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16. Abstract:

Safety Service Patrols (SSPs) provide motorists with assistance free of charge on most freeways and some key primary roads in Virginia. This research project is focused on developing a tool to help the Virginia Department of Transportation (VDOT) optimize SSP routes and schedules (hereafter called SSP-OPT). The computational tool, SSP-OPT, takes readily available data (e.g., corridor and segment lengths, turnaround points, average annual daily traffic) and outputs potential SSP configurations that meet the desired criteria and produce the best possible performance metrics for a given corridor. At a high level, the main components of the developed tool include capabilities to: a) generate alternative feasible SSP beat configurations for a corridor; b)predict incidents and SSP characteristics (e.g., incident frequency, SSP service time) for a given SSP beat configuration; c) estimate performance measures (e.g., SSP response time, number of incidents responded to); and d) identify and present the best SSP configuration(s) through visual aids that facilitate decision making.

To generate the incident data needed for the simulation-based SSP-OPT tool, a hierarchical negative binomial model and a hierarchical Weibull model are developed for incident frequencies and incident durations, respectively, based on the historical incident data. These models have been found to be effective in simulating the spatiotemporal distribution of incidents along highway corridors and for generating their attribute data (e.g., incident type, duration). The simulation program employs a discrete event-based approach and requires a few calibration parameters (e.g., SSP vehicle speed). After calibrating the model, the validation results show good agreement with field observations when applied to a sample SSP corridor from I-95. A user interface is created for the SSP-OPT tool in MS Excel to facilitate data entry and visualization of the output metrics for a given corridor. The output includes the list of alternative feasible beat configurations and aggregated performance measures from multiple runs for each individual beat, as well as for each alternative beat configuration spanning the entire corridor. The proposed SSP optimization model could be applied to corridors with or without existing SSP service. The tool will help identify the best beat configurations to minimize SSP response times and maximize SSP response rates for a given number of SSP vehicles on a corridor. Implementing these optimal solutions in the field will result in travel time savings and improve highway safety since the SSP resources will be more efficiently utilized, thus reducing the impacts of incidents on traffic flow.

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FINAL REPORT

IMPROVING SAFETY SERVICE PATROL PERFORMANCE

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Each contract report is peer reviewed and accepted for publication by staff of the Virginia Transportation Research Council with expertise in related technical areas. Final editing and proofreading of the report are performed by the contractor.

ABSTRACT

Safety Service Patrols (SSPs) provide motorists with assistance free of charge on most freeways and some key primary roads in Virginia. This research project is focused on developing a tool to help the Virginia Department of Transportation (VDOT) optimize SSP routes and schedules (hereafter called SSP-OPT). The computational tool, SSP-OPT, takes readily available data (e.g., corridor and segment lengths, turnaround points, average annual daily traffic) and outputs potential SSP configurations that meet the desired criteria and produce the best possible performance metrics for a given corridor. At a high level, the main components of the developed tool include capabilities to: a) generate alternative feasible SSP beat configurations for a corridor; b) predict incidents and SSP characteristics (e.g., incident frequency, SSP service time) for a given SSP beat configuration; c) estimate performance measures (e.g., SSP response time, number of incidents responded to); and d) identify and present the best SSP configuration(s) through visual aids that facilitate decision making.

To generate the incident data needed for the simulation-based SSP-OPT tool, a hierarchical negative binomial model and a hierarchical Weibull model are developed for incident frequencies and incident durations, respectively, based on the historical incident data. These models have been found to be effective in simulating the spatiotemporal distribution of incidents along highway corridors and for generating their attribute data (e.g., incident type, duration). The simulation program employs a discrete event-based approach and requires a few calibration parameters (e.g., SSP vehicle speed). After calibrating the model, the validation results show good agreement with field observations when applied to a sample SSP corridor from I-95. A user interface is created for the SSP-OPT tool in MS Excel to facilitate data entry and visualization of the output metrics for a given corridor. The output includes the list of alternative feasible beat configurations and aggregated performance measures from multiple runs for each individual beat, as well as for each alternative beat configuration spanning the entire corridor. The proposed SSP optimization model could be applied to corridors with or without existing SSP service. The tool will help identify the best beat configurations to minimize SSP response times and maximize SSP response rates for a given number of SSP vehicles on a corridor. Implementing these optimal solutions in the field will result in travel time savings and improve highway safety since the SSP resources will be more efficiently utilized, thus reducing the impacts of incidents on traffic flow.

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INTRODUCTION

Safety Service Patrol (SSP) programs are increasingly popular for highway safety and incident management on heavily traveled corridors. They provide essential incident management functions including detecting, verifying, and clearing incidents as well as helping stranded motorists on the freeways. Traffic incidents account for more than fifty percent of the non-recurring traffic delay in urban areas and for almost all delay incurred in rural areas.[1] Incidents of various types that occur on freeways include, but are not limited to: disabled vehicles, debris on the roadway, spilled loads, vehicle crashes, obstruction to traffic, dead animals, and other potential hazards.[2] Rapid removal of incidents from the freeways reduces delays, improves safety, protects the lives of travelers, and restores the performance of the transportation network quickly. Therefore, SSP programs are essential for the safety and efficiency of transportation systems.

To realize the full benefits of SSP programs, they need to be carefully designed, with consideration given to multiple factors, and methodically optimized. Traffic and network conditions change, so they also must be dynamically managed and structurally planned, inter-jurisdictional and multidisciplinary, and relevant performance metrics need to be documented.[3]

An incident management program generally consists of seven steps including detection, verification, response, site management, traffic management, clearance, and recovery.[4] The core services and benefits of SSPs include detecting incidents disrupting traffic, reducing incident duration, clearing obstructions, setting temporary traffic control for emergency responders, and other types of assistance functions that improve traffic operations and safety. The longer the incident lasts, the worse its impact on traffic. The total incident duration has various components including detection time, verification time, response time, clearance time, and recovery time.[5] SSP programs are designed to reduce these component times (especially detection and response times) so overall incident-induced delays are minimized.

The operational and safety benefits of SSPs have been studied and documented by many states, including Virginia. In 2006 and 2007, two studies conducted by Virginia Transportation Research Council[6, 7] showed the core functions of SSPs in urban and rural areas and their direct and indirect benefit-to-cost ratios. SSP deployment planning tools were also developed in those studies. Given the limited resources available to state Departments of Transportation, the continuing growth of traffic on major routes, and changes in roadway conditions, a more robust and dynamic optimization tool is needed to ensure optimal allocation of SSP resources when making deployment decisions. Such an optimization tool would aim to maximize benefit-to-cost ratios, efficiency, and the return on investment.

Tackling SSP design problems requires dealing with three major considerations. The first step is beat configuration, in which the patrolled corridor is divided into segments, with each referred to as a *beat*. A freeway network is segmented into links, and each link is assigned to at least one beat. The second consideration is the fleet size constraint, which determines the optimal number of trucks required to fully cover the network, taking into account the costs associated with additional trucks. Finally, truck allocation decisions are made based on how best to assign SSP trucks to beats to minimize the overall delay caused by incidents. In most cases, one truck is assigned to each beat.

This study aimed to develop a tool, hereafter referred to as SSP-OPT, to assist the Virginia Department of Transportation (VDOT) with optimizing SSP routes and schedules. The computational tool SSP-OPT will process readily available data (e.g., corridor and segment lengths, turnaround points, and Annual Average Daily Traffic (AADT); and will output potential SSP configurations that meet a set of desired criteria to produce the best possible performance metrics for a given corridor.

