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Performance Evaluation of Smart Intersections for Emergency Response Time based on Integration of Geospatial and Incident Data

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Abstract: The major objective of this research is to evaluate performance of improved intersections for response time to emergency vehicle preemption. Smart technologies have been introduced to civil infrastructure systems for resilient communities. The technologies need to evaluate their effectiveness and feasibility to confirm their introduction. This research focuses on the performance of emergency vehicle preemption, represented by response time, when smart intersections are introduced in a community. The response time is determined by not only intersections but also a number of factors such as traffic, distance, road conditions, and incident types. However, the evaluation of emergency response has often ignored factors related to emergency vehicle routes. In this respect, this research synthetically analyzes geospatial and incident data using each route of emergency vehicle and conducts before-and-after evaluations. The changes in performance are analyzed by the impact of smart intersections on response time through Bayesian regression models. The result provides measures of the project's performance. This study will contribute to the body of knowledge on modeling the impacts of technology application and integrating heterogeneous data sets. It will provide a way to confirm and prove the effectiveness of introducing smart technologies to our communities.

Key words: emergency vehicle preemption, smart intersections, Bayesian regression model, emergency response time, trajectory data integration

1. INTRODUCTION

Improving emergency response time is extremely important for better emergency service and reduction in fatalities. For example, among the fatalities from car accidents, 85% of all deaths occurred within an hour after the accident, while 10% of the total deaths occurred within a few minutes [1]. It is no exaggeration to say that 75% of lives depend on emergency response time. Emergency vehicles (EVs) should be able to travel uninterruptedly by having the highest priority on roads [2]. Although EVs make loud sounds through sirens to secure their priority, they cannot help but slowdown in places dominated by existing rules, such as traffic lights at intersections, because crossing vehicles can miss the sound and just follow their traffic lights. With the introduction of new technologies, emergency vehicles do not simply rely on sirens to secure their priority. For example, traffic signal controllers can secure the right-of-way to EVs at intersections by giving them green lights along their routes [3]. Traditional traffic systems do not include this kind of functions, but smart intersections incorporating information technology (IT) are introduced and it allows us to control the traffic signals according to the situation.

While smart intersections can benefit for the emergency response, it is difficult to evaluate the effects of introducing new technologies because there are no direct measures of intersections and EVs. The duration of emergency response time is generally used for benchmarking the performance of emergency services [4]. It includes information for incidents, such as incident type and location, but not for intersections. Also, the response time is influenced by many factors, for example, if a new system is introduced but traffic congestion in the area gets worse, the travel time of EVs would increase. In this respect, this research proposes a method for integrating geospatial and incident data to get more specific data for the performance evaluation of smart technologies. After that, the research conducts before-and-after study by assessing conditional effects using a Bayesian regression model.

2. RESEARCH BACKGROUND

This research is based on a smart city project in Valdosta, Georgia [5]. In this section, several main terms and related studies are reviewed. First, the most important performance indicator, response time, is defined. Next, existing data and systems are reviewed. Finally, the smart technology, emergency vehicle priority system (EVPS), applied in the city of Valdosta, GA, for improving the performance of emergency vehicle preemption is described.

2.1. Response time and other times

Duration of incident or emergency can be divided into several phases depending on the criteria. For example, as of the arrival time of incident response teams such as fire department, incident duration is disaggregated emergency waiting time and treatment time (Figure 1). Also, based on starting a report on the incident or actual action, the waiting time can be divided into detection time and response time. Finally, based on dispatch time, the response time is divided into preparation time and travel time. This study focuses on the travel time within the response time.

