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Optimizing First Responder Routes Based on Railroad Crossings and Street Traffic Information

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14. ABSTRACT
From August 2021 to August 2023, the Federal Railroad Administration (FRA) funded a research team from the University of South Carolina, in partnership with the city of Columbia, South Carolina, and CSX to develop an optimized dispatching strategy to assist 911 dispatch centers in identifying optimal routes for emergency responders. In this research, the team specifically studied potential delays caused by railroad grade crossing blockages. To address these challenges, the research team developed a shortest-path optimization model designed to minimize overall response times for emergency dispatch operations. This model incorporates a dynamic framework that predicts grade crossing blockages by estimating train arrival and departure times, and creating time windows to account for expected closure periods. Additionally, the model integrates real-time traffic information to improve dispatch accuracy.

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From August 2021 to August 2023, the Federal Railroad Administration (FRA) funded a research team from the University of South Carolina, in partnership with the city of Columbia, South Carolina, and CSX to develop an optimized dispatching strategy to assist 911 dispatch centers in identifying optimal routes for emergency responders. In this research, the team specifically studied potential delays caused by railroad grade crossing blockages.

Grade crossing blockages caused by train activity present a significant and unpredictable challenge for both everyday commuters and emergency responders. Vehicles must yield to trains at grade crossings, resulting in potentially prolonged delays. For emergency services, these delays can critically hinder response times, especially during urgent situations such as fires, medical emergencies, or natural disasters. Addressing these delays is vital for enhancing public safety, as blocked crossings can severely impact the efficiency of emergency response.

To address these challenges, the research team developed a shortest-path optimization model designed to minimize overall response times for emergency dispatch operations. This model incorporates a dynamic framework that predicts grade crossing blockages by estimating train arrival and departure times and creating time windows to account for expected closure periods. Additionally, the model integrates real-time traffic information to improve dispatch accuracy. Case studies conducted in Columbia, South Carolina, demonstrated that the proposed model can reduce response times by up to 61.6 percent for fire station dispatches and 55.3 percent for law enforcement, compared to existing practices.

The model development involved certain assumptions (e.g., treating left and right turns equally, prioritizing wider roads, and not accounting for time delays caused by traffic signals). Future studies will seek to address these limitations by incorporating further practical considerations and feedback from first responders to enhance model accuracy and applicability. This project highlights the potential of technology-driven solutions in improving emergency response efficiency and suggests infrastructure improvements that may support interactions between train operations and emergency services.

1. Introduction

From August 2021 to August 2023, the Federal Railroad Administration (FRA) funded a research team from the University of South Carolina, in partnership with the city of Columbia, South Carolina, and CSX to develop an optimized dispatching strategy to assist 911 dispatch centers in identifying optimal routes for emergency responders. In this research, the team specifically studied potential delays caused by railroad grade crossing blockages.

1.1 Background

The term “first responders” refers to a range of professional occupations, including police officers, firefighters, search and rescue personnel, ambulance personnel, and military personnel (Arble et al., 2018). In 2019, Columbia-Richland Fire & Rescue responded to nearly 32,000 calls – an average of more than 2,600 calls per month. Among these calls, 53 percent were related to Emergency Medical Services (EMS), motor vehicle accidents, or rescue, and six percent were fire related calls, with 1,920 fire related emergencies (*Public Fire Education - Columbia Fire Department*, SC). The major goals of first responders are to save lives, reduce injuries, and limit damages to properties (Jafari et al., 2003; Kevany, 2007; Neuvel & Zlatanova, 2006), and research shows that rapid first responses are associated with high survival rates (Bürger et al., 2018).

The National Fire Protection Association (NFPA) Standard 1710 outlines fire and EMS response time standards, including a 146-second “turnout time” for 95 percent of alarms received and processed and a 240-second “travel time” for not less than 90 percent of dispatched incidents. First responders must use current and future traffic network information to determine the most suitable route accurately and swiftly, a task that can be particularly challenging in densely populated metropolitan areas. In regions that include railway routes, first responders must consider potential delays caused by trains at highway-rail grade crossings, in addition to street traffic conditions, when planning routing for first responders.

A grade crossing is the location where a railway and road intersect at the same level. In a protected grade crossing, gate arms block the road once a train approach is detected and remain closed until the train clears the crossing. Grade crossing blockage time varies depending on the length and speed of the train and the specific buffer time. During the blockage, it is unsafe and illegal for any vehicle or person, including first responders, to cross the track. Unexpected delays at grade crossings can present significant challenges to first responder operations.

1.2 Objectives

The objective of this project was to develop dispatching algorithms for first-responder vehicles that consider train blockage information. Researchers sought to develop an optimized dispatching strategy to assist the 911 dispatch center in identifying optimal routes for emergency responders, paying specific attention to potential delays caused by railroad grade crossing blockages.

1.3 Overall Approach

In this project, the research team incorporated train blockages into the dispatch process for first-responder vehicles and developed a train blockage window estimation framework. Within this framework, the team represented potential blockages as a time window that reflects crossing closure periods based on estimated train arrival and departure times. The team also developed an optimization model for shortest path planning to minimize the total response time for first-responder dispatching. This model dynamically updates crossing blockage time windows and street traffic information to enhance the accuracy of dispatch strategies.

1.4 Scope

This research included a train blockage window estimation framework, an optimization model considering train blockage information for shortest path planning, and corresponding case scenarios. However, it excludes real-time predictions of train trajectory movements.

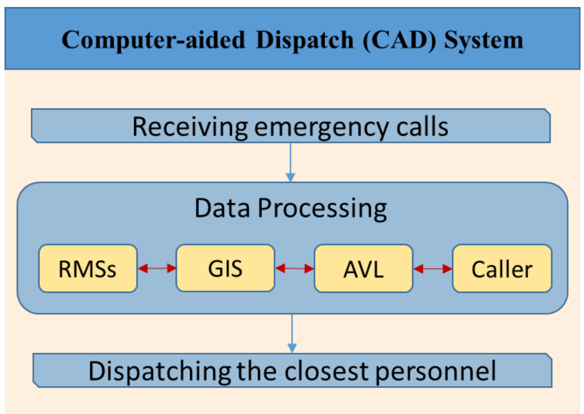
1.5 Organization of the Report

Section 2 includes a literature review. Section 3 provides the analysis of train trajectories and blockage estimations, followed by the network configuration of Columbia. Section 4 develops the route planning optimization framework. Section 5 presents the case study results. Section 6 provides research conclusions.

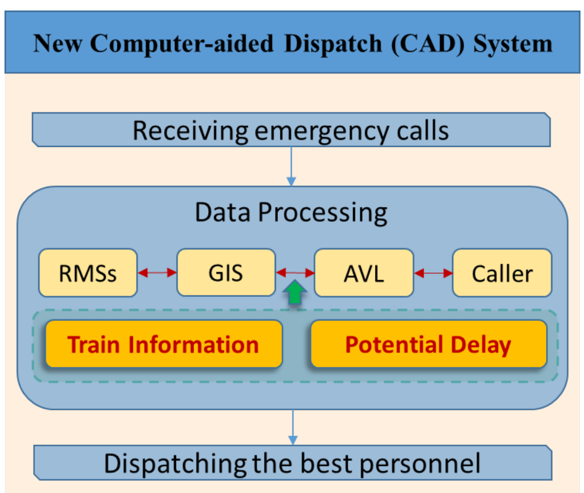
2. Literature Review

2.1 Current First Responder Dispatching Practices

A computer-aided dispatch (CAD) system is currently used to help first-responder vehicles (e.g., police, fire, and ambulance services) to respond to emergencies, as shown in Figure 1 (a) (Colton, 1980; Dawe & Pagotto, 2014; Shahrah et al., 2017). A CAD system consists of records management systems (RMS), geographic information systems (GIS), automatic vehicle location (AVL), and caller ID. RMS provides relevant data for the current service call, such as previous incidents or medical conditions of the caller. GIS provides geographical and geospatial data that can be used to help determine the best route for responders and to identify any potential hazards or obstacles. AVL pinpoints the location of response vehicles, allowing the CAD system to determine the most suitable unit for the response. Caller ID verifies the exact location of an incoming call and/or incident.



(a) Current CAD System



(b) New CAD System

Figure 1. Computer-aided Dispatch Systems

Once a call is received, the CAD system collects relevant information about the location and nature of the emergency, such as the caller's address, the type of emergency, and any available medical information. The system then assigns the emergency to the appropriate responders, based on their proximity and availability, and sends them real-time updates and instructions.

During the emergency response, the CAD system allows dispatchers and first responders to communicate with each other in real-time through mobile devices or radios to share information and coordinate their efforts. The system also tracks the status of the emergency and responders, providing updates to all involved parties and adjusting the response as necessary.