PURPOSE AND SCOPE

The primary objective of this research was to develop a methodology and a tool for optimizing the VDOT SSP routes, schedules, and vehicles needed to service a given freeway corridor. The methodology incorporates various decision variables and parameters to accommodate the complexities in real-world deployments. More specifically, the research study had the following objectives:

- Review and document the current state of the practice by other states and their implementation of SSP optimization procedures.
- Identify and specify the functional requirements for the SSP-OPT tool in terms of its objectives (performance measures or targets), decision variables (e.g., required resources, beat lengths), constraints (e.g., resource limitations, weekday vs. weekend operations), and model outputs (e.g., SSP routes, performance metrics).
- Develop an optimization framework that accounts for all factors identified and a computationally efficient method to perform the optimization process.
- Create an optimization tool for VDOT staff to execute the SSP deployment optimization methods and determine the most feasible solutions to a given scenario.
- Validate and test the SSP-OPT tool by conducting sample analyses for selected corridors under various operating conditions.
- Document the steps required to execute the SSP-OPT tool in a reference manual for VDOT users.

The spatial scale for this project is defined at the corridor level. Therefore, optimizing SSP routes at a regional or state level is beyond the scope of this project. However, the tool developed in this research is considered flexible and incorporates multiple factors, including traffic characteristics, historical incident patterns, network coverage, response times, rural vs. urban setting, and available turn-around points. These factors and other considerations and constraints are incorporated into the SSP-OPT tool as appropriate by allowing the user modify input parameters for the scenarios. The prediction models supporting the tool are built based on the historical incident and SSP data provided by VDOT. The tool is designed to support the overall route planning for SSP services and does not include uncommon operational practices including overlapping SSP routes and multiple vehicles within one beat. The majority of SSP routes in the state have one SSP vehicle per beat.

METHODS

Overview

The following tasks were conducted to achieve the study objectives:

1. Literature review
2. Data collection
3. Development of methods for incident frequency and duration prediction
4. Development of algorithms for simulating SSP operations
5. Model calibration and validation
6. Programming the SSP-OPT tool (Figure 1) and creating a user interface.

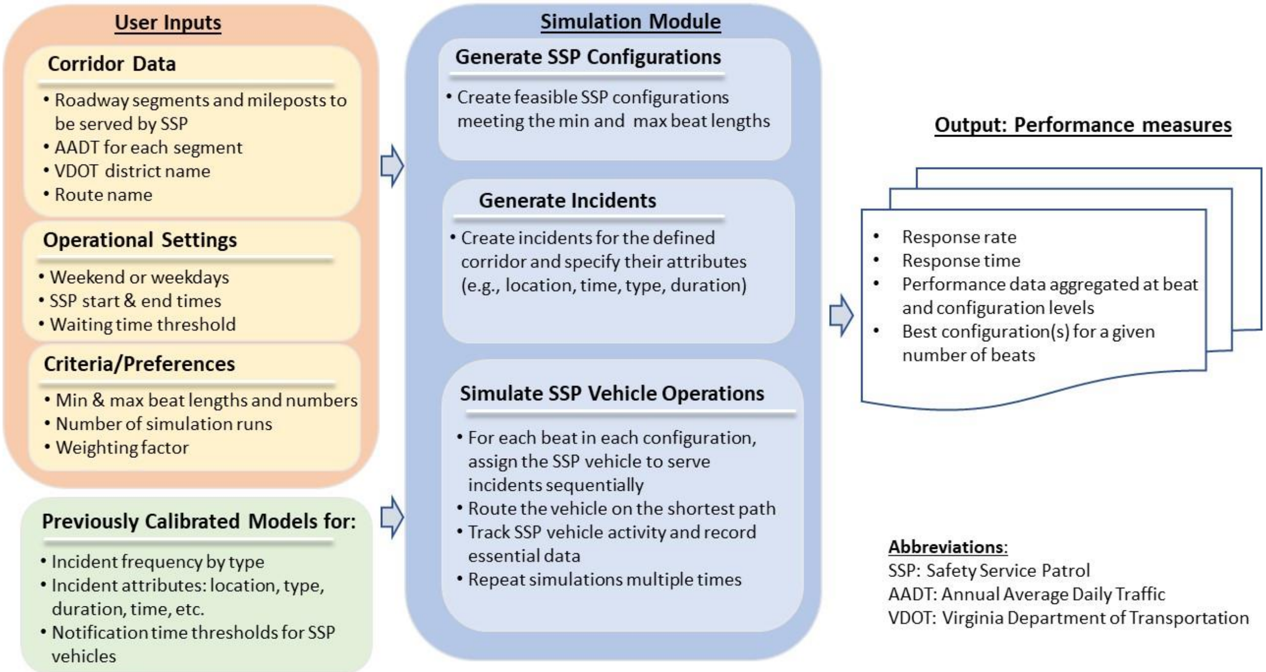


Figure 1. Key Components of the SSP-OPT Tool. SSP = Safety Service Patrol, AADT = Annual Average Daily Traffic, VDOT = Virginia Department of Transportation

The core component of the methodology is a discrete event-based simulation model for capturing the daily operations of an SSP vehicle within a beat. The simulation-based approach captures detailed performance data and complex dependencies. Figure 1 shows the main elements of the SSP-OPT program, which allows the user to specify the parameters needed to define the corridor, settings, and desired criteria. In addition, the model takes in calibrated statistical models for generating incident data consistent with historical incident profiles for the defined corridor. The simulation module includes the necessary algorithms to generate feasible beats, generate incident data, and simulate SSP vehicle operations. Output from the model includes key performance metrics, such as response time, rate, and the best beat configuration(s).

Following the literature review, subsequent sections describe these model components, beginning with the incident frequency and duration models. Next, the details of the SSP simulation model are presented, along with how specific performance measures are computed and aggregated.

Literature Review

The research team conducted a literature review that included a survey of existing methods for estimating incident frequency and duration and SSP route planning and optimization. There is large body of academic papers on incident modeling. The literature review helped identify the main factors typically used in incident frequency and duration modeling, as well as appropriate state-of-the-art techniques for generating reliable predictions from the available data. For SSP beat design and planning, the available literature is reviewed to identify the key considerations and optimization approaches. The literature review was conducted using multiple online databases of academic articles, conference proceedings, and reports.

Data Collection

To create the SSP-OPT tool, field data are needed for model development, validation, and testing. The incident data in Virginia are collected through two traffic incident management systems: the Advanced Transportation Management System (ATMS) and the statewide Virginia Traffic System (VATraffic). Only ATMS provides detailed information about the SSP and other agents (e.g., Virginia state police) responding to each incident. This level of information is needed to obtain the on-scene time for each responding agent. The on-scene time is needed to identify and calculate incident durations (i.e., response time and service time for the SSP) for each incident. Only VATraffic data have the longitude and latitude for each incident, which is essential to geocode incidents on road segments and model incident frequencies. In addition, this study uses three-year (2017-2019) incident data to model incident frequencies and durations to avoid any potential impact of COVID-19 pandemic on the typical traffic patterns. Furthermore, the three-year traffic volume information was also obtained from VDOT.[8]

Incident Frequency Modeling

There are a variety of alternative incident frequency modeling approaches, including Poisson, negative binomial, and their zero-inflated versions. For this project, the negative binomial (NB) and the hierarchical negative binomial (HNB) are selected because they are found to be effective in addressing overdispersion issues in data and spatial heterogeneity. If sufficient historical data are available, sampling from such data could also be performed to predict frequencies for desired time periods. However, for such predictions to be reliable, the temporal variations in factors contributing to incident frequencies, such as traffic volumes, need to remain stable over time. This is typically not the case, as traffic volumes fluctuate over the years. Therefore, the historical incident frequency (HIF) method is not used in the SSP-OPT tool for generating incidents but is used as a benchmark for comparing the results from NB and HNB models.

