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# Energy Consumption and Routing Model for First Responder Vehicles

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# Energy Consumption and Routing Model for First Responder Vehicles

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**ABSTRACT:** The ongoing research and prototyping of electric vehicles (EVs) offers numerous opportunities to investigate their performance in various service contexts. As EVs are integrated into society, the reliable prediction of fuel consumption and routing time becomes particularly important in emergency response services. This project develops a preliminary stochastic model that can route and predict the energy consumption and travel time for hypothetical emergency vehicles operating on an electric battery cell. Using a Monte-Carlo framework, we constructed a routing model designed to minimize travel time and resource consumption under various simulated conditions. In doing so, we establish the foundation for balancing the demands of time and energy in a relatively unexplored context and determined the impact of elevation, distance, time, and other factors on energy consumption for these large vehicle types. My model computes likely travel times, power consumption, and best-suited resulting route for emergency vehicles from the Orange County Fire Station to four locations on the University of Central Florida campus: Millican Hall, Lake Claire, Jay Bergman Field, and the Creative School for Children. My model provides consistent results that are comparable to real-world travel times recorded by the Orange County Fire Station. Future work will include more robust and accurate iterations of the model that could ultimately be a useful tool for both first responders as well as other EV services that require efficient resource allocation and time forecasting in routing.

**KEYWORDS:** routing, model, first response, energy, stochastic, electric vehicles

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## INTRODUCTION

As technology moves towards the use of renewable energy sources, it becomes necessary to identify how these energy sources are implemented in various systems. The demand for and research into electric vehicles has increased dramatically in past decade; continuously improving electric (EV), hybrid-electric (HEV), and fuel-cell vehicles (FC) (Chan, 2007) has created an opportunity for their application in personal and emergency vehicles. Hybrid transit buses have experienced 50% or more fuel savings due to their fixed routes and stop-and-go pattern, and emergency vehicles are modeled similarly (Chan, 2007). Therefore, the use of hybrid EVs in emergency vehicles can be considered imminent.

In preparation for these upcoming technologies, I have developed a routing operations model for emergency vehicles operating on an electric battery cell. With this model, I intend to lay the foundation for emergency vehicle routing in this hypothetical context under a variety of conditions. Not only have relatively few travel time studies been published for emergency vehicles, there is also a need to investigate the use of this technology under realistic road conditions (Zhang et al., 2016). Simulation models have enabled us to find optimal solutions as well as observe the emergency vehicle system under various assumptions and constraints (Haghani et al., 2003). In pursuit of a preliminary set of results that can be used to guide future research, this project examines the energy dimensions of electric emergency vehicles under realistic deployment patterns within a confined service area.

One important potential outcome of this research is the ability to predict costs for municipalities associated with the transition to a hybrid or fully electric emergency vehicle fleet and determine the return on investment. Such a transition requires predictive data on how vehicles will perform, and in turn, how often they can operate, where they may operate from, and how far their operations can extend. A lack of reliable forecast data can have adverse impacts to routing vehicles in a transitioning infrastructure, such as the failure to accurately anticipate charging time requirements in such a time-sensitive yet unpredictable context. In response to this knowledge gap, I created a prototype model designed to simulate emergency response by EVs accounting for energy consumption alongside recharging time.

My stochastic prototype model routes and predicts the energy and time efficiencies for hypothetical emergency vehicles operating on an electric battery cell under a limited set of constraints. The time efficiency of an emergency first response is crucial to saving lives, as evidenced by the proposed 1974 Emergency Medical Services Systems Act, which attempted to mandate that 95% of all calls must be responded in 10-30 minutes (P. Law 93-154). Likewise, the proper management of resources—particularly energy—is absolute necessary, as it minimizes time spent restocking/refueling and enables real-time responses from disparate locations. Laying the groundwork for a suitable solution between these two competing forces is the focus of this project.

Specifically, my model provides statistical information regarding the consumption of energy in this unexplored context, where quick responses to various locations from a single origin point and recharging stations is required. If proven reliable, the model can be subsequently leveraged to determine the impact of distance, time, and other factors on energy consumption for these large vehicle types. There are few presently published studies on emergency vehicle fuel consumption (Chan, 2007), and even less so in this specific context. The creation of this model explores this space while providing the foundation for more advanced forms that could be integrated into future practice for emergency response operators to use in mission critical workflows.