Several studies have used data-driven algorithms to dispatch first responder vehicles for emergencies. Zlatanova et al. developed a database management system that contains information related to emergency services (Zlatanova et al., 2008). By performing various queries, the system combines information on emergency service vehicle locations and the nature of the emergency to identify suitable vehicles to dispatch, then allowing vehicles autonomy in route selection. Rodriguez implemented a Mento-Carlo framework to simulate all possible routes to determine the route with minimum travel time and energy consumption (Rodriguez, 2019). Wang et al. developed a system that used historical spatial information, real-time meteorological data, and a hazard simulation model to predict the occurrence of natural disasters and notify first responders about potential hazards to use in route planning (Wang & Zlatanova, 2016). Shiri and Salman studied the online, multi-agent, Canadian traveler problem (i.e., finding at least one feasible route from the origin to the destination within a minimum response time), proposed a corresponding online heuristic policy, and tested the strategy on both real and generated networks (Shiri & Salman, 2020). And recently, machine learning or artificial intelligence have been applied to first-responder vehicle navigation (Brown & Taylor, 2018; Tofighi et al., 2021). The decisions made in these studies heavily rely on drivers' experience or exhaustively enumerating all possible alternatives when dispatching first responder vehicles.

2.2 The Shortest Path Problem

Dispatching first responders involves determining the shortest path to the emergency site. From an academic perspective, the shortest path problem has been extensively studied in the field of vehicle routing problems (VRP) since the 1960s (Dreyfus, 1969; Festa, 2009). The initial focus of shortest path problems was primarily on travel distance using commonly employed route planning algorithms such as Dijkstra's Algorithm (Dijkstra, 1959; El-Sherbeny, 2014; Johnson, 1973), the Label Setting Algorithm (Dreyfus, 1969), and the Bellman-Ford Algorithm (Awerbuch et al., 1994; Schambers et al., 2018).

Figure 2 shows an example of a basic graph. Each arrow in the figure stands for an edge/link, and each edge connects two nodes on each side (e.g., Edge (B, C) connects Node B and Node C). The numbers displayed along the edges indicate the "cost" of the edge, which can be either traveling distance or traveling time (e.g., the travel cost for Edge (A, C) is four minutes or four miles). All the edge costs are positive; therefore, the graph can be defined as a non-negative graph.

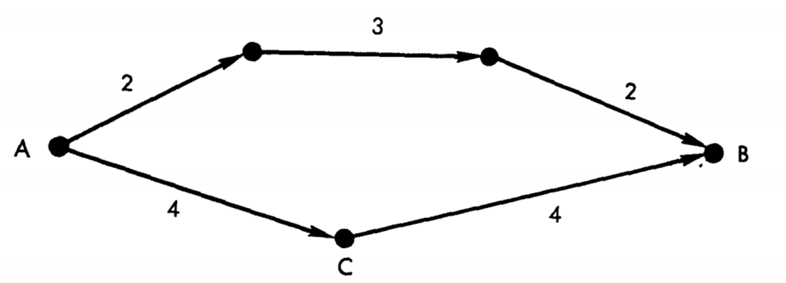


Figure 2. Example of a Non-negative Graph

The classic Dijkstra's Algorithm is a search algorithm that finds the shortest path between two nodes in a weighted graph. It works by selecting the node with the smallest tentative distance and updating its neighbors' tentative distances. The algorithm continues until the destination node is reached, and the shortest path can be reconstructed by following nodes with the smallest tentative distances. The algorithm only works correctly if there are no negative weight edges in the graph.

Like Dijkstra's Algorithm, a Label Setting Algorithm also finds the shortest path in a network with non-negative edge weights, but it maintains a set of permanently labeled nodes and a set of temporarily labeled nodes. The algorithm starts with the source node being permanently labeled as zero, and all other nodes are temporarily labeled as infinity. At each step, the algorithm selects the temporarily labeled node with the smallest label and updates the distances of its neighbors. The algorithm continues until the destination node is permanently labeled or there are no more temporarily labeled nodes. The shortest path can be generated by following the path of permanently labeled nodes. Apart from being unable to process negative-weighted edges in the graph, the Label Setting Algorithm may not be as efficient as Dijkstra's algorithm in terms of running time, especially when using a dense graph.

The Bellman-Ford Algorithm is a graph search algorithm which can deal with either negative or non-negative edge weights in a graph. It works by iteratively relaxing each edge in the graph, and it terminates after V-1 iterations, where V is the number of nodes in the graph. If there is a negative cycle in the graph, the algorithm terminates and reports that no shortest path exists. This algorithm can handle graphs with negative edge weights and can detect negative cycles. The Bellman-Ford Algorithm is slower than Dijkstra's Algorithm and the Label Setting Algorithm, as it iterates over all edges V-1 times. However, it can handle graphs with negative edge weights and can also detect negative cycles in the graph. As this project does not involve negative-weighted edges and is intended for first responders, the team did not use the Bellman-Ford Algorithm due to concerns about its solving time efficiency.

Both the existing literature and the current CAD system do not consider train blockages when dispatching first-responder vehicles, which poses a potential challenge to the efficiency of emergency response efforts. Based on current CAD techniques, the research team focused on developing algorithms for dispatching first responder vehicles with a particular focus on blockages at train grade crossings, as shown in Figure 1 (b). Also, in contrast to the traditional time window constraints found in the existing literature, periods of crossing blockage can be viewed as time windows that restrict the passage of all on-road vehicles, including first responders.

Unfortunately, the majority of shortest path problems fall into the categories of non-deterministic polynomial time hard (NP-hard) or NP-complete problems. (Carrabs et al., 2020; Chassein et al., 2019; Ferone et al., 2020; Saraiva & de Andrade, 2021; Yu & Yang, 1998; Zhen et al., 2020). This indicates that finding efficient solutions for this class of problems poses significant challenges due to their computational complexity, especially for large-scale/size networks.

Table 1 provides a comparison between the road network scales examined in the existing literature and the scale considered in this project. The findings indicate that the network scale in this project is significantly larger than those explored in the existing literature.

Table 1. Network Scale Comparison

References	Time window	First responder	# of Nodes	# of Edges
Dreyfus, 1969	×	×	5	7
Johnson, 1973	×	×	7	42
Sancho, 1994	√	×	7	12
Güner et al., 2012	×	×	30	98
Festa et al., 2013	×	×	Up to 100	Up to 9,900
Shahabi et al., 2015	×	×	24	78
Wang & Zlatanova, 2016	×	√	1,780	1,586
Chassein et al., 2019	×	×	538	1,308
Shiri & Salman, 2020	×	√	Up to 500	Up to 1,500
Ferone et al., 2020	×	×	Up to 450	Up to 1,710
Carrabs et al., 2020	×	×	6	11
Pugliese et al., 2020	√	×	7	7
Saraiva & de Andrade, 2021	×	×	Up to 350	Up to 900
This project	√	√	7,668	21,502

The objective of this project was to develop a practical and time-efficient system that can identify the optimal route for first responders in emergency vehicle dispatching. This system will consider both potential blockages at railroad crossings and the dynamic conditions of street traffic. The system uses train operation data to calculate the expected delay time at crossings along the track, which is then used to determine the route requiring the least travel time considering potential delays due to grade crossings. Time windows will be created during periods of railway crossing blockage, and the developed algorithm will solve the shortest path problem based on dynamically updated road network. Case studies were conducted in Columbia, SC, to verify the system's potential to assist first responders in identifying the optimal route with the lowest response time during emergencies.

Compared with the traditional shortest path problems using time windows in the existing literature, there are three major challenges in this project.

1. This problem involves finding the shortest path from multiple origins to a single destination, whereas the traditional problem only requires finding the shortest path between a given Origin-Destination (OD) pair. In the case of an emergency service request, there may be several available fire stations from which to choose as potential origins.
2. There is interdependency between crossing blockage time windows, whereas most existing literature only considered shortest problems with independent time windows (Desaulniers et al., 2014; Di Puglia Pugliese et al., 2020; El-Sherbeny, 2014; Hiermann et al., 2016; Sancho, 1994; Zhen et al., 2020). Interdependency between time windows requires the shortest path search algorithm to dynamically update travel time during routing.
3. The road network in this project is much larger in scale than those in previous studies, as shown in the detailed comparisons presented in Table 1. This large network presents a significant challenge in terms of computational demands for the algorithm.

3. Train Information and Street Configuration

This section presents real-world freight train operational data from CSX Transportation, Inc (CSX) and discusses the street configurations used in this research.

