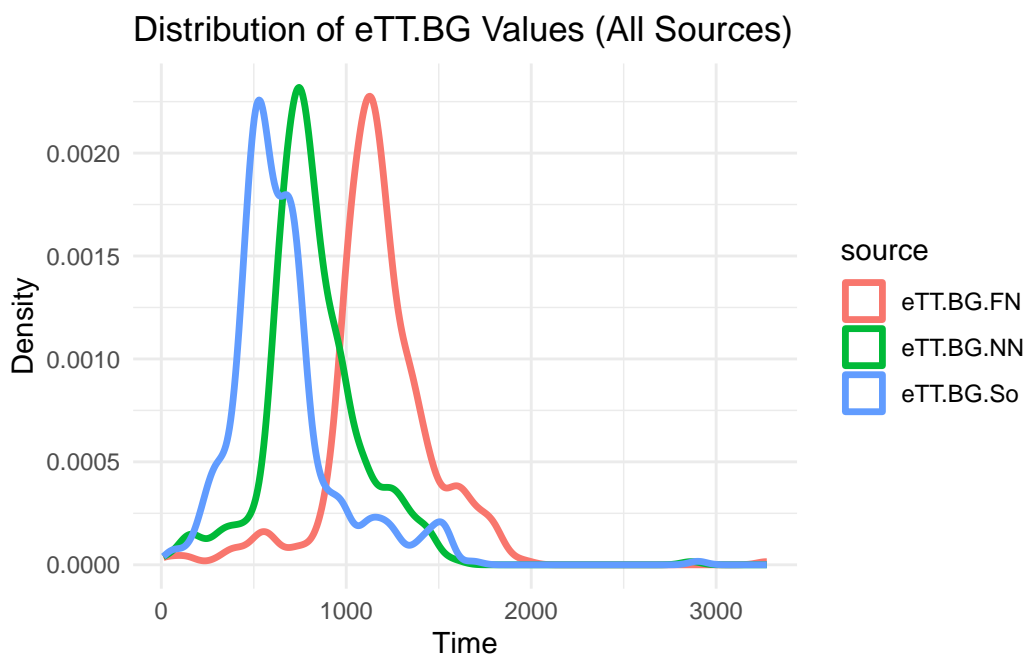
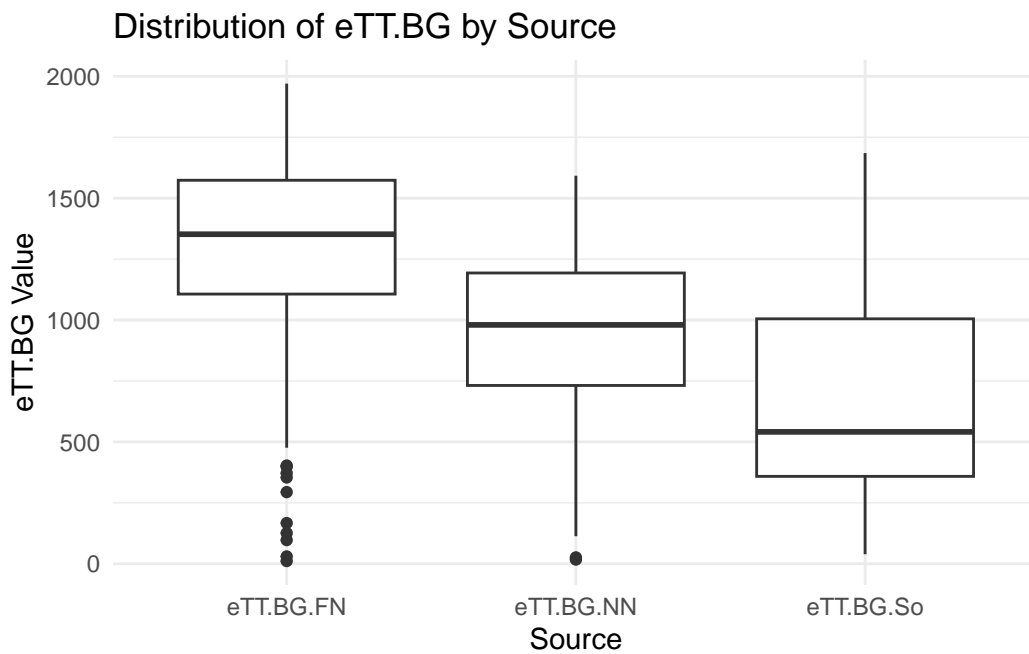
Our analysis showed that relocation to far north resulted in faster response times than near north. We have also shown that it is better to move central ambulances up north than moving the south ambulance and saw that relocating one ambulance from central to far north station reduces response times by about 4%. Therefore from our analysis we saw scenario 4 which is 1 far north, 2 central, and 1 south was the most optimal layout of the 4 ambulances as it reduces the average response time by 4% compared to the baseline of scenario 0.