## METHODOLOGY

I recreated the stochastic prototype model for the time and energy efficiency of emergency vehicles using the Anaconda Python 3 distribution. In doing so, the model and all its dependencies are platform independent, and all code is open-source and freely available. The Python modules used included Pylab, SciPy, NetworkX, and MatplotLib. Many of the statistical, networking, and graphical display functions could not be readily performed without these existing packages. For experimentation purposes, the current model uses the University of Central Florida campus as its simulated service area due to the proximity of Orange County Fire Station 62 and its relatively small size (compared to an actual municipality). The initial network diagram began as a simple set of nodes to key locations on campus, as shown in Figure 1. The network was then projected onto a geographical map and the nodes were given both a set of "relative" and real-world coordinates, as shown in Figure 2.

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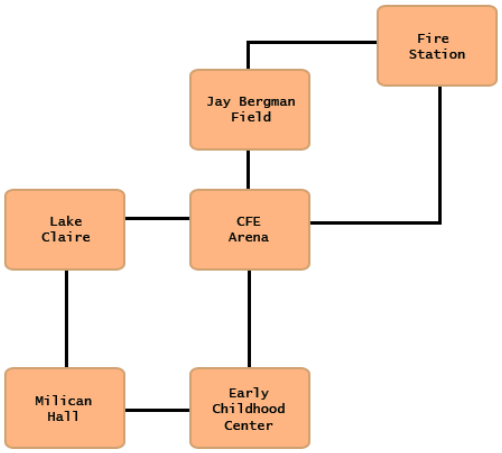


*Figure 1: Preliminary schematic node-link mappings for the roadway network*

From there, I recorded travel times between each node at various times of the day and on different days. These sampled travel times were then used to model the distribution of travel times. For simplicity, I assumed these were independent distributed samples that followed a Gaussian distribution due to how my gathered data fitted during the collection phase. This procedure was due to the limitations involved in our sampling process; for example, traffic signals are equipped with preemption control to give emergency vehicles the right-of-way at intersections when they are near, unlike normal passenger vehicles (Zhang et al., 2016). For the purposes of a prototype model that can display consistency in results and provide directional guidance for energy consumption as a significant factor in emergency vehicle routing, my Gaussian distribution assumption was sufficient.

After the network was created and sample input data were gathered, the model was encoded in Python. At its most basic level, the model calculated a "weight" value for each link between nodes for each hour of the standard 24 hour day. This weight value was calculated based on the mean of randomly sampled travel times. These travel times were sampled from a Gaussian distribution based on the mean (most probable) value and standard deviation of the input data. As the expected travel time from a source node to a destination node increased, so did the weight value for the corresponding link. As the weight value for a link increased, the less desirable it became as an option for travel. Despite requiring a variety of input data from the developer, this approach was necessary to compensate for a lack of real-time data inputs. In the future, a comprehensive corpus of routing data from the fire station could be leveraged to calculate time-dependent route weights, with continuous updating based on the stream of real-time routing data.

After calculating the weight values for each link, the model used the Dijkstra algorithm (Dijkstra, 1959) to find the best path using every possible combination of links between nodes. This task was performed over a user-defined number (typically on the order of 10,000) of iterations with a different generation of weights for each iteration in order to introduce a sufficient amount of realistic noise into the system. The concept of travel time variability (reliability) is accepted as one of the key indicators for the performance of transport systems (Tu et al., 2012); thus, I built this noise into the model to reflect this property. Two matrices were then formed from these results: one that contained the best paths based on time, and one that contained the best paths based on energy efficiency. All path results were stored electronically for reference.

From a user-defined origin to destination, the model then referenced these two matrices to suggest to the user the most optimal path to take. It determines this "optimum" path based on the differences between the travel time efficient path and energy efficient path. The projected travel time a vehicle takes to go from an origin to a specific destination was considered first to simulate time as the dominant factor in emergency vehicle routing. Then, if the energy efficient path caused a delay greater than the time efficient path, plus 0.5 standard deviations of all recorded trips the vehicle has thus far taken, the model would recommend the time efficient route. Otherwise, the model would recommend the most energy efficient route. This logic is based on the possibility of back-to-back service calls, where the emergency vehicle may have to respond to a second incident without returning to the station to recharge. Thus, the conservation of on-board energy is given priority when it does not cause a significant delay in response.