3.1 Train GPS Data Analysis

The research team obtained detailed freight train GPS data from CSX (e.g., train ID, locomotive ID, locomotive speed, locomotive coordinates, locomotive altitude, and locomotive heading data). The GPS data records train trajectories within a 20-kilometer radius of the city center of Columbia, SC, from October 31 to November 10, 2020. Using the provided latitude and longitude data, the team plotted the train trajectory coordinates in ArcGIS Pro. Six major train routes were identified (see Figure 3) from a total of 39,773 GPS records. The proportions of each pattern in the figure are: (a) 12.1 percent, (b) 12.9 percent, (c) 3.4 percent, (d) 39.7 percent, (e) 5.2 percent, and (f) 25.9 percent, respectively. Note that for security reasons, specific train IDs and their routes are not used.

Figure 3 shows how the trains go through Columbia, and train direction is predicted in the following minutes. Given current train length, location, and speed information, it is possible to estimate blocked nodes with corresponding blockage windows.

(a) Pattern I: Northeast-Southwest (b) Pattern II: Southeast (c) Pattern III: Northwest-Southeast

(d) Pattern IV: Southern (e) Pattern V: Northwest-Southern (f) Pattern VI: Northwest

Figure 3. Major Patterns of CSX Freight Train Routes in Columbia, SC (1:242,000 shown in ArcGIS Pro)

Table 2 shows the statistics on train length from the CSX dataset. The table indicates that the train length ranges from 40 ft (a locomotive) to 17,028 ft (a locomotive with carriages), with an average of 5,719 ft and a standard deviation of 3,773 ft.

Table 2. Descriptive Statistics of Train Length

Index	Value (ft)
Mean	5,719
Standard Deviation	3,773
Min	40
25 % Quantiles	3,000
Median	5,448
75 % Quantiles	9,022
Max	17,028

Figure 4 displays the distribution of instantaneous velocities of 33,617 trains from the GPS data within the area. The figure shows that train speeds range from 0 to 60 mph, with an average speed of approximately 13 mph. Notably, the distribution reveals that the instantaneous velocity of zero has the highest proportion, indicating that trains may make multiple complete stops while passing through Columbia. This contributes to the uncertainty of the predictions of the train blockage windows, particularly for blockage durations.

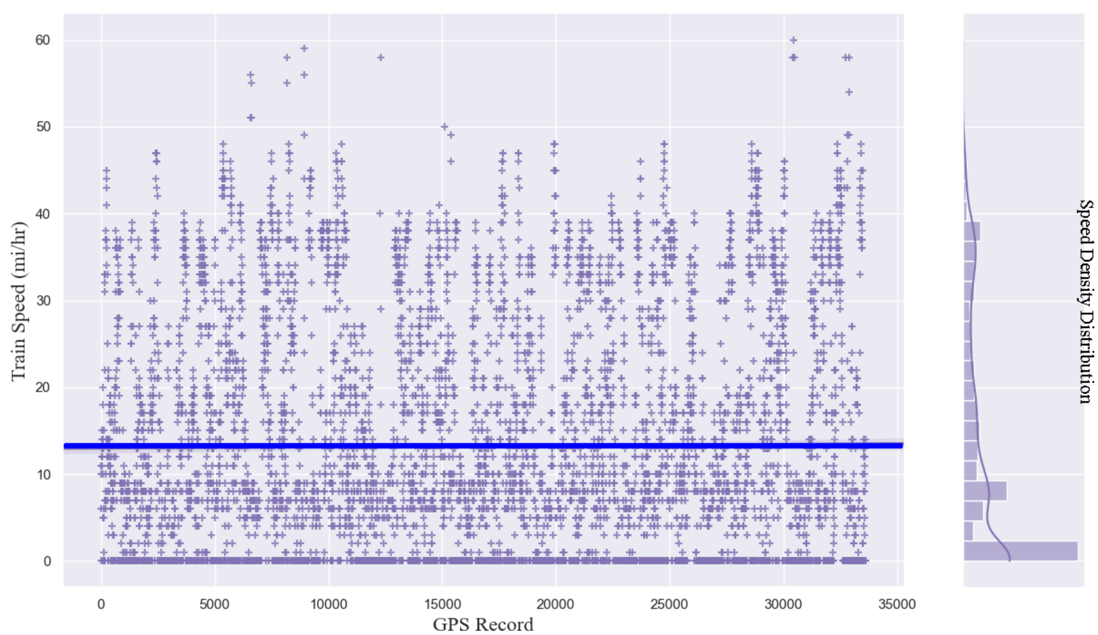


Figure 4. Distribution of Instantaneous Train Speed

3.2 Blockage Time Estimate

To estimate train blockage windows, the team used train length (l_{train}), current location (d_{train}^{t}), and operating speed (v_{train}^{t}). Given the train information above, it is assumed that at time $t = t_0$, a train is going through the city. The locomotive is currently at the location $d_{train}^{t_0}$, and the instantaneous speed is $v_{train}^{t_0}$.

It is important to note that trains can change their speed, slow down, or even stop completely. Since the GPS device records separate instantaneous velocities, the team used the updated average speed to predict the speed of the train for the next time interval between two recorded instances:

$$\bar{v}_{train}^{t_i} = \frac{d_{train}^{t_i} - d_{train}^{t_0}}{t_i - t_0} \tag{1}$$

where i is the time index of the record instances, t_i is the ith recorded time point, $d_{train}^{t_i}$ indicates the locomotive location at $t = t_i$.

The GPS data also provides the train locomotive location information that directly tells how far the train has traveled between two recorded instances:

$$d_i = d_{train}^{t_i} - d_{train}^{t_{i-1}} \tag{2}$$

But for any $t \in [t_i, t_{i+1}]$, the estimated traveling distance for the period is used:

$$d_i^{estimate} = \int_{t_i}^{t_i+\Delta t} v_{train}^{t} \cdot \Delta t \tag{3}$$

According to the principle of integral calculus, the closer Δt to zero, the more accurate the estimation will be. However, in reality, GPS devices cannot record time periods that are extremely close to zero. In implications, the average speed between two neighboring records is usually used to estimate $d_{estimate}$.

$$d_i^{estimate} = \bar{v}_{train}^{t_i} \cdot \Delta t \tag{4}$$

Then, the start time t_v^{s} of the train blockage window at next grade crossing node v is:

$$t_v^{\mathrm{s}} = t_0 + \frac{D_0 - \sum_i d_i}{\bar{v}_{train}^{t_i}} \tag{5}$$

where D_0 stands for the initial distance between the locomotive location and the grade crossing at $t = t_0$.

The duration time of the train blockage can be estimated by:

$$t_{duration} = \frac{l_{train}}{v_{train}^{t}} \tag{6}$$

Therefore, the estimate of the end of the blockage time at node v is:

$$t_v^{\mathrm{e}} = t_v^{\mathrm{s}} + t_{duration} = t_0 + \frac{l_{train} + D_0 - \sum_i d_i}{\bar{v}_{train}^{t_i}} \tag{7}$$

A detailed estimation example is discussed in the next section.

3.3 Blockage Estimation Examples

To estimate the blockage time of each grade crossing, researchers calculated the time it takes for the train to completely clear the crossing. An example calculation for a blockage window period estimation when a train is going through a sequence of grade crossings, based on the CSX train GPS data on November 1, 2020, is provided below.

3.3.1 Case 1: T=17:09:10

According to the GPS records, the locomotive of Train #F772** (note the last two digits are hidden for security) is located at the light blue highlighted position in Figure 5 with an instantaneous velocity of zero at 17:09:10 on November 1, 2020. The train is 5,097 ft long, and it is traveling through Columbia from the southeast to the west. There are three grade crossings along the train trajectory.

Assume $t_0 = 17{:}09{:}10$, the locomotive is 1,776 ft away from grade crossing #1, the distance between the first and the second grade crossings is 1,979 ft, and the distance between the second and the third crossings is 1,461 ft.

Figure 5. Blockage Window Estimate Example with Train #F772**

Therefore, for $t_0 = 17{:}09{:}10$, there will be no estimated blockage windows at three grade crossings, as the train completely stops in Figure 5.

3.3.2 Case 2: T=17:12:09

For $t_1 = 17{:}12{:}09$ (Figure 6), the instantaneous velocity is 14 ft/s, and the estimated blockage windows are:

For grade crossing #1, the estimated blockage window is:

$$t_1^s = t_1 + \frac{D_{0-1} - \sum_i d_i}{\bar{v}_{train}^{t_1}} = 17{:}12{:}09 + \frac{1776 - 752}{\frac{752}{179}} = 17{:}16{:}13$$

$$t_1^e = t_1 + \frac{l_{train} + D_{0-1} - \sum_i d_i}{\bar{v}_{train}^{t_1}} = 17{:}12{:}09 + \frac{5097 + 1776 - 752}{\frac{752}{179}} = 17{:}36{:}25$$

where D_{0-1} indicates the initial distance between the train locomotive and grade crossing #1.