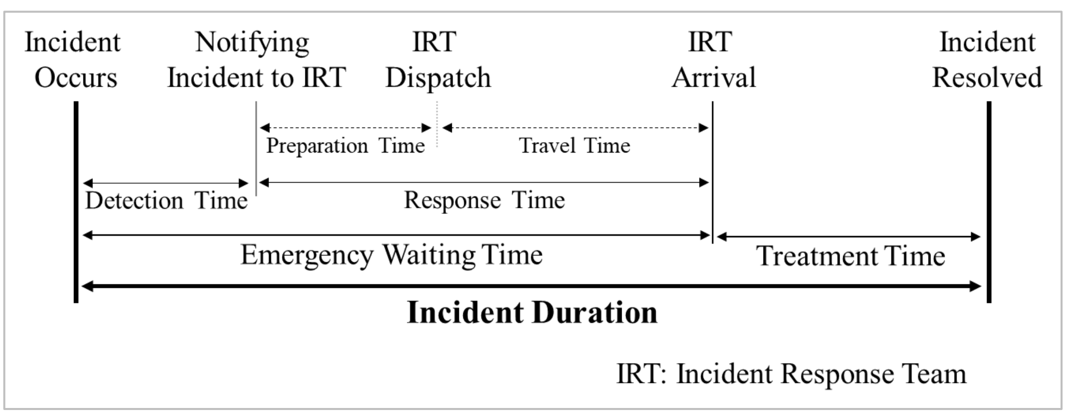

Figure 1. Emergency response time adapted from [6, 7]

2.2. Response time data from fire departments

In general, response time is considered as one of the most important factors for the performance measure of incident response teams. For example, it can be measured by average response time per incident or % of times less than targeted minutes [8]. Many systems have been introduced to reduce the response time, such as Computer Aided Dispatch (CAD) system. These systems not only integrate for managing incidents from in-call to treatment, but also support navigating for EVs. With the introduction of these systems, records related to incidents are organized and managed systematically. The systems continue to develop and are now combined with the latest technologies such as mobile computing, cloud computing, and Internet of Things (IoT) in line with IT trends [9].

2.3. Emergency Vehicle Priority System (EVPS)

Traffic light controllers play a crucial role in traffic flow. Most traffic light controllers have fixed sequences and durations of traffic signals, but as technology advances, more flexible signal controls that can be adapted to a dynamic environment have been introduced to our communities [10]. One of the advanced systems, emergency vehicle priority system (EVPS), supports EVs to pass signaled intersections safely by giving them priority. This project applied cloud computing-based cellular vehicle to everything (C-V2X) technology using equipment and technologies from Applied Information (appinfoinc.com) and Temple Inc (temple-inc.com). The new system prioritizes the signal to the EVs considering the access direction of the EVs. It makes EVs always pass intersections on green. The city of Valdosta upgraded its all 128 signaled intersections to the new system for the project and the upgrade was finalized in May 2021.

3. METHODOLOGY

This study analyzes existing response time data before proceeding before-and-after study. First, we conduct a preliminary study on the response time data in 2019 and 2020. After that, data processing using Google application programming interface (Google API) is performed to identify spatial distribution of the data. The processed data is visualized and compared by using geographic information system (GIS) with the point density method. After verifying that there is no significant difference in the past data, we apply a proposed method for merging data along with each route of EVs to import geospatial data into the response time data. Finally, this study conducts the before-and-after study using Bayesian Regression Model (BRM) based on the integrated data to estimate the performance improvement.

3.1. Preliminary study and Visualization

The main purpose of the preliminary study and visualization is to check if there is a statistical difference in the response time data before conducting the before-and-after study. This study compares the average and variance of response time in 2019 and 2020. It also detects any major changes in the spatial distribution of incidents through visualization using GIS. Several analysis and methods, such as T-test, F-test, time-series, point density, focusing on certain locations, sorting by weekday, incident type, etc., have been used for the preliminary study and visualization.

3.2. Data processing with Google application programming interface

This research processes the response time data with Google APIs, mainly Geocoding API and Directions API in Google maps platform, using R programming language. The response time data from the fire department does not include geographic coordinates for spatial analysis. The geocoding API enables us to convert addresses into geographic coordinates. Also, merging data along with each route needs trajectories of EVs, but the response time data includes only incident locations, not such trajectories. A new system introduced with smart intersections provides these trajectories, however, the trajectory before the improvement is unknown. Directions API provides the fastest route from locations of fire stations to incident locations such as navigation systems.