Along this thread and in anticipation of other possible emergencies, the model recommends the next best course of action after the primary incident is resolved. A sample is drawn from a binomial distribution of the probability that an emergency would occur for each hour of the day. Two random scenarios are drawn over many iterations: one for the next hour, and one for the hour after that. If the dominant probability was that both sample integers were 0 (no emergency), the model would

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recommend that the vehicle return to base to recharge. If, on average, at least one of these samples indicated that an emergency would occur within the next two hours, the model recommended that the emergency vehicle remain mobile. However, if the vehicle did not have sufficient energy to respond to a subsequent emergency, the model would recommend a return to base.

The model continuously simulates the energy consumption and times for predicted emergency locations and times in which they would theoretically occur until user intervention to stop the model run. The energy consumed is modeled based on the fuel tanks of transit vehicles in Kyoto, Japan. While this benchmark has been proven to be a good analog for estimating power demand in the past (Koyanagi & Uriu, 1997), this assumption has limitations. At the end of the simulation, the model provided aggregate statistical output based on what it had calculated on startup. The model then performed a sensitivity analysis for each generated travel time to display the consistency and convergence of its results.

While flexible in its operation, a carefully constructed series of input data were required to develop the model's operations. A coordinate map containing various attributes was also required. Each node had its own attributes and its own set of input data. Each node had to possess the following elements: coordinates on the image map, GPS coordinates, elevation in feet with respect to a consistent datum (i.e. mean sea level), mean number of emergencies per year, and the fraction of these occurrences compared to other nodes. The elevation was intended to include energy consumption, but could not be properly implemented due to time constraints. Each link also needed a series of actual measured travel times used to model the distribution. All model input data was readable from a format-specific excel file, or alternatively by a combination of text file and program configuration parameters.

A sample of the excel file is displayed in Tables 1, 2 and 3. Table 1 displays the basic inputs for the experiment, including starting time and fuel amount (based on gauge read). The inputs shown in Table 2 focuses primarily on each property for the nodes in the model, such as display parameters and geographical data. The node connections and sample times between each node are inputs as well and are shown in Table 3. Emergency frequency data was also required; one specific input was a table listing the number of emergencies per year for each hour of the day. This table, a sample of which is shown in Table 4, also needed to include a computed probability of an emergency occurring, the calculated probabilities for emergency occurring each hour of the day based on this parameter and the table listings.

| Start Node | End Node | # Iterations | Obstruction % | Starting Fuel (kW) | Starting Time (s) |
|---|---|---|---|---|---|
| Fire Station | Millican Hall | 1000 | 0.1 | 2.00 | 540 |

*Table 1: Basic input parameters used for experiment's Monte-Carlo run*

| Node | Grid X | Grid Y | World Long | World Lat | Elevation | Occurrences /Year | Fraction |
|---|---|---|---|---|---|---|---|
| **Fire Station** | 95 | 4 | 28.611611 | -81.191553 | 5 | 0 | 0 |
| **Jay-Bergman Field** | 65 | 18 | 28.609303 | -81.196937 | 20 | 3 | 0.023622 |
| **Softball Field** | 93 | 38 | 28.605804 | -81.192265 | 1 | 16 | 0.125984 |
| **CFE Arena** | 60 | 35 | 28.606383 | -81.19787 | 25 | 72 | 0.566929 |
| **Lake Claire** | 22 | 34 | 28.597994 | -81.197269 | 18 | 22 | 0.173228 |
| **Early Childhood Center** | 60 | 83 | 28.606475 | -81.20364 | -4 | 9 | 0.070866 |
| **Millican Hall** | 22 | 87 | 28.597363 | -81.203363 | -1 | 5 | 0.03937 |

*Table 2: Hypothetical input parameters for each node in a sample experiment and Google Map*

| Neighboring Nodes | Fire Station, Jay-Bergman Field | Fire Station, Softball Field | Jay-Bergman Field, CFE Arena |
|---|---|---|---|
| **Time (s)** | 118 | 68 | 107 |
| | 107 | 69 | 124 |
| | 92 | 74 | 127 |
| | 105 | 86 | 79 |
| | 132 | 92 | 74 |
| | 102 | 97 | 85 |
| | 112 | 102 | 112 |
| | 68 | 105 | 68 |
| | 69 | 107 | 69 |
| | 86 | 112 | 86 |
| | 97 | 118 | 97 |
| | 74 | 132 | 74 |

(For a complete version of this table, see Table 5 in the Appendix)