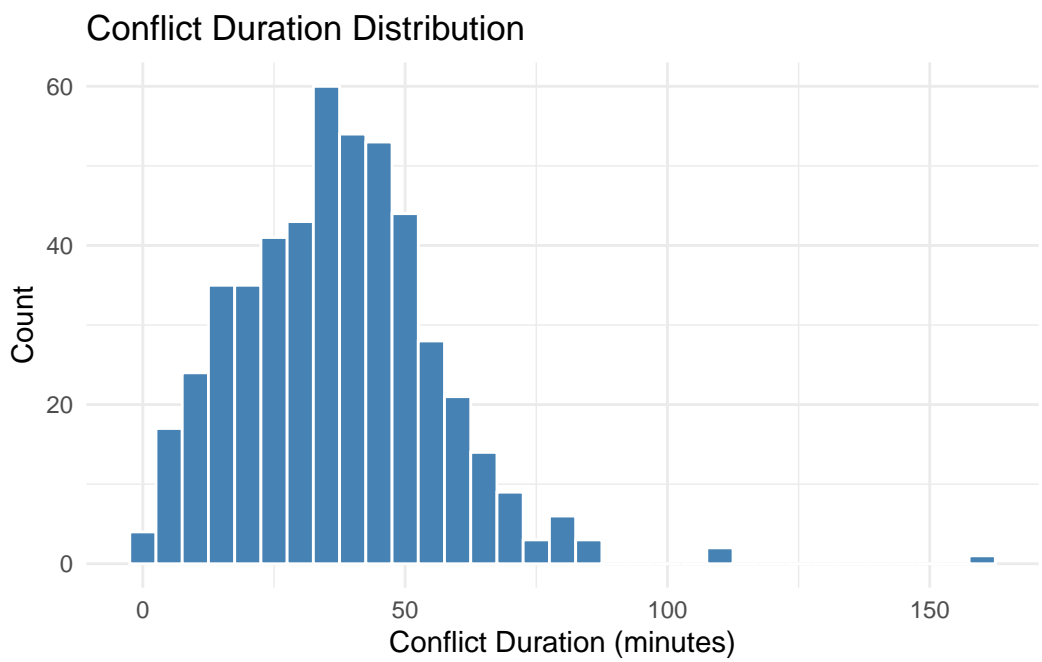
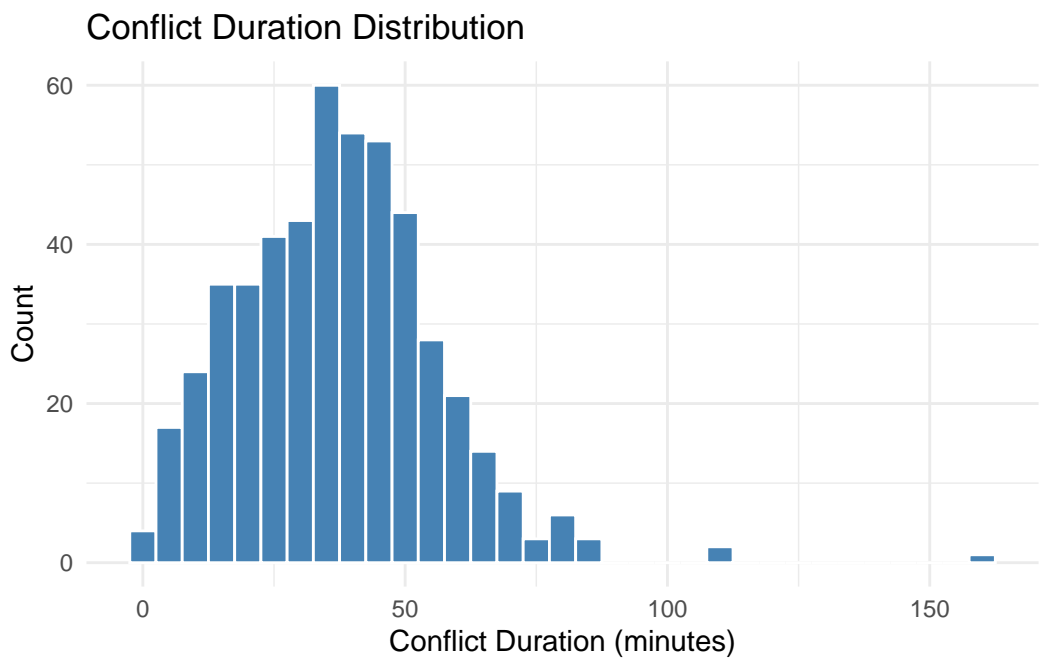
Some limitations is that our model assumes traffic level to be constant throughout non-vs rush hour. We also are dealing with data that has error introduced by data randomization from the HIPAA protection so there is some marginal error in the distance calculation that stems from this. We are also limited from the smaller sample size and also from the best guess Google API which assumes average conditions.

In the future we can try adding time of day for a random effects which could provide a deeper insight into temporal variation in the response times. We can model