To fit the NB and HNB models to the incident data, contributing factors (explanatory variables) need to be identified. Traffic volumes and road lengths are two commonly used contributing factors in incident frequency modeling in practice. In addition, for the HNB model group identifiers need be determined to account for the spatial heterogeneity of incident frequencies among different road segments. As explained in the Results section, route names and VDOT district names are utilized to create these groups.

Figure 2 shows the distributions of incident counts and two explanatory variables (i.e., AADT, road length), collected at the AADT road segment level in 2017-2019. The plots suggest the AADT and road length are skewed, and, therefore, the two explanatory variables are log-transformed in developing the incident frequency models. In addition, the response variable for the models is the annual incident frequency for each segment. Figure 2 also reveals the overdispersion issues on incident frequencies due to a large number of zero-incident observations. The NB model is suitable for addressing the overdispersion issue observed in this data.

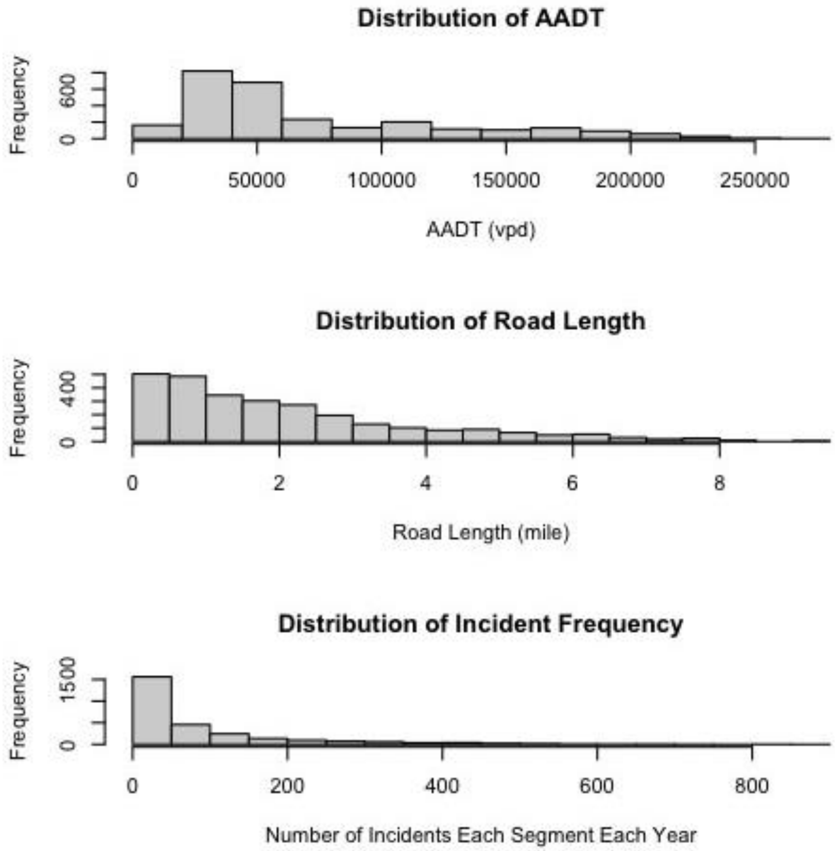


Figure 2. Distributions of Annual Average Daily Traffic (AADT), Road Segment Length, and Incident Frequency

To formally define the methods utilized in the report, let $y_{ij,t}$ denote the observed incident frequency for road segment i $(i = 1,2,3, \dots, n)$, group identifier $j(j = 1,2,3, \dots, m)$ and year t $(t = 2017, 2018, and\ 2019)$. Let $\lambda_{ij,t}$ denote the corresponding expected incident frequency.

(1) HIF Method

The HIF method assumes that incident frequencies in the current year $y_{ij,t}$ are equal to those in the last year $y_{ij,t-1}$ (Eq. 1). The main assumption of the HIF approach is that the contributing factors and incident occurrence patterns do not change over time.

$$y_{ij,t} = y_{ij,t-1} \qquad \text{[Eq. 1]}$$

(2) NB Method

For the NB models, the observed incident frequency for road segment i and year t, is given by $y_{i,t} \sim NB(\lambda_{i,t})$, where NB(.) represents the negative binomial distribution function.

(3) HNB Method

For the HNB model, the probability of observing incident frequency $y_{ij,t}$ is given by Eq. 2:

$$P(y_{ij,t}|\lambda_{ij,t}) = \frac{e^{-\lambda_{ij,t}}{\lambda_{ij,t}}^{y_{ij,t}}}{y_{ij,t}!} \quad \text{[Eq. 2]}$$

The Poisson parameters $\lambda_{ij,t}$ could be specified by a series of explanatory variables, $AADT_{ij,t}$, $Road\ length_{ij}$, and the group identifiers j as shown in Eq. 3:

$$\ln(\lambda_{ij,t}) = \beta_{0j} + \beta_{1j}\ln(AADT_{ij,t}) + \beta_{2j}\ln(Road\ length_{ij}) + \varepsilon_{ij,t} \quad \text{[Eq. 3]}$$

where exp $(\varepsilon_{ij,t})$ is assumed to be gamma-distributed with a mean equal to 1 and a variance equal to α^2. $\beta_{0j} = \gamma_{00} + \varepsilon_{0j}, \varepsilon_{0j} \sim N(0, \sigma_0^2)$; $\beta_{1j} = \gamma_{10} + \varepsilon_{1j}, \varepsilon_{1j} \sim N(0, \sigma_1^2)$; $\beta_{2j} = \gamma_{20} + \varepsilon_{2j}, \varepsilon_{0j} \sim N(0, \sigma_2^2)$.

The model parameters are found by fitting these models to the incident data from VaTraffic system by using glmmTMB package in the statistical programming language R.[9]

Incident Duration Model

Hazard-based duration models and hierarchical hazard-based models are used for incident duration prediction in this study. To be more specific, the estimation of incident duration could be regarded as the continuous survival time T of incidents following Weibull distributions. Let $F(t)$ denote the cumulative distribution of survival time T and $f(t)$ be the corresponding probability density function. Thus, the survival function $S(t)$ is the probability of observing an incident duration longer than the survival time t as shown in Eq. 4:

$$F(t) = 1 - S(t) \quad \text{[Eq. 4]}$$

The hazard function $h(t)$ is defined by Eq. 5

$$h(t) = \frac{f(t)}{S(t)} = \lambda p(\lambda t)^{p-1} \quad \text{[Eq. 5]}$$

where λ and p are the location and the scale parameters for the Weibull distribution, respectively. The log-transformed survival time t is specified by the linear combination of explanatory variables.