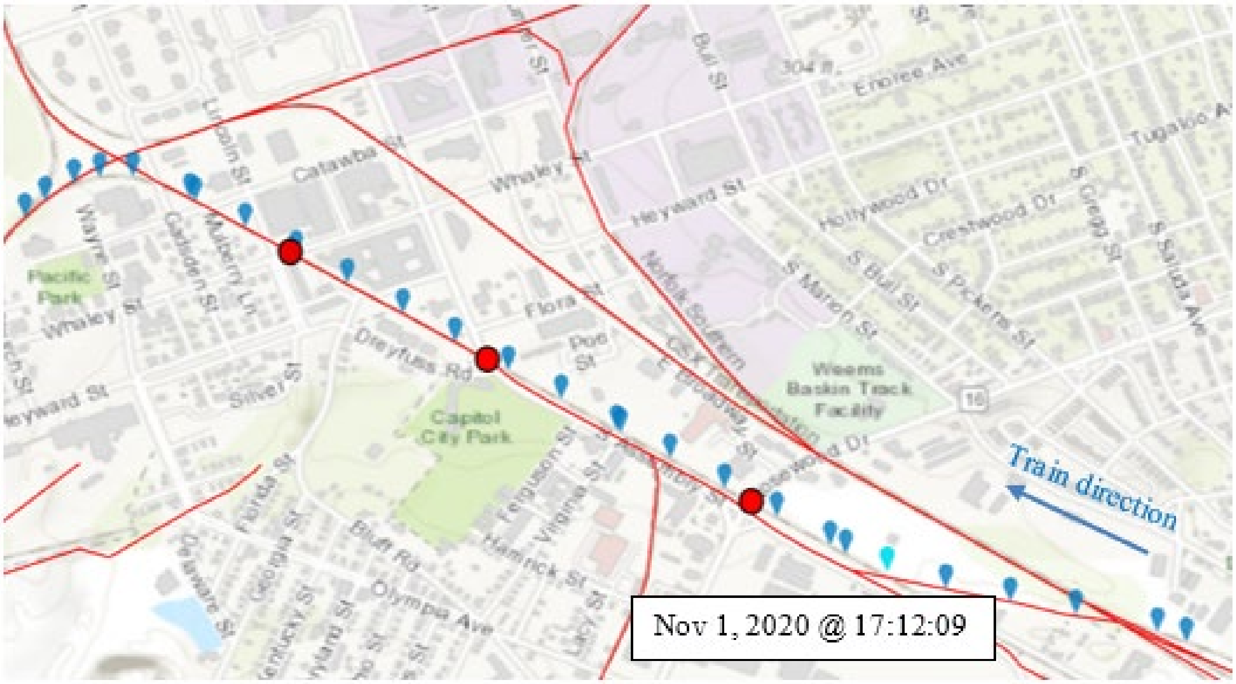


Figure 6. Train #F772 at 17:12:09**

Therefore, the estimated blockage window of grade crossing #1 is **[17:16, 17:36].**

Similarly, for grade crossing #2:

$$t_2^s = t_1 + \frac{D_{0-2} - \sum_i d_i}{\bar{v}_{train}^{t_1}} = 17:12:09 + \frac{3755 - 752}{\frac{752}{179}} = 17:24:07$$

$$t_2^e = t_1 + \frac{l_{train} + D_{0-2} - \sum_i d_i}{\bar{v}_{train}^{t_1}} = 17:12:09 + \frac{5097 + 3755 - 752}{\frac{752}{179}} = 17:44:17$$

The estimated blockage window of grade crossing #2 is **[17:24, 17:44].**

For grade crossing #3:

$$t_3^s = t_1 + \frac{D_{0-3} - \sum_i d_i}{\bar{v}_{train}^{t_1}} = 17:12:09 + \frac{5216 - 752}{\frac{752}{179}} = 17:29:52$$

$$t_3^e = t_1 + \frac{l_{train} + D_{0-3} - \sum_i d_i}{\bar{v}_{train}^{t_1}} = 17:12:09 + \frac{5097 + 5216 - 752}{\frac{752}{179}} = 17:50:05$$

The estimated blockage window of grade crossing #3 is **[17:30, 17:50].**

3.3.3 Case 3: T=17:13:49

For $t_2 = 17:13:49$ (Figure 7), the instantaneous velocity is 18 ft/s, and the estimated blockage windows are noted below. In this case, although the train locomotive has passed grade crossing

#1, the end of the train remains behind the crossing, which means the grade crossing is still blocked.

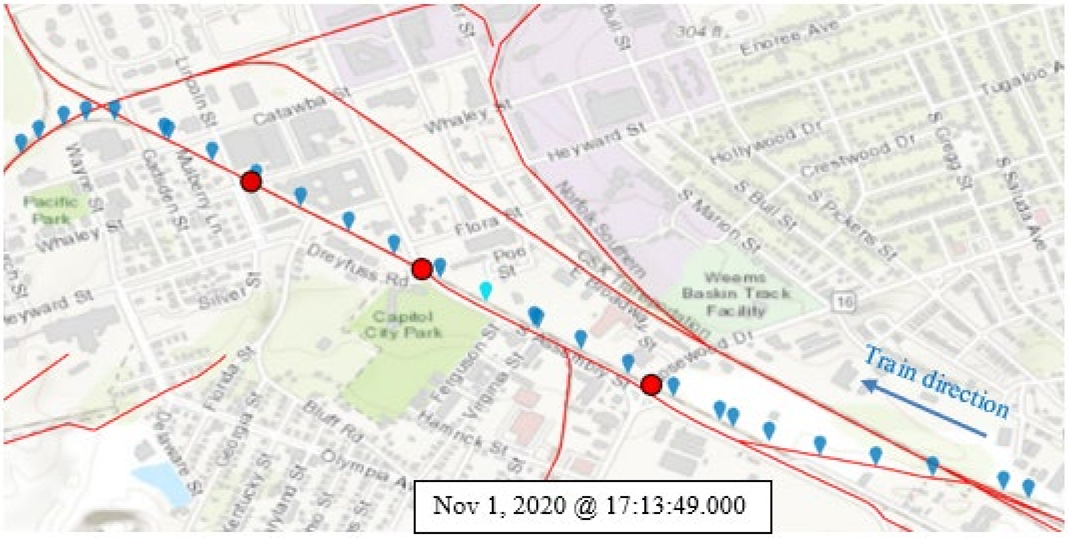


Figure 7. Train #F772 at 17:13:49**

For grade crossing #1:

$$t_1^{\mathrm{s}} = current\ time = 17{:}13{:}49$$

$$t_1^{\mathrm{e}} = t_2 + \frac{l_{train} + D_{0-1} - \sum_i d_i}{\bar{v}_{train}^{t_1}} = 17{:}13{:}49 + \frac{5097 + 1776 - 3171}{\frac{3171}{279}} = 17{:}19{:}15$$

The estimated blockage window of grade crossing #1 has been updated from [17:16, 17:36] to **[current, 17:19].**

For grade crossing #2:

$$t_2^{\mathrm{s}} = t_2 + \frac{D_{0-2} - \sum_i d_i}{\bar{v}_{train}^{t_2}} = 17{:}13{:}49 + \frac{3755 - 3171}{\frac{3171}{279}} = 17{:}14{:}40$$

$$t_2^{\mathrm{e}} = t_2 + \frac{l_{train} + D_{0-2} - \sum_i d_i}{\bar{v}_{train}^{t_2}} = 17{:}13{:}49 + \frac{5097 + 3755 - 3171}{\frac{3171}{279}} = 17{:}22{:}09$$

The estimated blockage window of grade crossing #2 has been updated from [17:24, 17:44] to **[17:15, 17:22].**

For grade crossing #3:

$$t_3^{\mathrm{s}} = t_2 + \frac{D_{0-3} - \sum_i d_i}{\bar{v}_{train}^{t_2}} = 17{:}13{:}49 + \frac{5216 - 3171}{\frac{3171}{279}} = 17{:}16{:}49$$

$$t_3^{\mathrm{e}} = t_2 + \frac{l_{train} + D_{0-3} - \sum_i d_i}{\bar{v}_{train}^{t_2}} = 17{:}13{:}49 + \frac{5097 + 5216 - 3171}{\frac{3171}{279}} = 17{:}24{:}17$$

The estimated blockage window of grade crossing #3 has been updated from [17:30, 17:50] to **[17:17, 17:24].**

This updating process can be consistently applied in cases where new GPS data becomes available, and the estimated time window for train blockage is adjusted accordingly.

Figure 8 displays the road network of Columbia, SC. A total of 7,668 nodes along with 21,502 edges can potentially be affected by train blockages. During the implementation phase in Section 4, the team conducted simulations involving various types of emergencies occurring in the specified area for which first-responder vehicles are dispatched from nearby stations or on-road patrolling units. In emergency cases, the first responders have to make prompt decisions on (1) which station should deploy vehicles or which nearby patrolling unit should be dispatched to the emergency and (2) which path should be taken to reach the destination within the minimum response time, while also avoiding any potential train blockages.