*Table 3: Gathered travel time input data for each node-link pair*

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The basic input parameters required for the model to run include the location of each node, its connectivity, a sample of travel times, the number of iterations to perform, the probability that a road obstruction is present, the vehicle's starting gauge read fuel, and the starting time in seconds. As input data, the model used sampled time data from drives throughout the UCF campus. Although the travel time along a road link will theoretically vary based on time of day, the travel time remained regularly consistent. My experiment accounted for this variation through random sampling from a realistic distribution.

| Hour | Occurrences/Year | Probability |
|---|---|---|
| **0:00** | 50 | 0.005704 |
| **1:00** | 50 | 0.005704 |
| **2:00** | 67 | 0.007643 |
| **3:00** | 39 | 0.004449 |
| **4:00** | 33 | 0.003765 |
| **5:00** | 14 | 0.001597 |
| **6:00** | 11 | 0.001255 |
| **…** | … | … |
| **21:00** | 75 | 0.008556 |
| **22:00** | 35 | 0.003993 |
| **23:00** | 37 | 0.004221 |

(For a complete version of this table, see Table 6 in the Appendix)

*Table 4: Emergency call frequencies for each hour of the day based on occurrence per year*

Further required background input included the frequency of calls during each time of the day. The above data in Table 4 was graciously provided by Fire Station 62 near UCF; these probabilities are based on frequency of real emergency calls made in 2015.

## RESULTS

A sample output for the shortest path time and route from the Fire Station to a random node is depicted in Figure 3. This route sample was based on the averaged shortest times for all potential paths from source to destination—in this instance, from the Fire Station to Lake Claire. This output of the model also provided average travel time and energy consumption for conveying the costs of travel along the route.

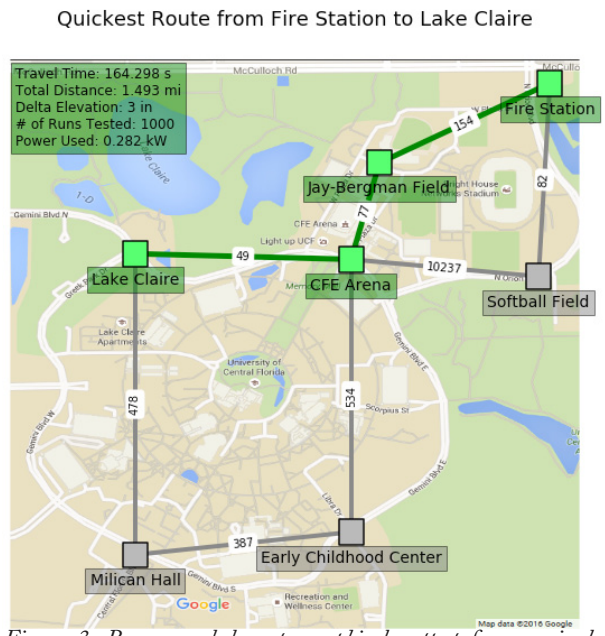


*Figure 3: Recommended route graphical output from a single routing run*

The weights of each node-node connector are represented by the values in white bubbles shown in Figure 3. Higher weight values indicate higher travel times and delays, thus the route with the minimum total weight is displayed. These weights were calculated based on distance, travel time, and energy consumption.

Similarly, the program provides a "final report" output with this information depicted in greater detail, as Figure 4 illustrates. The report compares the time-efficient path and energy-efficient path, states whether there is a significant enough difference in time between the two, and recommends the path based on how enough this difference is. The likelihood of a subsequent or concurrent emergency during response was also displayed, and the model suggested whether the operator is to remain on standby in anticipation of a subsequent emergency or to return to the station due to a low likelihood of another emergency within the hour.

```
---Report---

Quickest Path: 169.65017s, 0.34192kW
Fuel-Efficient Path: 169.65017s, 0.34192kW
Path Chosen: Fuel-Efficient (99.7% Confidence)

Current Time: 7:09
Energy Remaining: 1.658083 / 2.0 KW
Number of Operations Performed: 3

Chance of emergency event: 1.20922%
No emergencies predicted to occur within the next hour.
Directing to Fire Station on Fuel-Efficient path.
```