To develop the hierarchical hazard-based models, this study assumes that the parameter for each explanatory variable varies across the group identifiers, thus capturing unobserved heterogeneity of SSP service time.

The response variable is the service time for an incident responded to by an SSP vehicle. The explanatory variables include incident type, time of day (AM: 7 AM-9 AM, MD: 9 AM-3PM, PM: 3 PM-7 PM, and NT: 7 PM-7 AM), season, and the group identifiers (defined based on route names and VDOT district names). The model parameters are found by fitting these models to the observed field data by using INLA package in the statistical programming language R.[10]

SSP Simulation Model

The main components of the SSP-OPT tool (displayed in Figure 1) are explained below.

Alternative SSP Configuration Generation

For a given corridor consisting of multiple segments, there may be numerous ways to design the SSP routes and to schedule vehicles. For example, assume a corridor of 25 miles needs to be partitioned into nonoverlapping beats (the term ‘beat’ refers to an SSP route), each to be served by one SSP vehicle, and there is a turnaround point at each milepost. Without imposing a lower or upper bound on beat lengths, there are 16,777,216 unique ways to partition this corridor. The majority of these include beats that are just one or two miles long. If beats shorter than four miles are eliminated, we will be left with only 476 possible beat configurations. This example shows that the problem size can be reduced dramatically once unrealistic scenarios are eliminated. This section describes how all feasible beat configurations are generated for the simulation as input. Once performance metrics are computed for all these feasible SSP beat configurations, the best or optimum configurations can then be identified.

All beat configurations are based on the turnaround points or interchange mileposts. Once the start milepost and end milepost are selected for the corridor to be optimized, all possible beat configurations are generated by grouping the interchanges between the start and end points based on the milepost information. In this project, interchanges where the SSP vehicle can make a U-turn are considered as turnaround points. For example, if there are N interchanges in the corridor, the number of intermediate interchanges between the start and end points are N-2, and the total possible beat configurations can be computed by the combination formula given in Eq. 6 where K is the total number of beat configurations, M is the maximum number of beats selected for this corridor, n is the number of intermediate interchanges defining the boundaries of the beats, and N is the total number of interchanges.

$$K = \sum_{n=1}^{M-1} \binom{N-2}{n} \qquad [\text{Eq}.6]$$

Figure 3 shows examples where different beat configurations are generated for the corridor with two or three beats. In the simulation program, the total possible beats are generated by Eq. 6 and infeasible ones (those shorter or longer than thresholds defined by the user) are eliminated so that the problem size is manageable.

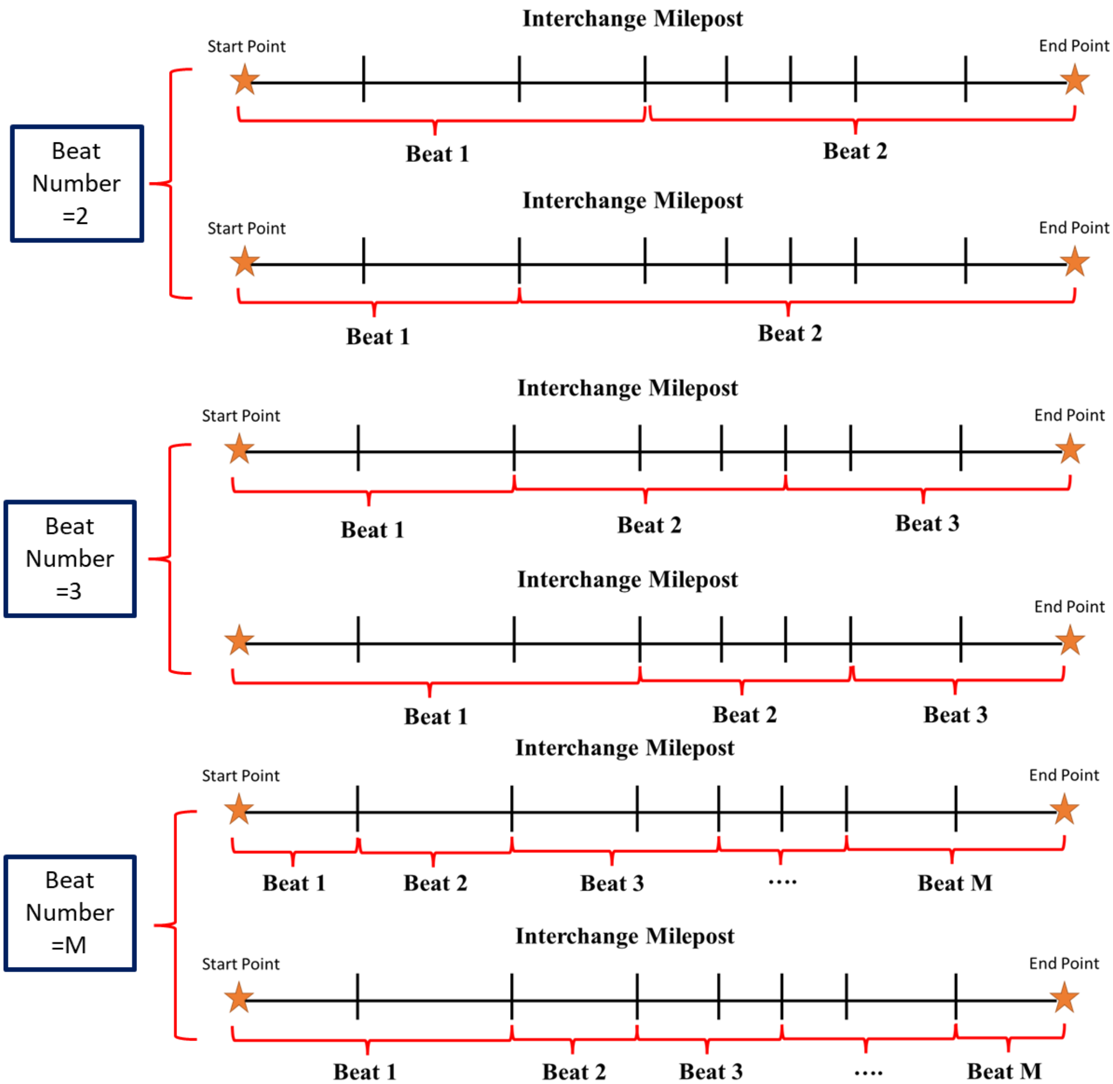


Figure 3. Sample Beat Configurations

Incident Generation

Incidents and their characteristics, such as location, occurrence time, and type, are needed as input for the simulation model. The first step is to estimate the total count of incidents for each segment making up the corridor being analyzed. This is accomplished by using a Monte Carlo (MC) method to generate incidents from the incident prediction model (i.e., HNB model) described before. For these generated incidents, various attributes need to be specified so that they can be adequately simulated. Some of these attributes include incident type, time of day the incident occurs, and SSP service time. SSP service time refers to the amount of time it takes for the SSP vehicle to service the incident after arriving on the scene. Service time is generated by using the duration models (i.e., hierarchical Weibull model) described previously.