Figure 8. Road Network of Columbia, SC (Shown in SUMO)

4. Route Optimization Considering Crossing Blockages

The objective of this project was to develop dispatching algorithms for first-responder vehicles considering train blockage information. The problem can be treated as a variant of the shortest path problem with a time window. This section describes the problem, defines variables, and estimates train blockage time windows. The team then developed an optimization model and algorithm, and conducted computational experiments.

4.1 Problem Description

The shortest path problem for first-responder vehicles with train blockage windows is to find the shortest path in a train crossing network for emergency vehicles. Given a directed non-negative weighted graph, the set of nodes and the set of weighted arcs is determined. For each grade crossing node, a blockage window will be generated at the node. Variables used in this research are listed in Table 3.

Table 3. Variables and Definitions

Set Variables	Description
$G = (V, A)$	Directed non-negative weighted graph
V	The set of nodes in G, $v \in V$
A	The set of weighted arcs/links, $a_{ij} \in A$
Train Related Variables	
l_{train}	Train length
v_{train}^{t}	Train operating speed at time t
$d_{train}^{i,j}$	Train route distance between grade crossing nodes i and j
$[t_v^s, t_v^e]$	Train blockage window at node v starting at $t = t_v^s$ and ending at $t = t_v^e$
Road Network Related Variables	
(r, s)	OD pair, from origin node r to destination node s
$\bar{t}_{ij}$	The average road traveling time on the arc/link a_{ij}
b_{ij}	A binary variable, $b_{ij} = 1$ if the arc/link a_{ij} is blocked by a train, otherwise, $b_{ij} = 0$
T_v	Accumulative time after an emergency occurs when the emergency vehicle arrives at node v
D_v	Expected time delay at node v
D_{total}	Total time delay
Decision Variable	
x_{ij}^{rs}	A binary decision variable, $x_{ij}^{rs} = 1$ if the link a_{ij} lies on the path (r, s), otherwise, $x_{ij}^{rs} = 0$
Objective Function	
Z	Response time after an emergency occurs

4.2 Modeling

The shortest path algorithm is mainly based on the Label Correcting Algorithm and will be modified while considering train blockage windows. The key to the modified algorithm is to update the estimated vehicle arrival time.

$$T_j = \begin{cases} t_v^{\mathrm{e}} \ \ if \ t_v^0 < T_i + \bar{t}_{ij} < t_v^{\mathrm{e}} \\ T_i + \bar{t}_{ij}, Otherwise \end{cases}, \forall i, j \in V \tag{7}$$

Equation (7) estimates the updated arrival time of an emergency vehicle at node j. If the initial arrival time, $T_i + \bar{t}_{ij}$, falls into the train blockage window at the node j, then it will be adjusted to the end of the blockage window.

The expected time delay at node v is then calculated. Generally, the expected delay time at node v can be written as:

$$D_v = \begin{cases} 0, \ if \ T_v < t_v^s \ or \ T_v > t_v^e \\ t_v^e - T_v, Otherwise \end{cases} \tag{8}$$

Then the total time delay can be calculated as:

$$D_{total} = \sum_{v \in V} D_v \tag{9}$$

Initially, the shortest path with minimum response time will be found, then the optimization model can be generated as follows:

$$Z = \min T_s = \min_x \sum_{(i,j) \in A} \left(T_j - T_i\right) \cdot x_{ij}^{rs}, \forall r, s \in V \tag{10}$$

s.t.

$$\sum_j x_{ij}^{rs} - \sum_i x_{ij}^{rs} = \begin{cases} 1, \ \forall i = r \\ 0, \forall i \neq r, \forall j = s \\ -1, \ \forall j = s \end{cases} \tag{11}$$

$$x_{ij}^{rs} = \begin{cases} 1, if \ a_{ij} \text{ lies on the path } (r,s) \\ 0, otherwise \end{cases}, \forall a_{ij} \in A, \forall r, s \in V \tag{12}$$

The objective function (10) minimizes the accumulative response time when the emergency vehicle finally arrives at the destination after the emergency occurs. Equation (11) represents the flow balance constraints for a path between origin node r and destination node s, i.e., any node except the origin and destination should satisfy flow-in equals to flow-out; for the origin node, flow-out equals to one without flow-in; and similarly for the destination node, flow-in equals to one without flow-out. Equation (12) defines the binary decision variable.

Considering that mathematically minimizing the total response time equals minimizing the total delay time in Equation (9), then the original optimization model can be rewritten as:

$$\min D_{total} = \min_x \sum_{(i,j) \in A} D_j \cdot x_{ij}^{rs}, \forall r, s \in V \tag{13}$$

such that:

$$\sum_j x_{ij}^{rs} - \sum_i x_{ij}^{rs} = \begin{cases} 1, \ \forall i = r \\ 0, \forall i \neq r, \forall j = s \\ -1, \ \forall j = s \end{cases} \tag{14}$$

$$x_{ij}^{rs} = \begin{cases} 1, if \ a_{ij} \text{ lies on the path } (r,s) \\ 0, otherwise \end{cases}, \forall a_{ij} \in A, \forall r, s \in V \tag{15}$$

The objective function (13) calculates and then minimizes the total time delay when the emergency vehicle goes through each node on the path. Equation (14) represents the flow balance constraints for a path between origin node r and destination node s. Equation (15) defines the binary decision variable.

4.3 Algorithm

The pseudo-code for the modified Label Correcting Algorithm is provided in Figure 9.

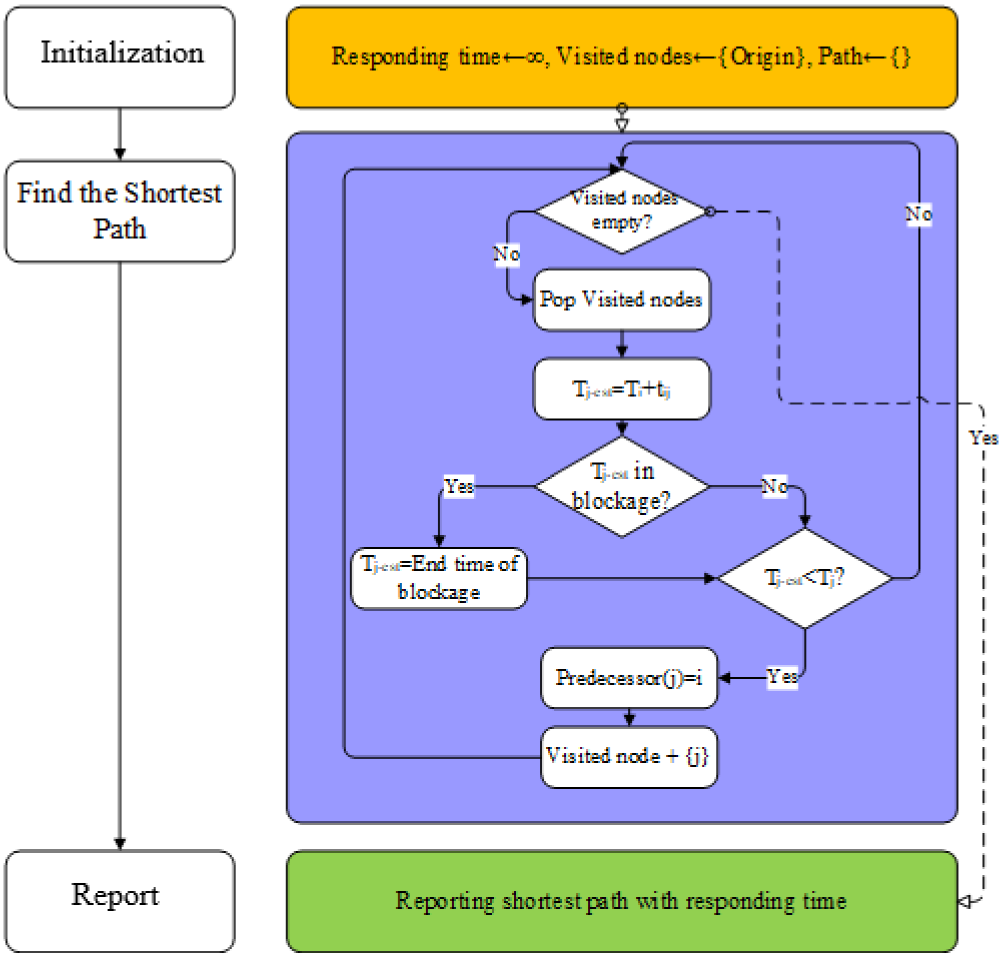


Figure 9. Flowchart of the Modified Label Correcting Algorithm

5. Results and Discussion

This section details a series of case studies in Columbia, SC. Various emergency scenarios are discussed, including cases where fixed stations and patrolling units dispatch emergency vehicles at different time points.