*Figure 4: Report provided at the end of a single routing run*

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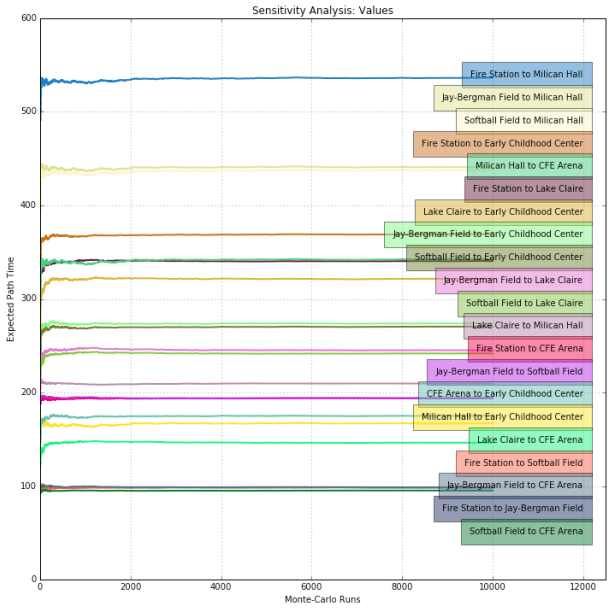
The average path travel times for each iteration the program performed in the sample run is displayed in Figure 5 through a graphical sensitivity analysis. The predicted values were averaged over time and graphed on a per-iteration basis. By the Law of Large Numbers, the expected value should theoretically converge towards a single value (Hsu & Robbins, 1947). In this instance, the predicted total path times did indeed converge after about 2000 iterations.



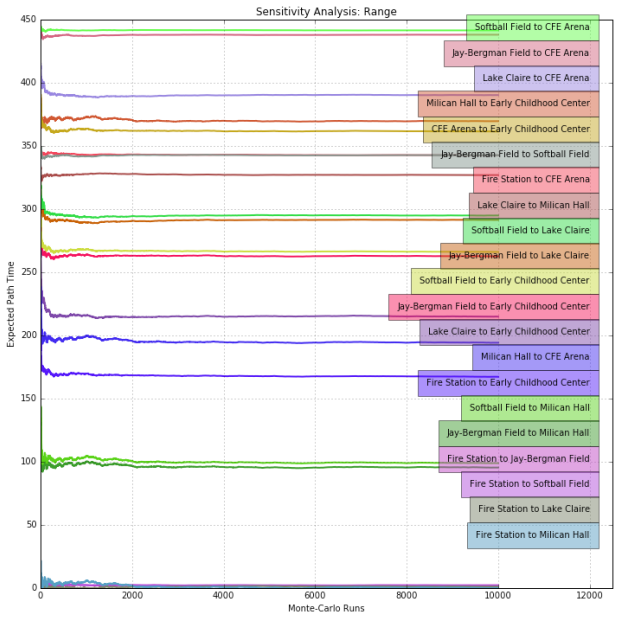




*Figure 5 (top): Sensitivity Analysis for average destination times based on number of Monte-Carlo runs*
*Figure 6 (bottom): Sensitivity Analysis for path time ranges based on number of Monte-Carlo runs*

Model validation was performed by analyzing the average values and comparing it to field data. Model reliability was also tested. First responders must minimize as much travel time as possible to respond to the emergency quickly. Travel time optimization would be very difficult to perform if there was high variability. Thus, I also conducted a sensitivity analysis based on the range of values produced, as shown in Figure 6. The decreasing ranges after about 2500 iterations indicates there were smaller differences between the longest and shortest travel times. Thus, the travel times were more easily predictable after this point.

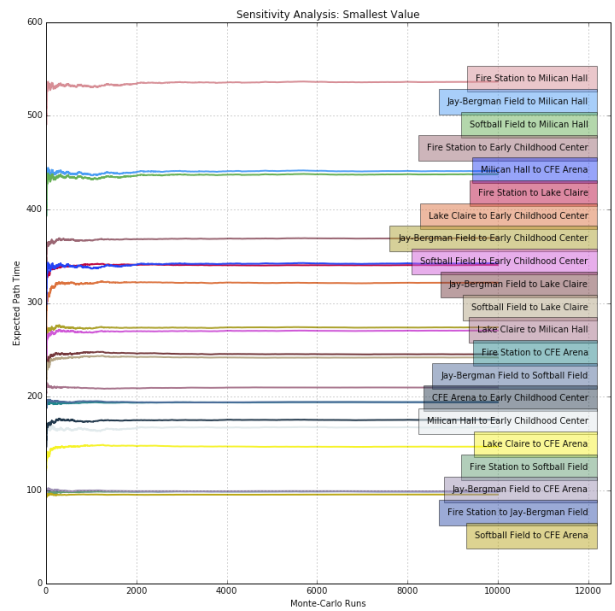



*Figure 7: Sensitivity Analysis for shortest destination times based on number of Monte-Carlo runs*

To provide further evidence towards the decreasing variability of the model, I also performed a sensitivity analysis using the shortest path time, as shown in Figure 7 above, as well as on the variance of the path times, as shown in Figure 8 below. Although range aided in displaying the differences in extremes, displaying the actual values of one of the extremes shows that the target value (the shortest path) converged earlier than the range of values, after about 2000 iterations. Conversely, the variance curve smoothed out after 2000 iterations, but did not attain a single flat value until 8000 iterations were performed.