this using a continuous smooth spline approach using mgcr or poly to capture the nonlinear daily trends without overfitting. We can also try a Bayesian approach to improve interpretability, particularly in regions with fewer calls. Through partial pooling and uncertainty propagation, the use of this approach would allow information sharing across districts while accounting for data sparsity. Finally, a hierarchical modeling approach could be implemented to account for further subdivisions in call type and urgency and this would allow our model to distinguish between the emergency severity levels and incorporate medical criteria for the urgency of each call which could change how we allocate the ambulances across the systems.

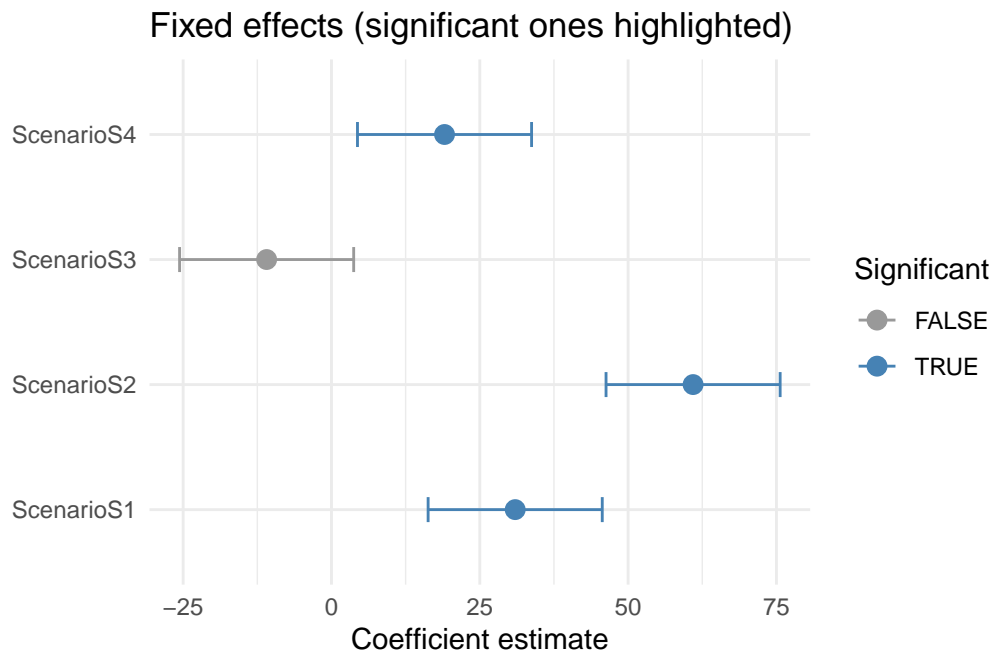
6 Appendix

Exploratory Data Analysis





Linear Mixed Model



Modeling

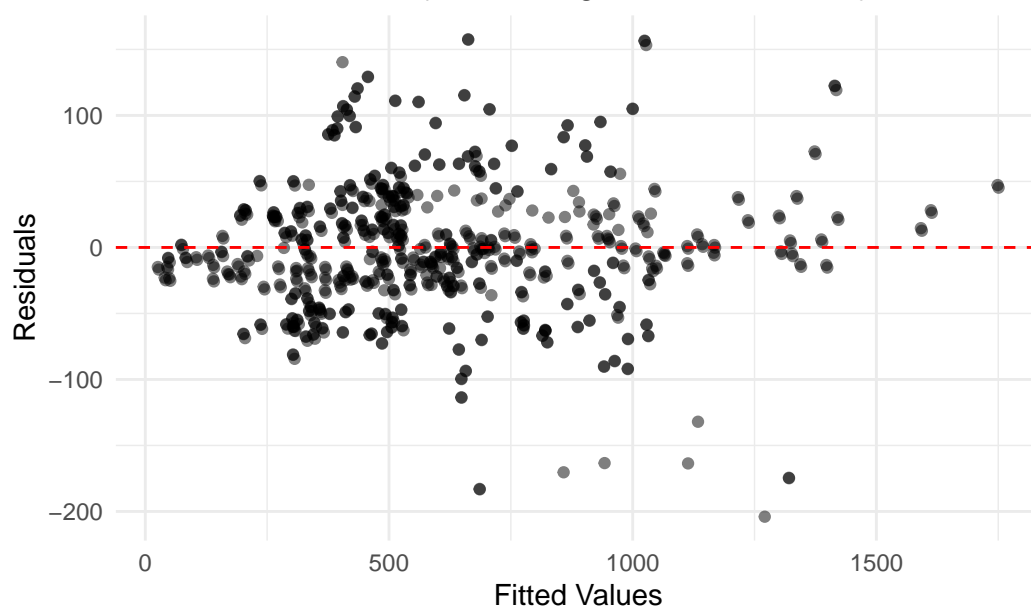
Scenarios	S0 (Current)	S1	S2	S3	S4
Far North	0	0	1	0	1
Near North	0	1	0	1	0
Central	3	3	3	2	2
South	1	0	0	1	1

```
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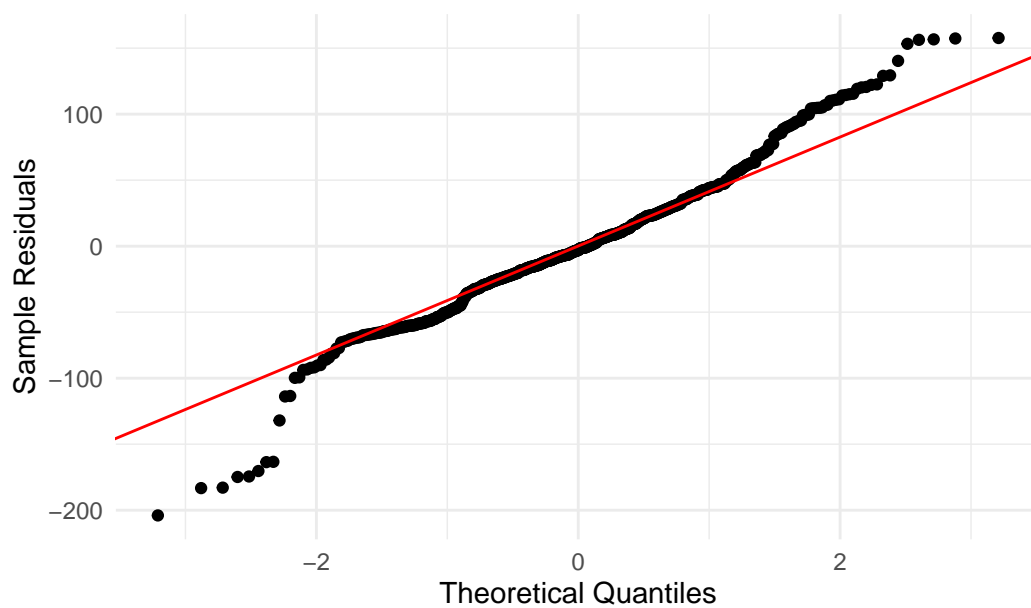
Table: Linear Mixed Model for EstTravelTime

Linear Mixed Model for EstTravelTime				
<i>Predictors</i>	EstTravelTime			
	<i>Estimates</i>	<i>std. Error</i>	<i>CI</i>	<i>p</i>
(Intercept)	112.04	8.75	94.85 – 129.22	<0.001