In this report, fire stations and police patrolling units are used as examples to implement the algorithm, while in real-world activities, these can be any first responders.

The study assumes two trains depart at 9:00 am and 9:09 am, respectively. The train blockage windows along their routes are estimated using Equations (1) through (6). Table 4 shows the estimated train blockage windows at the first eight grade crossing nodes for each train.

Table 4. Train Blockage Windows at Grade Crossings

Train #1 Departing at 9 am		Train #2 Departing at 9:09 am	
Nodes	Blockage Windows	Nodes	Blockage Windows
1	[9:00, 9:14]	1	[9:09, 9:34]
2	[9:01, 9:15]	2	[9:12, 9:36]
3	[9:01, 9:19]	3	[9:13, 9:29]
4	[9:04, 9:41]	4	[9:15, 9:30]
5	[9:07, 9:42]	5	[9:16, 9:31]
6	[9:08, 9:45]	6	[9:19, 9:36]
7	[9:48, 10:04]	7	[9:20, 9:51]
8	[9:52, 10:08]	8	[9:36, 10:01]

Given the train blockage window and road network information above, fire emergencies were simulated at different time point scenarios and the team studied how the train blockages affected the fire station vehicle dispatch strategies.

Figure 10 shows the geographic locations of fire stations and the fire emergency destination, which is near an Italian restaurant. Table 5 shows the shortest path distance from each fire station to the destination. Priority is given to dispatching vehicles according to the distance from each fire station to the destination.

To provide a basis for comparison, a baseline dispatch strategy is used to calculate response time. In the baseline strategy, decision-makers do not consider train blockages when dispatching emergency vehicles. Instead, they dispatch vehicles directly from the closest fire station and follow the distance-based shortest path to the destination. If any train blockages are reported at grade crossings, a new vehicle is dispatched from the next closest station (as per the "priority" column in Table 5) until one vehicle finally arrives at the destination, or all regional fire stations have dispatched at least one vehicle, but all dispatched vehicles have been blocked at crossings.

Figure 10. Locations of Fire Stations and Destination (shown in ArcGIS Pro)

Table 5. Shortest Path Distance from Each Fire Station to the Destination

Fire Stations	Distance (mi)	Dispatch Priority
Headquarters	1.58	2
Station 2	1.19	1
Station 9	1.63	3

According to the NFPA Standard 1710, the "turnout time" can vary from 80 seconds to 146 seconds, depending on different credible intervals. To simplify and standardize the model, an additional 120 seconds of "turnout time" was assumed as a time delay when dispatching a new vehicle from another fire station.

For the patrolling unit dispatching cases, it was assumed that there was a general emergency happening at a United States Postal Service (USPS) building (see Figure 11) and there are two first-responding units patrolling the areas nearby. In this case, a similar baseline dispatching strategy as described in fire station cases above was implemented.

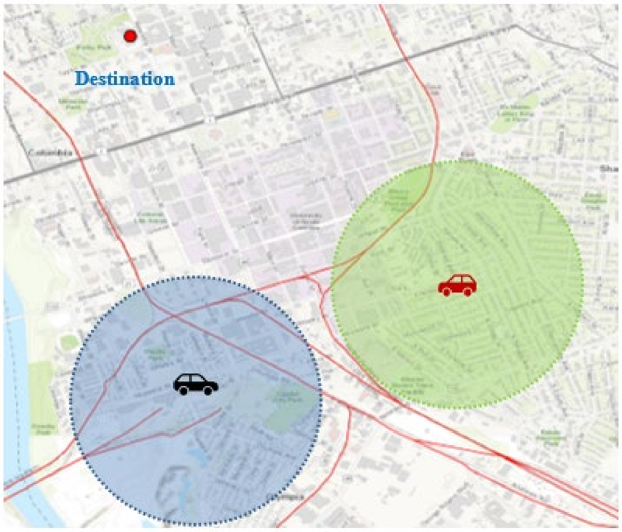
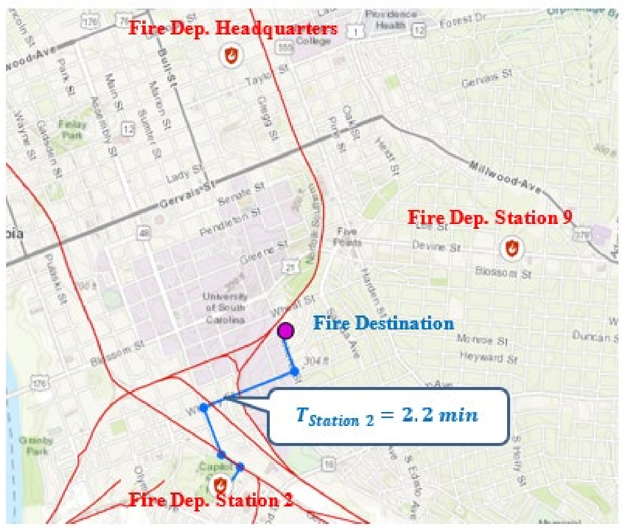


Figure 11. First Responding Units and Corresponding Patrolling Areas

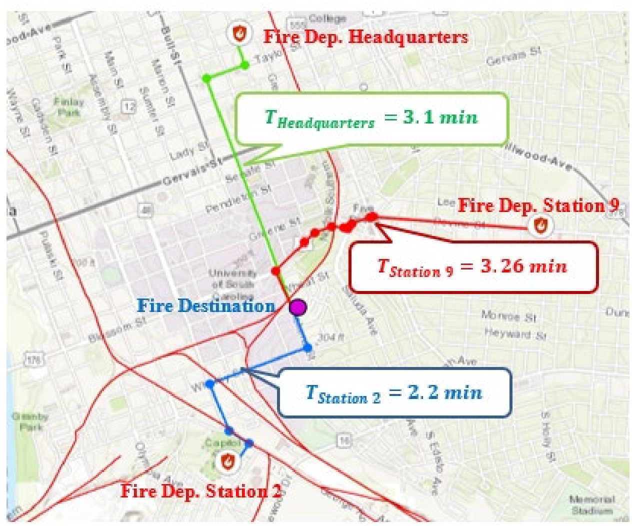
5.1 Scenario #1: Fire Emergency Call at 8:50 am

5.1.1 Station Dispatching Cases

In this scenario, a fire emergency occurs near an Italian restaurant at 8.50 a.m. The baseline dispatching route is shown in Figure 12 (a), and the minimum response time from each fire station is reported in Figure 12 (b).



(a) Baseline Calculation



(b) Minimum Response Time Route

Figure 12. Comparison of Baseline and Optimized Dispatching Routes (T=8:50 am)

Based on Figure 12 (a) and (b), the dispatching center dispatches vehicles from Fire Station 2, and the optimal dispatching route is the same as the baseline dispatching route. This is because, at the time of the fire emergency, no trains are passing through the city, and this is a typical shortest path problem where the distance-based shortest path is also the least time-consuming. Furthermore, the baseline strategy also follows the same route to dispatch vehicles directly; therefore, no time is either saved or wasted in this scenario.

5.1.2 Patrolling Unit Dispatching Cases

In this scenario, an emergency occurs near a USPS building at 8:50 am, and the closest first-responder unit is reported by GPS, as shown in Figure 13.

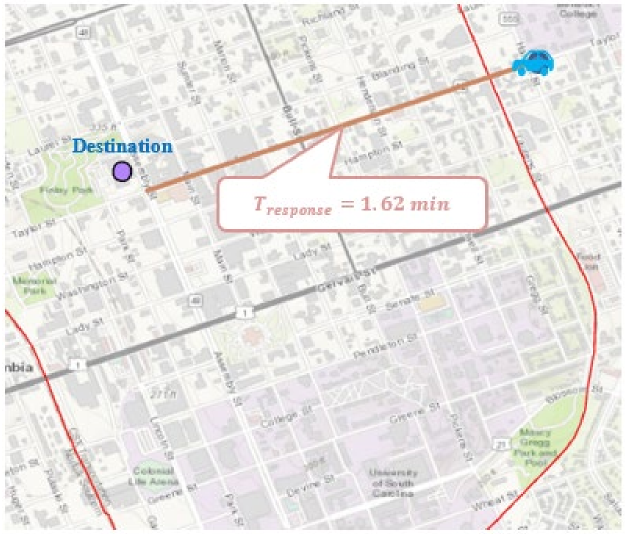


Figure 13. Stochastic First-responder Unit Dispatching (T=8:50 am)

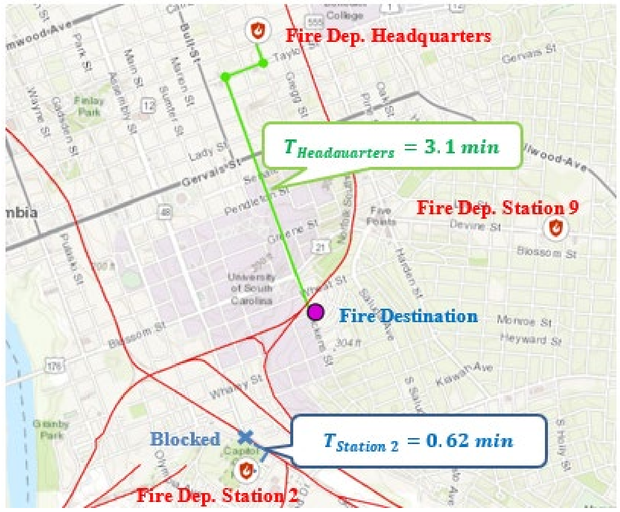
As with the fire station dispatching case, in this scenario, the optimized route is the same as the baseline dispatching route at the current time. The closest first responder unit is dispatched, and there are no train blockages reported on the way to the emergency location. Therefore, the distance-based shortest path is also the time-efficient path, and no time is saved or wasted in this scenario.