The duration model requires certain input variables (e.g., time of day, incident type, season), and the values for these are randomly sampled based on the distributions of the empirical data obtained from VDOT for years 2017-2019. Since such distributions may vary across different VDOT districts and different routes, these distributions are calculated for different groups defined based on VDOT districts and route names (see Appendix C). In summary, the needed incident data are generated by using both the statistical models developed and the empirical distributions for a given road segment:

- Incident counts or frequencies are determined based on the HNB model.
- SSP service times are determined based on the hierarchical Weibull model.
- Incident type, time of day, and other pertinent data are estimated based on empirical distributions created for respective groups defined by VDOT districts and route names.

Figure 4 shows the overall process of generating incidents and their characteristics using the MC method. The first step is to estimate the empirical distributions of attributes or contributing factors X_j for incident duration modeling (SSP service in this case). For example, the incident frequency distributions for weekdays and weekends might be significantly different due to changes in travel patterns. Therefore, the empirical distributions of incident frequencies for weekdays and weekends are used to adjust the daily incident frequencies by weekdays and weekends. The empirical incident frequency distributions for other contributing factors are also considered, such as the hour of the day, incident type, and season of the year. All the empirical distributions are aggregated by the VDOT districts and route names (see Appendix C) to accommodate potential heterogeneity at spatial scales.

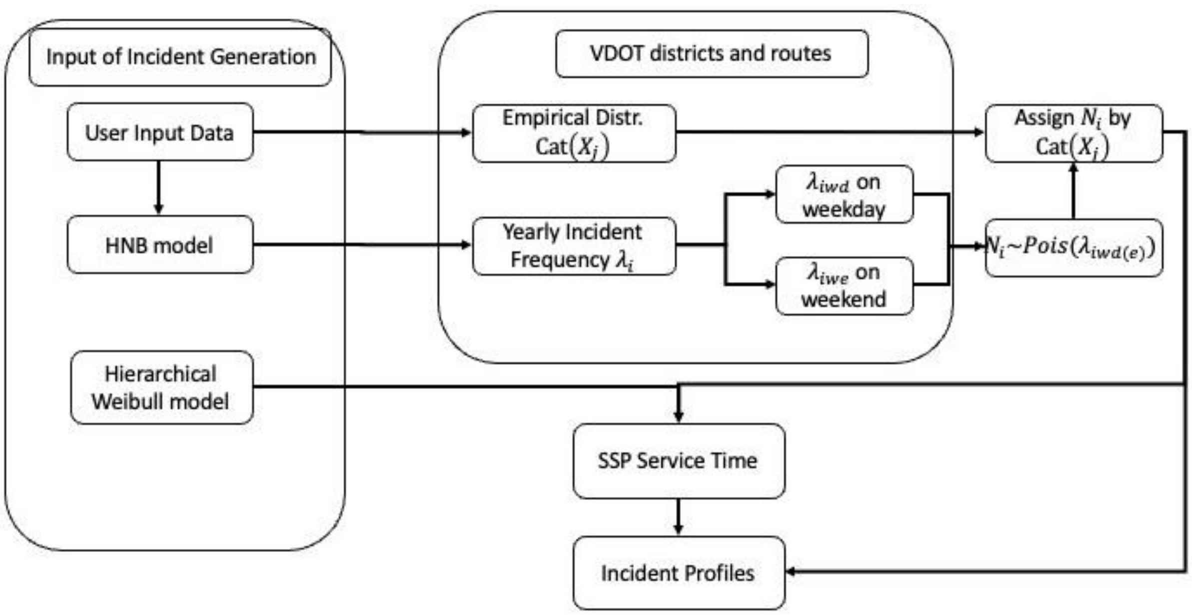


Figure 4. Incident Data Generation Process

The second step of the MC method is to generate two patterns of incident frequencies by weekdays and weekends. Four input variables (traffic volumes, road length, VDOT districts, and route names) are required to apply the incident frequency model discussed above. The model yields the number of incidents on each road segment for each day using the input data and the empirical distributions for weekdays and weekends. To be consistent with the assumptions made in the incident frequency modeling process, Poisson distributions are used with different mean values of daily incident frequencies (at different VDOT districts and routes).

After generating the incidents for each road segment and their attributes, the exact incident occurrence time is randomly determined within the hour using a uniform distribution. The simulation's time resolution is in seconds. Therefore, clock times are recorded in seconds for all events. The generated incidents are then simulated and served by the SSP under different beat configurations. Figure 5 shows two different three-beat configurations with the same incident scenario and locations.

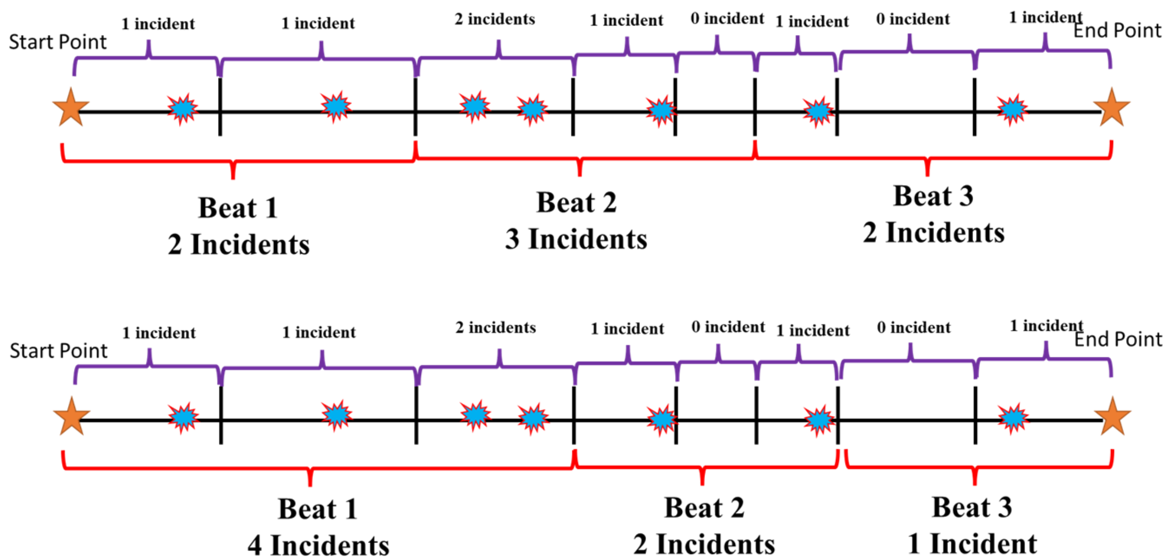


Figure 5. Two Different Beat Configurations with the Same Incident Data

SSP Simulation

A flowchart for the SSP simulation model is presented in Figure 6. First, all possible beat configurations are generated based on the start and end milepost. Then, the SSP vehicle profile, which contains the SSP vehicle speed and location, is initialized, and incidents are generated as input to the SSP simulation model. When an incident occurs while SSP vehicles are patrolling, the simulation checks the SSP's working status. If an SSP vehicle is available in the vicinity of the incident, then the vehicle is dispatched to the incident location. Moreover, when an incident happens in the opposite direction, the SSP vehicle is directed to the nearest interchange to turn around to get to the incident scene (e.g., if the incident happens in the southbound direction, and the SSP is patrolling the northbound direction, the SSP is instructed to turn around at the nearest interchange). The SSP vehicle is notified a certain amount of time after the incident occurs, rather than immediately. The delay in notification is needed to model real-world operations since not all incidents are detected immediately; nor are SSP vehicles informed straightaway. Various sources detect incidents, including surveillance cameras monitored by the traffic operations centers (TOCs) and state police, but patrolling SSP vehicles detect a significant percentage of incidents (especially disabled vehicles). The delay in notification allows time for the SSP vehicle detect (or discover) the incident in the simulation environment as it traverses the road section where the incident is located. However, the delay in notification time needs to be calibrated for the simulation to yield incident detection rates by SSPs that are consistent with field observations. The calibration data for the notification time (or threshold) are presented in the Results section.