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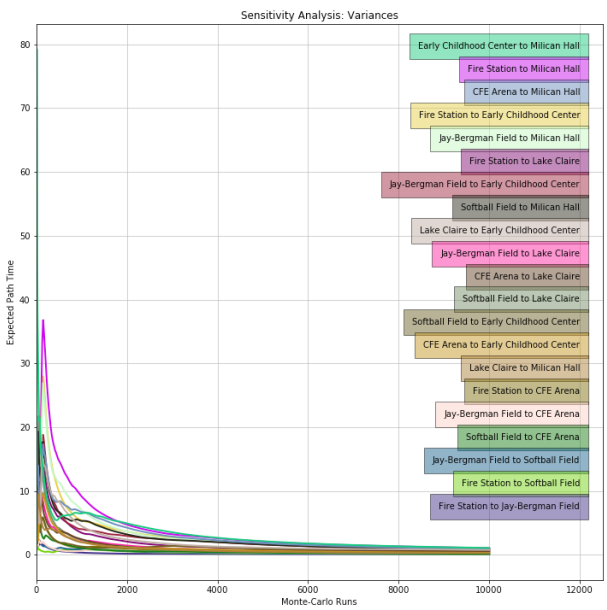


*Figure 8: Sensitivity Analysis for variance shortest destination times for Monte-Carlo runs*

## DISCUSSION

As displayed in Figure 5, the predicted travel time values stabilized completely after approximately 2,000 runs, with a gradually reducing variance as expected. The shortest potential travel time shown in Figure 7 also converged after approximately 2,000 runs, but the variance of the system depicted in Figure 8 did not completely converge until after approximately 8,000 runs. This result signifies that while the shortest path time—the "ideal" value—became more easily predictable, the "true" value of each individual run still had a degree of uncertainty. This result is a natural consequence of introducing noise into the system by generating scenarios of varying inputs, and coupled with the early converging averages and ranges, it is likely that any edge cases of improbable scenarios (such as all roads being blocked), the model produced did not have a significant impact overall on the expected travel time. Thus, even with the introduction of new data and noise, the predictions continued to exhibit patterns of consistency, as shown in the smoothing curves of Figure 8. Thus, the model can be considered usable for purpose of making consistent predictions.

Using the Kolmogorov–Smirnov test in MatLab, I found that there was a significant difference between the output travel time data and the travel time data provided by the Orange County Fire Station based on a significance level of 0.05; the lack of consideration to traffic signals very likely played a prominent role in this difference. As such, the real-world data likely did not follow a normal distribution as originally assumed based on sampled data. To be explicitly used as a predictive tool in its current state, the model would need to generate values based on an empirical distribution, as I could not identify any suitable distribution fit for the real-world data. Furthermore, the fundamental issue lies in the assumption of ignoring traffic signals; traffic signals would only add significantly more variance as well as shift the values forward with regards to time, thus also changing fuel consumption. The acceleration changes and starting-and-stopping motions that would be required to abide by traffic signals would also play a major role in these factors. Although a distribution change is as simple as changing a single line in the code and can be experimented with in future iterations of the model; the model itself would require major changes due to one its core assumptions being invalidated. In future iterations, the model could readily be modified to more accurately reflect what prior studies have found: response times dependent on a 3-parameter inverse Gaussian distribution, with the 3rd parameter being location (Zhang et al., 2016). The network mapping and corrective routing capabilities were successful, but this only verifies rather than validates the model.

The model was built upon both self-sampled data, performed via timing the route in a non-emergency vehicle (which may have resulted in data skew), as well as data provided by Fire Station 62, which had over one hundred times as many samples. The concept of travel time variability is accepted as one of the key indicators for the performance of transport systems (Tu et al., 2012); thus, our model's consideration of a realistic level of noise is further consistent with the reality of emergency transportation. Furthermore, my predictions were based upon on the concept of aggregating "micro-trips" (making predictions for each route to and from each destination) providing the best confidence for energy consumption (Cauwer et al., 2015). In this respect, the model functioned well as a tool for emergency response teams to determine fuel and time efficient routes.