3.3. Merging data along with a trajectory of each incident

This paper proposes a method harvesting spatial information in order to import more data to the response time data. Harvested data is mainly GIS data from Southern Georgia Regional Commission (SGRC). The GIS data contains spatial information related to most infrastructure in Valdosta, GA. Among them, road network information such as locations of intersections, types of roads, and speed limits of roads, is used for the project. The harvesting process is coded with R programming language. Each trajectory from an incident is turned to a set of lines and based on the coordinates of endpoints of each line, it is specified in a square range ($x_1 - \varepsilon < x_0 < x_2 + \varepsilon$ when $x_2 > x_1$, $y_1 - \varepsilon < y_0 < y_2 + \varepsilon$ when $y_2 > y_1$) considering positioning errors (ε) considering intersection size (Figure 2). If the distance between any line of trajectory and an intersection is smaller than positioning errors (ε), the intersection is considered as a passed intersection by EVs during the incident. Not only counting passed intersections, but also harvesting other information in the same way, all harvested information is merged to the response time data.

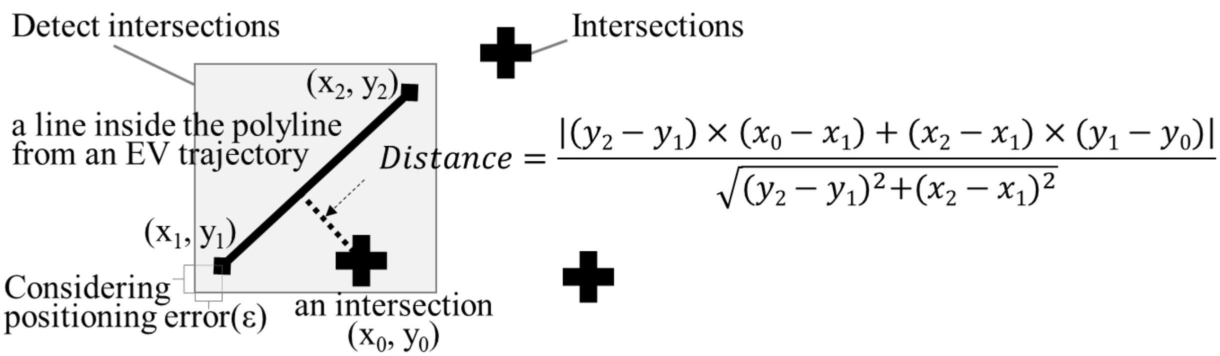

Figure 2. Detect the intersection where emergency vehicle passed by

3.4. Bayesian regression model

To evaluate the performance of improved intersections for the response time, the research conducted Bayesian Regression Model (BRM) using R programming language with "brms" package. BRM can consider group effects in variables, and it has less uncertainty issues compared to linear models. More than 50 models are tested and compared with a cross-validation technique and the research finally chooses the best fit one for the research. Before-and-after study is conducted by comparing the results from the model and it will be discussed in the next session.

4. RESULT

There is no statistical difference in the response time data for 2019 and 2020. First, the total number of incidents increased by 0.5% and the average response time by 1.1%. At a significance level of 0.05, this study performs T-test for the mean assuming unequal variances and F-test for the variance and the differences are not significant. In addition, the distributions of incidents in visualization through GIS with the point density method also show that there is no significant difference in the response time spatially (Figure 3).