When an SSP vehicle is notified to respond to an incident, but it is already in service (e.g., serving a different incident), then the incident will remain in waiting mode until this SSP vehicle is available. If the waiting time exceeds a specific threshold, the SSP service or request for the incident will be canceled. This threshold is another parameter that needs to be calibrated based on field data. If there is no incident when the SSP vehicle becomes available, the SSP vehicle will resume patrolling the beat it is assigned to.

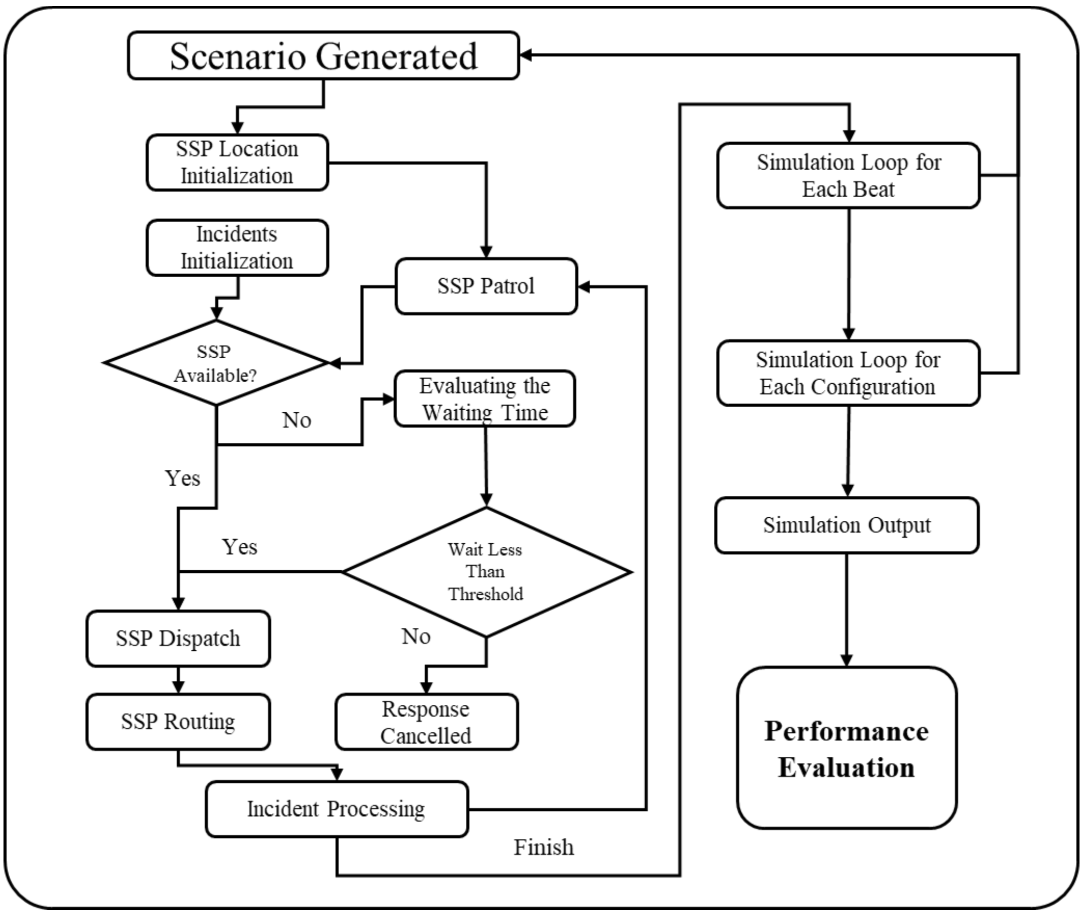


Figure 6. Flowchart for the Safety Service Patrol (SSP) Simulation Model

All incidents in each beat are simulated for all beat configurations. It should be noted that the SSP simulation model relies on a few assumptions. Based on the incident datasets (2017-2019), the average SSP response rate for crashes along the SSP corridors is around 87%. It is assumed that 15% of the crash incidents do not require an SSP vehicle; therefore, that percentage of incidents is randomly selected and excluded from the simulation. The simulation model also assumes each SSP vehicle patrols its beat continuously for the assigned shift: SSP rest time is not considered in the simulation model. The simulation is conducted for each beat independently of others.

Performance Metrics

There are two commonly used performance metrics for evaluating alternative SSP beat designs, response time (RT) and response rate (RR). RT is measured from the time the SSP operator was notified until the time the SSP vehicle arrives on the incident scene, while RR is the percentage of incidents responded by SSP vehicle in relation to the total number of incidents. These statistics can be aggregated at the beat or beat configuration level for a corridor. In addition to these two commonly used metrics, two additional metrics are generated by the SSP-OPT tool: response time-2 (RT2), and service time utilization (TU). RT2 is measured from the time the incident occurs to the time the SSP vehicle arrives on the scene. While highly correlated with RT, RT2 captures the additional time from incident occurrence to the time the SSP operator is notified. Data for RT2 are not generally collected in the field, as the exact incident occurrence times are unknown. However, in the simulation, this information is available. TU is used to compute the fraction of time the SSP vehicle is responding and attending to incidents in relation to the total patrolling time (or shift time).

After these four metrics are collected from the simulation, normalized RR and RT are computed by using data from all beat configurations with the same number of beats. The equations for these normalized metrics are below. The min and max values are computed based on the performance metrics of the configurations belonging to the same number of total beats. These normalized metrics are then used to generate one composite score. For this, their convex combination is calculated by using a weighting factor (α) as shown in Eq. 13. This weighting factor can be adjusted by the user depending on the importance placed on RR in comparison to RT. For example, setting α to 1.0 assigns all weight to RR.

All these metrics would be useful in comparing different beat designs and identifying potential areas for improvement in efficiency. The expressions for calculating these performance metrics are given below:

$$RR = \frac{Number\ of\ Incidents\ \text{Serviced}\ by\ SSP}{Total\ Number\ of\ Incidents} \qquad \text{[Eq. 7]}$$

$$RT = SSP\ Arrival\ Time\ on\ Scene\ - SSP\ Notification\ Time \qquad \text{[Eq. 8]}$$

$$\text{RT2} = SSP\ Arrival\ Time\ \text{on Scene} - Incident\ Occurence\ Time \qquad \text{[Eq. 9]}$$

$$TU = \frac{Total\ SSP\ Vehicle\ Service\ Time}{Simulation\ Period} \qquad \text{[Eq. 10]}$$

$$Normalized\ RR = \frac{RR - \min\ (RR)}{\max(RR) - \min\ (RR)} \qquad \text{[Eq. 11]}$$

$$Normalized\ RT = \frac{RT - \max(RT)}{\min(RT) - \max(RT)} \qquad \text{[Eq. 12]}$$

$$Composite\ Score = \alpha * Normalized\ RR + (1 - \alpha) * Normalized\ RT \qquad \text{[Eq. 13]}$$