5.2 Scenario #2: Fire Emergency Call at 9:07 am

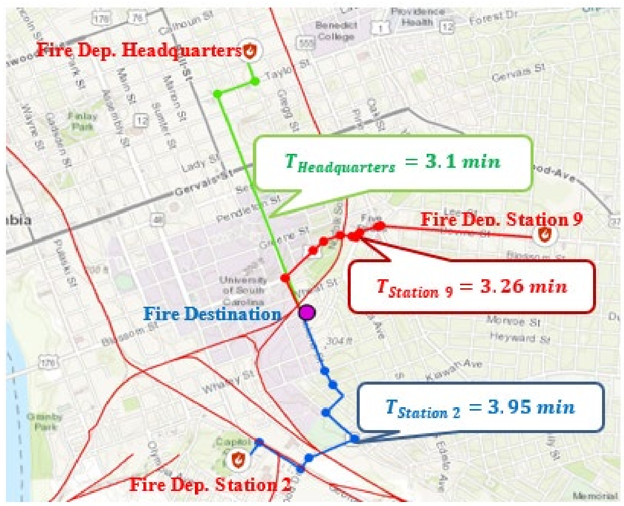
5.2.1 Station Dispatching Cases

In this scenario, the baseline dispatch strategy did not consider potential blockages at grade crossings and continued to dispatch vehicles from Station 2, following the same distance-based shortest path shown in Figure 12 (a). However, vehicles are blocked when they arrive at the fourth crossing node of Train #1 between 9:07 am and 9:08 am, which falls directly into the train blockage window, as indicated by the blue dash line in Figure 14 (a). As a result, a new vehicle is dispatched from Headquarters, taking the solid green line in Figure 14 (a) to reach the destination. However, in the baseline dispatch strategy, the time spent dispatching vehicles from Station 2 is wasted, and an additional two-minute delay is added to the total response time for communication and re-dispatching purposes.

By contrast, Figure 14 (b) shows that in this case, the optimized route determined by Headquarters follows the green-marked time-dependent shortest path, and the vehicle wasexpected to arrive at the destination within 3.1 minutes. Therefore, it was recommended to dispatch vehicles from Fire Department Headquarters, instead of Station 2, to minimize response time in case of train blockages.



(a) **Baseline**



(b) Minimum response time route

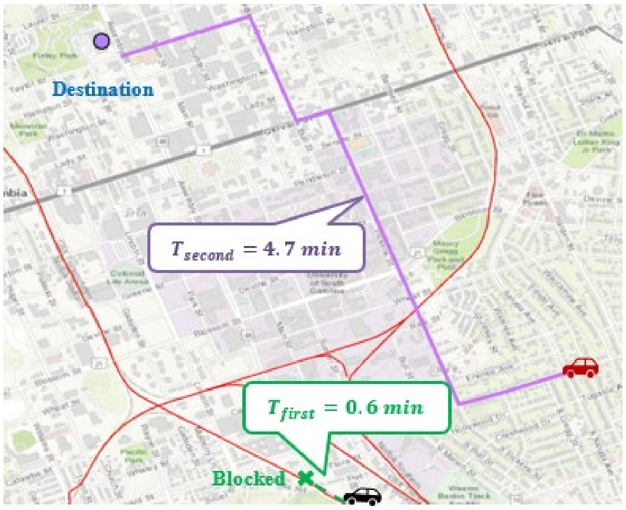
Figure 14. Comparison of Baseline and Optimized Dispatching Routes (T=9:07 am)

5.2.2 Patrolling Unit Dispatching Cases

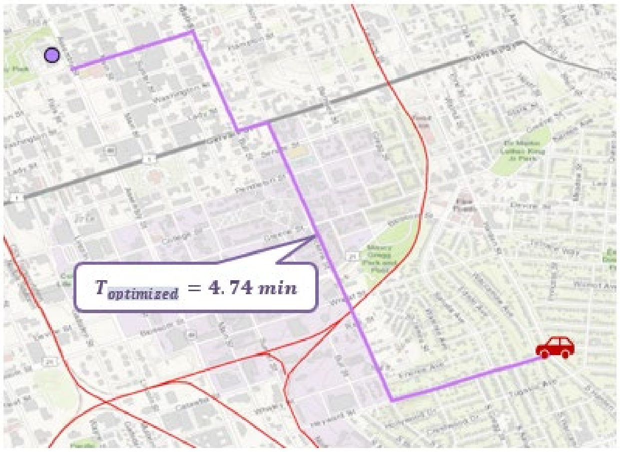
In this scenario, an emergency occurs near a USPS building at 9:07 am, and GPS reports that there are two first-responder units closest to the emergency, as shown in Figure 15.

By using the baseline dispatching strategy, the black unit is dispatched to the destination using the distance-based shortest path. However, due to the train blockage, the first-dispatched unit will be blocked after 0.6 minutes. As a result, a second unit (the red car in the figure) is dispatched one minute later (due to communication and re-dispatching procedures) after the first unit is blocked.

With the assistance of the dispatching algorithm, decision-makers can directly dispatch the red unit to the emergency location the first time the dispatching center receives the call, rather than dispatching the black unit based on a distance-based shortest path.



(a) Baseline



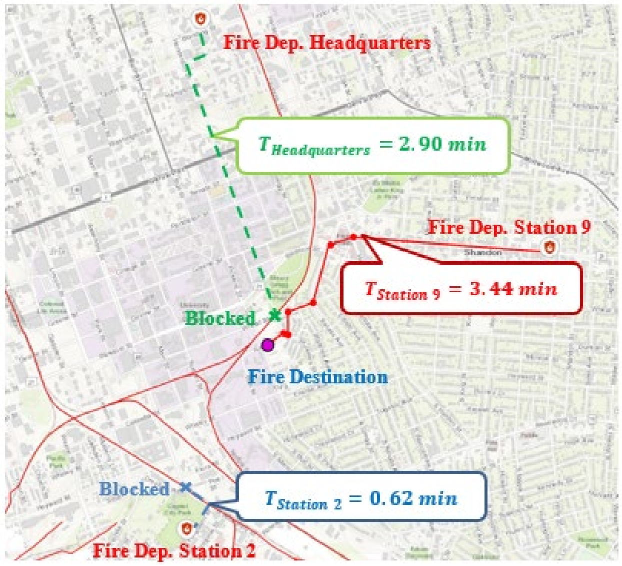
(b) Minimum response time route

Figure 15. Comparison of Baseline and Optimized Dispatching Routes (T=9:07 am)

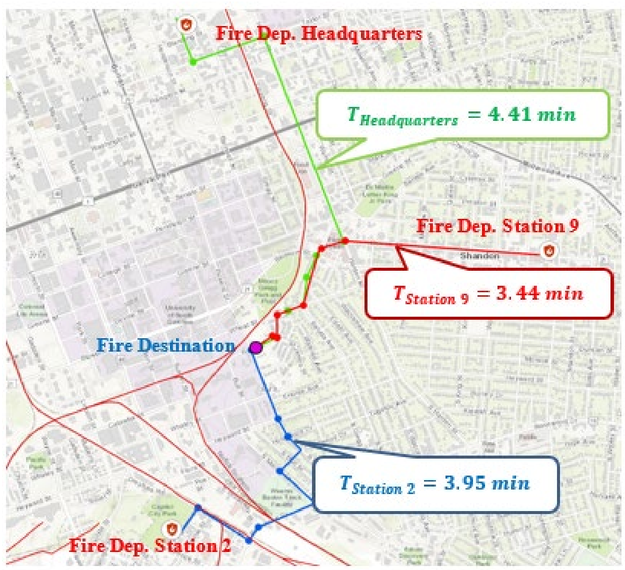
5.3 Scenario #3: Fire Emergency Call at 9:10 am

5.3.1 Station Dispatching Cases

In this scenario, a fire emergency occurs near DiPratos at 9:10 am. Both Fire Station 2 and Headquarters have distance-based shortest paths that are blocked at train crossing nodes, as shown by the blue and green dash lines in Figure 16 (a). Despite being the geographically farthest fire station from the destination, Fire Station 9 is the optimal station to dispatch vehicles from at this time, with the recommended route shown as the solid red line in Figure 16 (a). The algorithm suggests dispatching vehicles from Fire Station 9, which has the quickest responding time of 3.44 minutes, as demonstrated in Figure 16 (b).