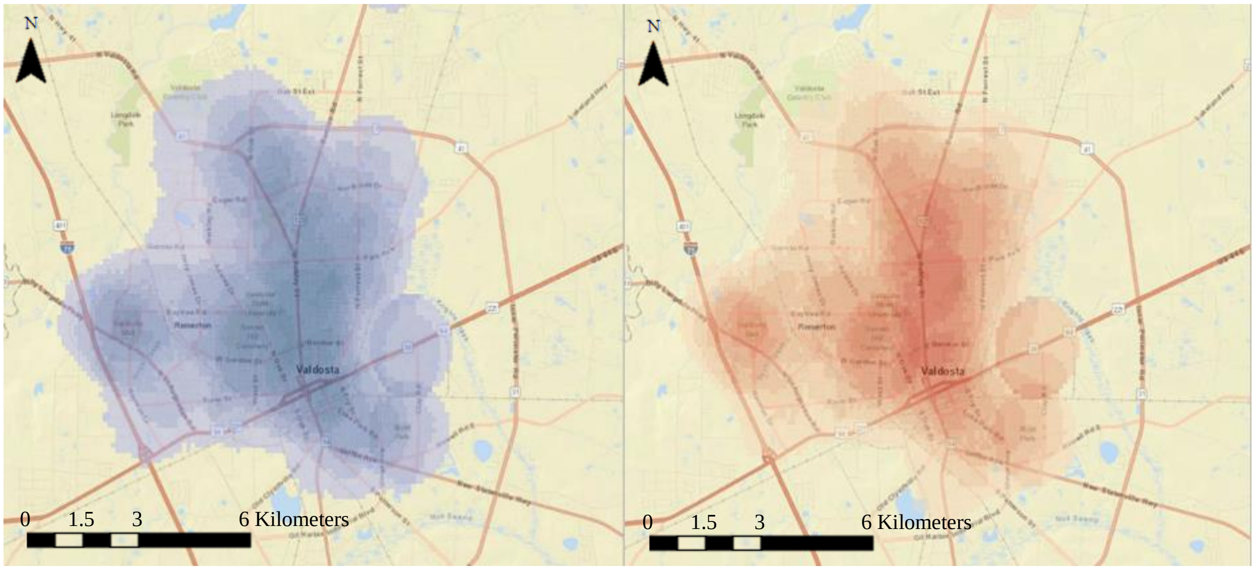

Figure 3. The distributions of incidents in 2019 and 2020

The before-and-after study is based on the data from January 2020 to September 2021. The data is divided before and after May 2021 when the intersection improvement is completed. Total incidents are 6521, 5215 for before-study and 1306 for after-study. With T-test and F-test at a significance level of 0.05, the response times before and after the improvement do not show any significant differences. Also, examples of the processed and merged data by the proposed method and Google APIs are in Table 1.

Table 1. Examples of the final data for before-after study

No.	Examples	Before	After	Difference
1	Response Time	-	-	- 1.6%
2	Number of signaled intersections	2.47	2.45	- 0.7%
3	Travel distance (km)	2165.74	2216.93	+2.4%
4	Number of turns	3.32	3.38	+1.7%
5	Number of lines	49.71	51.51	+3.6%

In Table 1, Number of signaled intersections is the average number of intersections an emergency vehicle passed in an incident, number of turns is the number of left or right turns, and number of lines is the average number of lines in a trajectory. Through a simple comparison, this study can find that smart intersections work well because response time has decreased although travel distance has increased in Table 1. However, the difference is not significant and may result from other factors, so this research uses BRM and conditional effects and conducts before-and-after studies. More than 50 BRM models are created and compared to each other with Leave-one-out cross-validation (LOO) to find the best fit model. The final model's variables and group effects are as follows:

- Variables: Number of signaled intersections, number of turns, distance of highway, distance of collector, distance of local; and
- Group effects: Fire department number, Incident type, geo-address, 24hour|weekday

Figure 4 and Figure 5 present the impacts of predictor variables. The y-axis is the response time, and the change in slope of each result shows the change in the impact of each x-axis. First, although the response time after the improvement is reduced only by 1.6% (Table 1), the impact of the number of intersections is significantly reduced (Figure 4). Also, the impact of the number of turns is significantly reduced even than the impact of the number of intersections. It can be assumed that having turns on green lights rather than red lights at intersections will greatly help EVs to save their travel time.