RESULTS

Literature Review

Incident Frequency

Incident frequency models generally include four types of factors: traffic characteristics, temporal factors, road geometry, and environmental factors.[11-14] In terms of traffic characteristics, traffic volumes are found to be positively associated with incident frequencies.[14] Such positive correlation has also been observed in crash safety research [15]. The temporal factors (i.e., peak hours vs. off-peak hours, weekdays vs. weekends) are also used to represent variations in traffic characteristics (such as vehicle speed, traffic congestion status, and driver behaviors attributed to different trip purposes).[11] For example, according to one study, incident frequencies vary by time of day at the 0.10 significance level. [11] For road geometry, the number of congested lanes is found to be positively correlated with incident frequencies during peak and off-peak hours.[11] Beside traffic characteristics and road geometry, environmental factors also influence incident frequency estimation. For instance, incidents are more likely to occur on rainy days.[12] However, different types of incidents might show negative correlations with the same weather conditions. Snowy days increase the likelihood of crashes, but do not appear to affect the likelihood of the occurrence of disabled vehicles.[14]

Despite the abundant literature on crash frequency modeling, incident frequency modeling still needs to be further explored. Various conventional count models have been widely used in incident frequency modeling, such as Poisson[12], negative binomial[11], and zero-inflated (i.e., Poisson or negative binomial).[12] However, the conventional count models assume the incident observations of each road segment are independent of each other, which is frequently violated due to unobserved factors that contribute to crash occurrence. To account for the potential correlation among incident observations, generalized estimating equations were used in modeling incident frequencies.[14] Furthermore, a classification and regression tree, a machine learning approach, was used to model incident frequencies compared to traditional negative binomial models.[11] Due to the limited extant literature on incident frequency modeling, this study summarizes incident frequencies extensively and borrows ideas from crash frequency modeling. Hierarchical models have been used in crash safety analyses[16, 17] by assuming a set of parameters for each selected group, which could capture the potential correlations among observational sites.

Incident Duration

Table 1 summarizes potential safety factors that could impact incident duration, including traffic characteristics, temporal factors, road geometry, environmental factors, and incident characteristics.[18-20] For traffic characteristics, traffic volumes are positively correlated with duration of incidents involving disabled vehicles.[20] The ratio of average traffic speed to the posted speed limit is also positively correlated with incident duration.[21] Regarding temporal factors, incident duration presents vast variations across the time of day, day of week, and season of year. For road geometry, the presence of shoulders or intersections is positively associated with longer durations of crashes[21], and as for environmental factors, dry road conditions are negatively associated with incident durations.[22] In addition to the commonly used four types of safety factors detailed above, incident characteristics are essential determinants of incident duration. For example, the number of responders is positively associated with incident duration. In contrast, the incidents detected by or responded to by safety patrolling services tended to be associated with lower incident durations.[20] The presence of injuries is also found to be negatively correlated with incident durations.[21] Finally, incident duration tended to be longer if more lanes were blocked.[23]

Table 1. Potential Factors Affecting Incident Duration

Type of factors	Factors
Traffic characteristics	Traffic volume, speed, lane occupancy, queue length
Temporal factors	Time of day, day of week, season of year
Road geometry	Shoulder, intersections, lane closures, road class
Environmental factors	Rain, snow, dry, wet
Incident characteristics	Incident severity, incident type, types of involved vehicles, number of casualties, number of lanes blocked, number of vehicles involved

For incident duration modeling, incident durations (i.e., response time plus clearance time) are often estimated by conventional statistical models and machine learning methods.[18] For statistical models, hazard-based duration models and traditional ordinary least squares models are used to estimate and predict incident durations. [18, 20, 24-28] More specifically, hazard-based duration models mainly denote accelerated failure time models and semi-parametric hazard-based models with commonly used assumptions (i.e., Weibull, log-normal, log-logistic, Gamma, and inverse Gaussian distributions) for the distributions of incident duration. [18, 29, 30] In addition, machine learning approaches involving the classical classification tree methods[31, 32], artificial neural networks[33], Bayesian networks[34], and support vector machines[35] are also developed to estimate and predict incident durations.

Incident Simulation & Optimization

There are various studies on SSP systems that document benefits and costs of existing or planned SSP programs. While researchers used historical data, as well as statistical methods to design SSP programs, very few have used mathematical frameworks to design SSPs. As a result, there is no consensus on how specific factors should be considered in the design of the SSP programs. These factors include reduction in delays, SSP response rates, SSP response times, reduction in the likelihood of secondary crashes, etc.

Decision makers need reliable tools for planning effective SSP program routes, given the size of transportation networks and the reality of budgetary constraints. Tennessee’s HELP program[36] and Maryland’s Coordinated Highways Action Response Team (CHART) program[37] are among the first programs to use traffic and incident indexes to select important locations for SSP coverage. In the state of Florida, Carrick and others have developed quantitative methods to assist decision makers in identifying road segments that warrant SSPs.[38] They extended this work by developing a decision table-based mechanism to collect information, analyze it, and recommend guidelines for deploying SSPs. However, to be accurately employed elsewhere, this method must be calibrated using local data. Khattak et al., have explored secondary incidents and proposed a priority ranking method for selecting locations to provide freeway service patrols.[39]

Various mathematical frameworks and optimization methods have been used to design the SSP programs. One such pioneering work was done by Haghani et al.[40] using a mixed integer programming model with the aim of determining the optimal beat configuration, fleet size, and allocation of patrol trucks to beats by minimizing incident-incurred delay while considering the operational cost of the patrol programs. Their study used Coordinated Highways Action Response Team (CHART) data for designing their SSP. Pal and Sinha[41] also proposed a mixed-integer programming model to determine optimal locations of incident response units that would minimize operational cost. With a goal of guiding SSP dispatching policy, Ma et al.[42] applied a quantitative assessment of the influences on the incident duration for different SSP strategies. Sherali et al.[43] formulated two mixed-integer models to determine the optimal assignment of multiple response units to multiple incidents considering operation and opportunity costs. Kim et al.[44] developed an integer-programming model to minimize the total incident-incurred delay, and Daskin[45] proposed a mixed-integer model to determine the dispatching policy and routing for incident response units. These studies determined the optimal locations and dispatching policy of response units without considering the patrolling of the incident response units.

Zografos et al.[46] proposed a districting model to minimize incident-induced delay by determining the optimal locations of emergency response units. Zhu et al.[47] evaluated the performance of the incident response units based on three different strategies, i.e., allocating response units near high-frequency incident locations, distributing the units equally over the network, or placing them at the traffic operation centers to dispatch to the incident location once an incident occurs. Another study by Zhu et al.[48] developed a methodology to evaluate and compare patrolling and dispatching strategies for allocating emergency response units based on field data. They concluded the effectiveness of those response strategies depends on critical factors such as incident frequencies, traffic characteristics, and available detection methods.

Petty[5] presents a model based on traffic theory, in combination with marginal benefit analysis, for determining where to place tow trucks to maximize the expected reduction in congestion. Yin[49] proposed a minimax bi-level programming model to calculate a fleet allocation that decreases the maximum system travel time that may result from incidents. Yin[50] formulated a mixed integer nonlinear programming model to allocate patrol trucks among beats by optimizing the performance of the SSP system. Also, Daneshgar et al.[51] presented a model based on two deterministic and probabilistic approaches to estimate the average response time to optimize patrol program performance by minimizing total response time and determining the best beat configuration among existing beat structures.