(a) Baseline

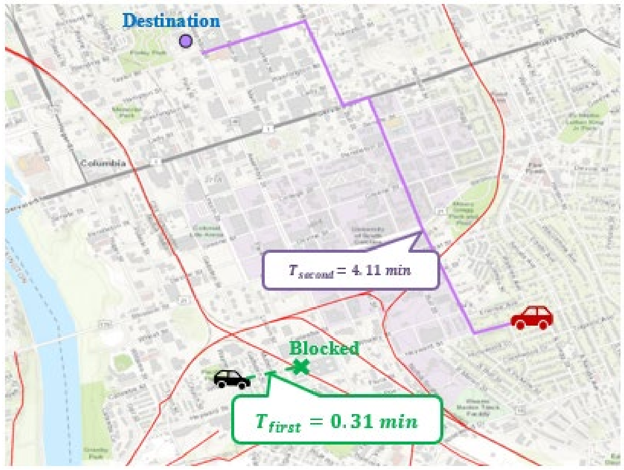


(b) Minimum response time route

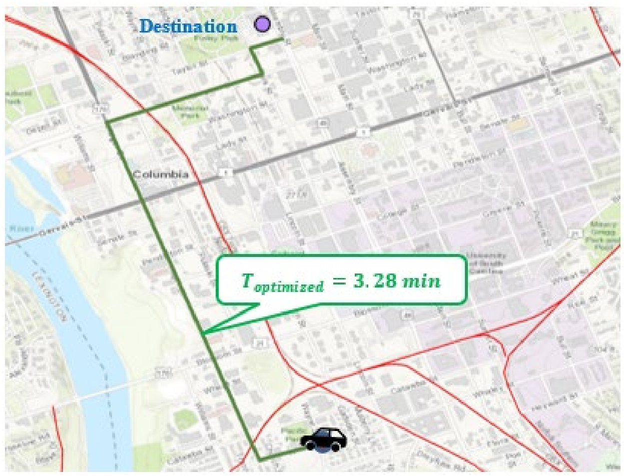
Figure 16. Comparison of Baseline and Optimized Dispatching Routes (T=9:10 am)

5.3.2 Patrolling Unit Dispatching Cases

In this scenario, there is an emergency occurring near a USPS building at 9:07 am, and GPS has reported two nearby first-responder units, as shown in Figure 17. As per the baseline calculation in this scenario, since the first dispatched unit is blocked, an additional one-minute penalty is applied to the total response time.



(a) Baseline



(b) Minimum response time route

Figure 17. Comparison of Baseline and Optimized Dispatching Routes (T=9:10 am)

5.4 Scenario #4: Fire Emergency Call at 9:45 am

5.4.1 Station Dispatching Cases

In this scenario, a fire emergency is reported near the fire destination at 9:45 am, after both trains have left downtown Columbia. As a result, the recommended shortest path is the same as shown in Section 5.1.1 (see Figure 12). This is a reasonable result because before and after train blockages, the problem becomes a traditional shortest path problem. Therefore, the time-dependent shortest path is the same route as the distance-based shortest path.

5.4.2 Patrolling Unit Dispatching Cases

In this scenario, there is an emergency near a USPS building at 9:45 am, and GPS has reported the closest first-responder unit, as shown in Figure 18.

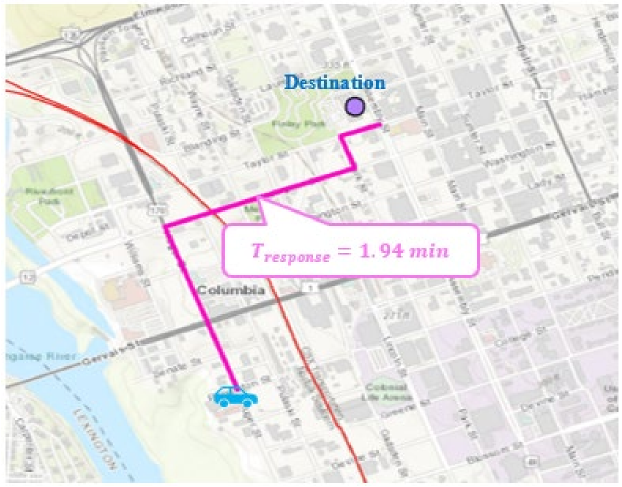


Figure 18. First-responder Patrolling Unit Dispatching (T=9:45 am)

Table 6 summarizes the conditions for dispatching emergency vehicles from each fire station and selecting the appropriate shortest path for each situation.

With reference to Table 6, significant time savings can be anticipated in dispatching first-responder vehicles while accounting for potential train blockages, a crucial prerequisite for saving lives, minimizing injuries, and reducing property damage.

Table 6. Summary of Emergency Vehicle Dispatch and Shortest Path Choosing Strategies

		T = 8:50 am (Scenario #1)	*T = 9:07 am (Scenario #2)*	*T = 9:10 am (Scenario #3)*	*T = 9:45 am (Scenario #4)*
Fire Station Cases	Fire Station	Station 2	Headquarters	Station 9	Station 2
	Travel Distance	1.19 mi	1.58 mi	1.54 mi	1.19 mi
	Response Time	2.20 min	3.10 min	3.44 min	2.20 min
	Baseline Response Time	2.20 min	4.72 min	8.96 min	2.20 min
	Time Saved	0 min	1.62 min	5.52 min	0 min
Patrolling Unit Cases	Unit	Blue	Red	Black	Blue
	Travel Distance	0.99 mi	2.63 mi	2.19 mi	1.21 mi
	Response Time	1.62 min	4.74 min	3.50 min	1.94 min
	Baseline Response Time	1.62 min	6.30 min	5.42 min	1.94 min
	Time Saved	0 min	1.56 min	1.92 min	0 min

Note: Baselines are calculated as the response time when fire departments dispatch vehicles without considering train blockages.

6. Conclusion

Every second counts when first responders are traveling to emergency situations. In this project, the research team worked to improve emergency response by considering train blockages when assigning shortest path to emergency vehicles. The team proposed an emergency vehicle route optimization model and developed a corresponding algorithm based on the Label Correcting Algorithm. The team conducted a series of numerical case studies in Columbia, South Carolina, to demonstrate the effectiveness and robustness of the proposed model. The results show that the algorithm can save emergency vehicle responding time for various responding units (e.g., stationary or patrolling units) compared with current dispatching practices that do not consider train crossing blockages.

However, some limitations to this research should be noted. First, while a mathematical model was developed to estimate train blockage windows, accurately predicting blockage windows in real-world conditions remains challenging. Secondly, it was assumed that other traffic participants would yield to emergency vehicles, allowing for a clear path, and delays due to traffic congestion or traffic lights were not considered. Other factors, such as weather conditions, left turns, and height limits also were not considered, although these factors can lead to additional response time. Lastly, some difficulties were encountered in matching grade crossing nodes between rail and road networks, leading to the elimination of some crossings during the case studies.Despite these limitations, the study provides valuable insights into the impact of railroad crossing blockages on emergency response time. The numeric case studies demonstrate the potential benefits of considering these blockages in dispatching strategies. Future research should focus on refining the model to account for the limitations mentioned above and incorporating additional real-world factors, such as traffic congestion, weather conditions, and various road restrictions. By doing so, the model can be further improved and contribute to more efficient and effective emergency response strategies, ultimately saving lives and reducing damages in critical situations.

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Abbreviations and Acronyms

ACRONYM	DEFINITION
AVL	Automatic vehicle location
CAD	Computer-aided dispatch
CSX	CSX Transportation, Inc.
EMS	Emergency Medical Services
FRA	Federal Railroad Administration
GIS	Geographic Information System
GPS	Global Positioning System
ID	Identification
NFPA	National Fire Protection Association
NP-complete/hard	Non-deterministic polynomial time complete/hard
OD	Origin-Destination
RMS	Records Management Systems
SC	South Carolina
USPS	United States Postal Service
VRP	Vehicle routing problem