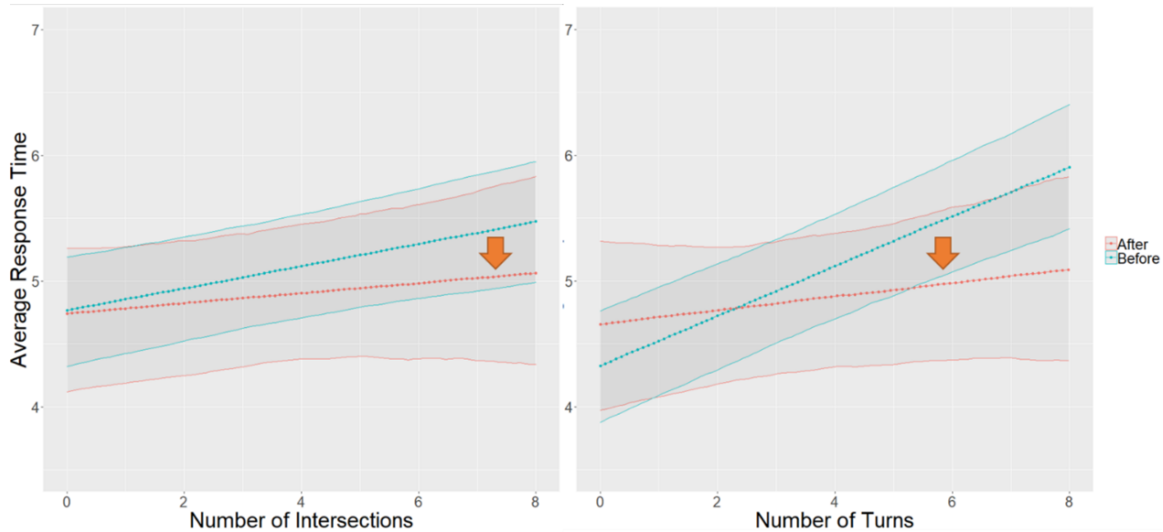

Figure 4. Changes of impacts of number of intersections and turns

Comparing the impacts of distance of highways and locals also supports that the intersection improvement has a great impact on the travel time of EVs. The impact of distance of highways, with few traffic lights, increased slightly, while the impact of distance of locals, with relatively many signaled traffic lights, decreased.

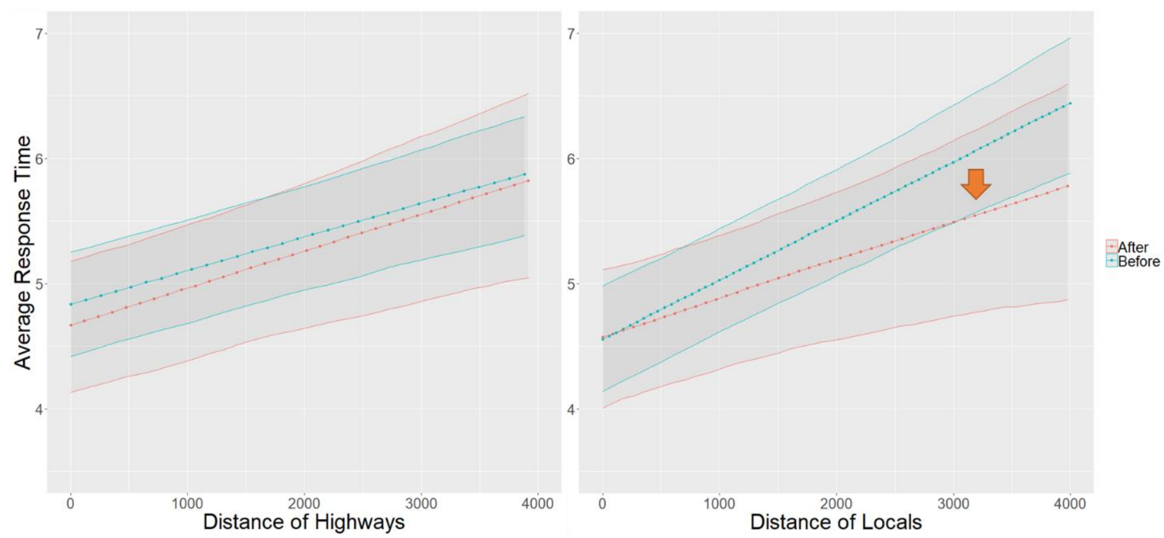

Figure 5. Changes of impacts of distance of highways and locals

5. CONCLUSION

The evaluation of smart intersections introduced to improve response time of EVs cannot be only measured by changes in the response time because it has a variety of factors that influence the response time of EVs. In this respect, this research proposes a data merging technique along with each route of incidents. It imports geospatial data into the existing response time data and enables to evaluate smart intersections by analyzing conditional effects using BRM. The study finally suggested the final BRM model and it confirmed that the impact of intersections on the response time of emergency vehicles was significantly reduced by introducing the smart intersections. The study also found the significant time savings when EVs were making turns at the intersections.