In this model, all path weights were pre-computed at the start of the simulation, and the vehicle path simply referenced one of these pre-computed pathways. The advantage of this approach is that the simulation could run many times over without using a large amount of resources, and can present results for long periods of

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time without requiring constant computations. As such, the model can be expanded to encompass larger, more complex networks without having to re-compute the link weights in real-time. This procedure would allow for scheduled matrix computations throughout the day, thereby making computing costs relatively fixed and independent of the number of requests. The disadvantage, however, is that unlike similar routing models, the travel time input data cannot be updated in real-time, as the predictions are computed a priori. Instead, the simulation would need to be re-run after updating the necessary input data. However, it is likely that an optimal frequency for weight matrix computations could be determined with additional research. For example, the advent of serverless or "lambda" function technology could enable the real time update of individual links throughout the day. A secondary matrix of multiplier values indicating the deviation from normal conditions could augment the primary matrix and adjust travel times based on current observed conditions in the service area.

While this model uses the terms "best" and "recommended" route, we caution that the "optimal route" an operator should take differs based on the decision maker's priorities and values. For example, the model in its present form displays only a single suggested route rather than a series of alternatives. In anticipation of this possibility, the model supports rejection of its suggestions and continues predictions according to the route decisions made by the user instead. Another notable limitation of the model is that it only considered emergencies occurring in series and not simultaneously. While the probability that an emergency would occur in an area of the size simulated at more than one location is sufficiently low (Badri et al.,1997), the possibility should be considered in future versions of the model. This possibility is especially salient in light of mass casualty events that first responders currently train for on an annual basis.

Further possible sources of error could be attributed to the assumptions made in the creation of the model. For instance, there was a lack of concrete electrical engine data on emergency vehicles for analysis, thus the calculations for energy consumption were based on public transportation systems. Data for fuel consumption was based on transit vehicles in Kyoto, Japan due to lack of reliable engine data for emergency vehicles, though this was proven to be a good analog for estimating power demand (Koyanagi & Uriu, 1997). This assumption, like the input data, can be easily remedied through single-line changes in the model code as more research is performed. Precision was also preferred over accuracy in this experiment due to my intended goal of modeling the routing itself and performing a factor analysis.

Moreover, the model, despite having used a real location, employed straight paths rather than following exactly along the roads for its simulation. Although the use of sampled times for calculations, rather than a second-the-second simulation of distance, mitigated the impact of this error, future work should focus on addressing this limitation. There was also a small amount of uncaptured variance due to traffic conditions and stoplights. Emergency vehicles are provided right-of-way by law and stoplights have sensors to turn green when they are near, thus average times are likely to be somewhat shorter in a more realistic scenario (Zhang et al., 2016). The consideration of traffic conditions is an avenue that this research can be continued upon, as the groundwork for such considerations have already been laid out in medical vehicles (Haghani et al., 2003) and can be expanded for all emergency vehicles.

The model also assumed the independence of service and stations—that no overlap occurred in serviced areas and emergencies were on a first-come, first-serve basis (Cauwer et al., 2015) as noted by the presence of only one fire station present in the model. It was also assumed that the emergency vehicles are standardized and have equal capability. These assumptions are made in other probabilistic models (Beraldi & Bruni, 2009) due to the complexity of simulating communications and individual vehicles, but these factors are simply beyond the scope of this research at this stage. Nonetheless, the factors involved in the status of the individual vehicles are an avenue that should be considered in future work. My hypothetical electric engine does not consider energy consumption due to auxiliary items (AC, heat, radio, etc.), nor does it account for the possibility of other on-board equipment drawing electric power (Cauwer et al., 2015). Moreover, driving in extreme temperatures can result in range reduction for batteries (Hayes, et al., 2011).

Regardless of these limitations, the model fulfilled its primary purpose in reliably routing and predicting the energy efficiency and time efficiency for emergency vehicles operating on an electric battery cell. With the creation of this model, we have laid the groundwork for routing analysis of vehicles with regards to energy rather than solely as a time efficiency optimization

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problem. This groundwork can be particularly useful for projects regarding energy considerations of private ride-share transportation and courier routing, as many upcoming renewable energy technologies would likely be implemented in the private sector rather than solely emergency vehicles.