Scenario [S1]	-5.35	6.48	-18.07 – 7.36	0.409
Scenario [S2]	-4.99	6.74	-18.22 – 8.24	0.459
Scenario [S3]	-3.37	6.38	-15.90 – 9.17	0.598
Scenario [S4]	-3.01	6.41	-15.60 – 9.59	0.639
Distance	0.05	0.00	0.04 – 0.05	<0.001
rush hour ind	11.86	13.32	-14.29 – 38.01	0.373
Random Effects				
σ^2	3068.93			
τ_{00} CallID	4157.26			
ICC	0.58			
N _{CallID}	151			
Observations	755			
Marginal R ² / Conditional R ²	0.928 / 0.969			

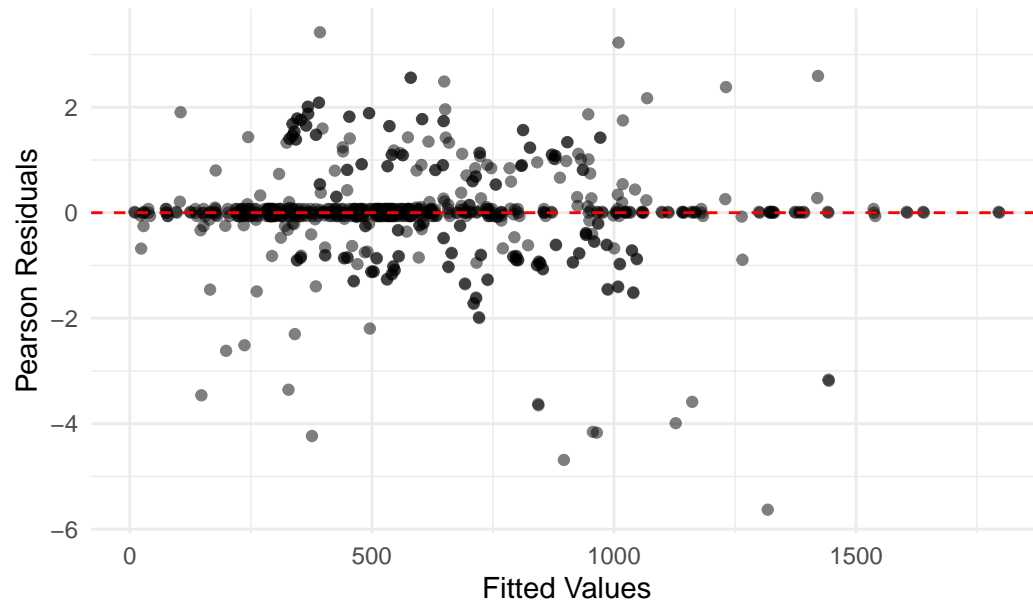
Residuals vs Fitted (No-Change Calls Removed)



QQ Plot of Residuals (No-Change Calls Removed)



Residuals vs Fitted (varIdent by Scenario)



QQ Plot of Residuals (varIdent Model)