Although this research has a short period of data collection after the improvement, additional research will be conducted with the future data for one year before and one year after the improvement. Future research will also include trajectory matching to compare the trajectories provided by the new system and the trajectories through Google Directions API. The actual trajectories from the new system will need additional corrections because they are recorded by sensors generating errors from processing and matching [11]. The final results will be conducted in the same steps as this paper and will be compared before and after the improvement.

REFERENCES

[1] M. Fogué, P. Garrido, F. J. Martinez, J.-C. Cano, C. T. Calafate, and P. Manzoni, "Automatic Accident Detection: Assistance Through Communication Technologies and Vehicles," *IEEE Vehicular Technology Magazine*, vol. 7, no. 3, pp. 90–100, Sep. 2012, doi: 10.1109/MVT.2012.2203877.

[2] K. Shaaban, M. A. Khan, R. Hamila, and M. Ghanim, "A Strategy for Emergency Vehicle Preemption and Route Selection," *Arab J Sci Eng*, vol. 44, no. 10, pp. 8905–8913, Oct. 2019, doi: 10.1007/s13369-019-03913-8.

[3] I. Yun, B. B. Park, C. K. Lee, and Y. T. Oh, "Comparison of Emergency Vehicle Preemption methods using a Hardware-In-The-Loop simulation," *KSCE J Civ Eng*, vol. 16, no. 6, pp. 1057–1063, Sep. 2012, doi: 10.1007/s12205-012-1447-2.

[4] H. Noori, L. Fu, and S. Shiravi, *A Connected Vehicle Based Traffic Signal Control Strategy for Emergency Vehicle Preemption*. 2016.

[5] "City of Valdosta | Smart Cities and Inclusive Innovation." https://smartcities.gatech.edu/city-valdosta (accessed Jan. 26, 2022).

[6] S. Yang, M. Hamedi, and A. Haghani, "Online Dispatching and Routing Model for Emergency Vehicles with Area Coverage Constraints," *Transportation Research Record*, vol. 1923, no. 1, pp. 1–8, Jan. 2005, doi: 10.1177/0361198105192300101.

[7] R. F. Mikalsen, Y. Ö. Durgun, N. Portal, K. Orosz, D. Honfi, and N. Reitan, *Efficient emergency responses to vehicle collision, earthquake, snowfall and flooding on highways and bridges: A review (accepted for publication)*. 2020.

[8] J. D. Flynn, *Fire service performance measures*. National Fire Protection Association, Fire Analysis and Research Division, 2009.

[9] A. Y. Shahrah, M. A. Al-Mashari, and M. A. Hossain, "Developing and Implementing Next-Generation Computer-Aided Dispatch: Challenges and Opportunities," *Journal of Homeland Security and Emergency Management*, vol. 14, no. 4, Dec. 2017, doi: 10.1515/jhsem-2016-0080.

[10] A. Khan, F. Ullah, Z. Kaleem, S. Ur Rahman, H. Anwar, and Y.-Z. Cho, "EVP-STC: Emergency Vehicle Priority and Self-Organising Traffic Control at Intersections Using Internet-of-Things Platform," *IEEE Access*, vol. 6, pp. 68242–68254, 2018, doi: 10.1109/ACCESS.2018.2879644.

[11] X. Gong, Z. Huang, Y. Wang, L. Wu, and Y. Liu, "High-performance spatiotemporal trajectory matching across heterogeneous data sources," *Future Generation Computer Systems*, vol. 105, pp. 148–161, Apr. 2020, doi: 10.1016/j.future.2019.11.027.