## CONCLUSION

In this paper, we developed a prototype stochastic model to predict the best route for an emergency vehicle based on both time and energy efficiency, as shown in Figure 3. This model was able to consistently predict an emergency vehicle's travel time and make key routing decisions during emergencies. Through sensitivity analysis and a variety of different inputs within a limited set of constraints, this model converges over a reasonable number of iterations, and as displayed by Figures 5, 6, 7, and 8, yields consistent results after a number of these iterations.

Through the construction of this model, I have laid the foundational work for assessing upcoming technological changes and implementation in emergency operations. This demand, which has been established in the literature, necessitates predicting travel times for emergency vehicles, exploring energy consumption for emergency vehicles, and understanding both aspects under various assumptions and constraints.

Nevertheless, my model has some limitations, including a lack of concrete engine data for predicting energy consumption. Another limitation is that the network model was simplistic rather than fully geospatially mapped. Moreover, the model assumed that all vehicles and stations were standardized and independent, and stoplights/traffic were indirectly considered through the time study rather than explicitly considered as elements within the model. Nevertheless, continued research in these aspects can yield much more accurate predictions for practice by operators in preparation for these upcoming technologies. At that time, a tool such as my model can enable municipalities and emergency service operators to evaluate the possibility and return on investment associated with the transition to an electric vehicle fleet.

## ACKNOWLEDGMENTS

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**Figure 2:** Google map displaying georeferenced node locations for the roadway network

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**Table 5:** Full gathered travel time input data for each node-link pair

| **Neighboring Nodes** | **Fire Station, Jay-Bergman Field** | **Fire Station, Softball Field** | **Jay-Bergman Field, CFE Arena** | **Softball Field, CFE Arena** | **CFE Arena, Lake Claire** | **CFE Arena, Early Childhood Center** | **Milican Hall, Lake Claire** | **Milican Hall, Early Childhood Center** |
|---|---|---|---|---|---|---|---|---|
| **Time (s)** | 118 | 68 | 107 | 132 | 119 | 97 | 196 | 111 |
| | 107 | 69 | 124 | 118 | 135 | 96 | 229 | 182 |
| | 92 | 74 | 127 | 112 | 153 | 188 | 205 | 242 |
| | 105 | 86 | 79 | 107 | 171 | 119 | 179 | 181 |
| | 132 | 92 | 74 | 105 | 204 | 177 | 173 | 285 |
| | 102 | 97 | 85 | 102 | 87 | 215 | 207 | 273 |
| | 112 | 102 | 112 | 97 | 148 | 140 | 207 | 124 |
| | 68 | 105 | 68 | 92 | 74 | 104 | 229 | 235 |
| | 69 | 107 | 69 | 86 | 78 | 143 | 191 | 93 |
| | 86 | 112 | 86 | 74 | 82 | 125 | 266 | 149 |
| | 97 | 118 | 97 | 69 | 91 | 159 | 199 | 248 |
| | 74 | 132 | 74 | 68 | 99 | 191 | 206 | 151 |

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**Table 6:** Emergency call frequencies for each hour of the day based on occurrence per year

| Hour | Occurrences/Year | Probability |
|---|---|---|
| **0:00** | 50 | 0.005704 |
| **1:00** | 50 | 0.005704 |
| **2:00** | 67 | 0.007643 |
| **3:00** | 39 | 0.004449 |
| **4:00** | 33 | 0.003765 |
| **5:00** | 14 | 0.001597 |
| **6:00** | 11 | 0.001255 |
| **7:00** | 25 | 0.002852 |
| **8:00** | 47 | 0.005362 |
| **9:00** | 59 | 0.006731 |
| **10:00** | 70 | 0.007985 |
| **11:00** | 70 | 0.007985 |
| **12:00** | 75 | 0.008556 |
| **13:00** | 123 | 0.014031 |
| **14:00** | 116 | 0.013233 |
| **15:00** | 122 | 0.013917 |
| **16:00** | 164 | 0.018709 |
| **17:00** | 153 | 0.017454 |
| **18:00** | 140 | 0.015971 |
| **19:00** | 109 | 0.012434 |
| **20:00** | 82 | 0.009354 |
| **21:00** | 75 | 0.008556 |
| **22:00** | 35 | 0.003993 |
| **23:00** | 37 | 0.004221 |
| Average | 73.58333333 | |
| Sum | 1766 | |
| Mean Hours / Year | 8766 | |
| Probability | 0.201460187 | |

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