Daneshgar and Haghani[51] developed a joint mixed-integer model to determine the beat configuration and fleet size, assuming a single depot and based on minimization of total response time without presenting a heuristic algorithm to solve the problem for large networks. One of the issues in several earlier studies[47, 52, 53] is that their methodologies only considered major incidents[54], although there is a need for a model that can allow for incidents with different severities while minimizing their clearance time. Finally, Lou[55] developed a non-linear model to determine beat configuration and fleet allocation with the objective of minimizing the overall average incident response time. The model, however, had many simplistic assumptions. Haghani and others have developed an improved version of Lou’s model that determines the beat configuration, fleet size, and truck allocation by minimizing incident-incurred delay as well as operational cost.[40, 56]

The SSP simulation model developed in this study considers the various aspects and limitations of past studies to create a robust tool for maximizing the impact of an SSP program. The use of a simulation-based approach allows the capture of spatial and temporal variations in incidents and their durations at a higher resolution and enables the generation of not only average performance metrics, but of their variability as well.

Data Analysis

Analysis of Incident Frequency

As previously stated, incident data in Virginia are collected in two databases: ATMS and VATraffic. ATMS data provide detailed information about incident management stages, as well as the event times for SSP. After analyzing the statewide data from ATMS and VATraffic, it was observed that ATMS data were not available for the Hampton Roads District for 2017-2019. Table 2 summarizes the total number of incidents for the two incident databases. Each database contains unique incident identifiers or IDs. These IDs are used to combine or merge the data elements from the two databases. However, not all incidents are recorded in both databases. Table 2 shows both the matched records as well as the total records when both databases are combined. The percentage values are calculated in relation to the total counts when the records from both datasets are combined.

Table 2. Number of Incidents in VATraffic and ATMS (Year: 2017-2019)

Datasets	Other Districts (All VDOT districts except Hampton Roads)		Hampton Roads	
	Count	Percentage	Count	Percentage
VATraffic	351,540	84.06%	75,526	99.13%
ATMS	286,369	68.47%	1,646	2.16%
Matched	219,692	52.53%	983	1.29%
Combined	418,217	100.00%	76,189	100.00%

Notes: $\text{Matched} = \text{VATraffic} \cap \text{ATMS}$; $\text{Combined} = \text{VATraffic} + \text{ATMS} - \text{Matched}$

The total number of incidents in VATraffic, recorded in all districts other than Hampton Roads, account for 84% of the combined incidents (481,217). For Hampton Roads District, 99% of the combined incidents in Hampton Roads are from VATraffic as the incident data are not generally available in ATMS for the selected years. Incidents from the ATMS dataset account for 68% of the combined incidents in the other districts. The matching records, incidents available in both datasets, constitute about 53% of the combined records.

Figure 7 shows the distribution of incidents in VATraffic (Figure 7a) and the matched records (Figure 7b) across the state. It is evident there are practically no matched records for the Hampton Roads District. Therefore, the study excluded Hampton Roads data when modeling incident frequencies and durations due to the lack of data. Hereafter, all analyses are performed with data from all VDOT districts except Hampton Roads. Therefore, “other districts” qualifier will not be included in the descriptions and table captions.

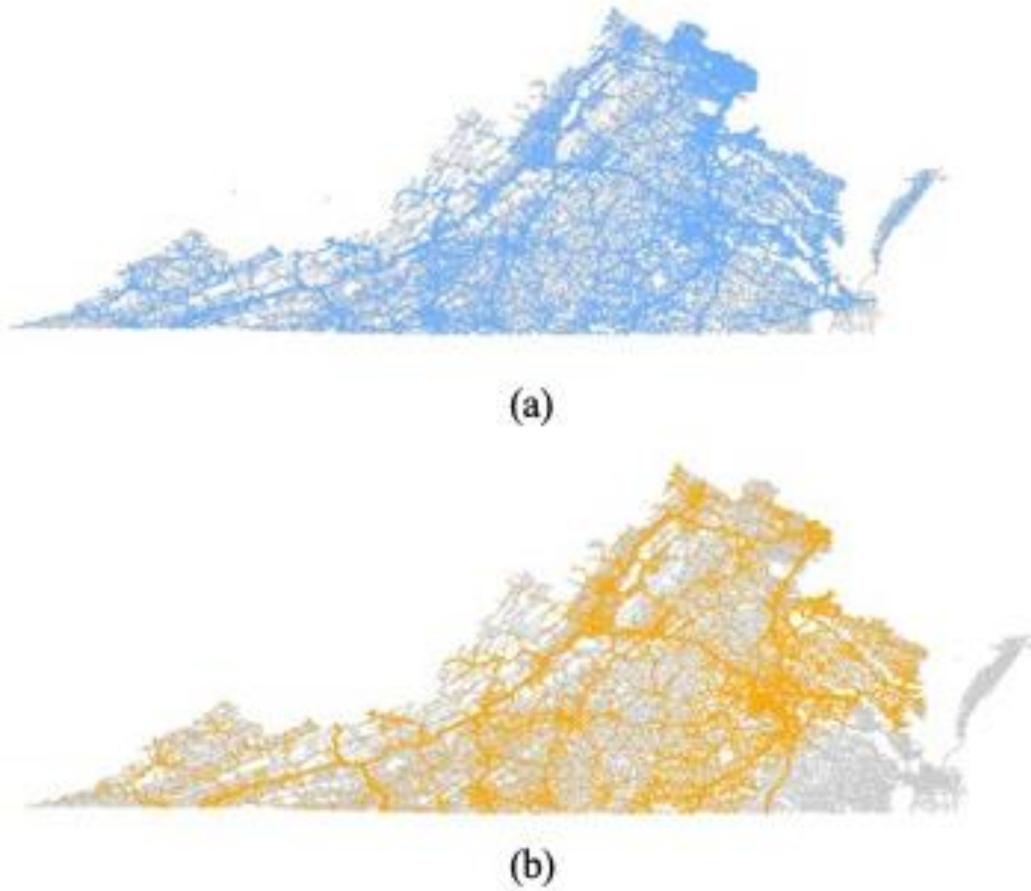


Figure 7. Geocoded 2017-2019 Incidents in VATraffic (a) and Matched Incidents (b)

To further understand the incident data, Table 3 presents the distributions of incident frequencies for corridors with and without SSP service (Hampton Roads data not included). The table shows that 90.39% of incidents are available in the VATraffic dataset for the SSP corridors, while this value is 66.68% for non-SSP corridors. Since most incidents that occurred along the SSP corridors are recorded in VATraffic, these data are used for incident frequency modeling. However, for incident duration (i.e., SSP service time) modeling, the matched records are used since data attributes from both VATraffic and ATMS are needed (e.g., latitude and longitude from VATraffic, durations from ATMS).

Table 3. Description of VATraffic and ATMS Incident Data (Year: 2017-2019)

Datasets	**SSP Corridors**		**Non-SSP Corridors**	
	Count	**Percentage**	**Count**	**Percentage**
VATraffic	277,059	90.39%	74,481	66.68%
ATMS	205,462	67.03%	80,907	72.44%
Matched	175,999	57.42%	43,693	39.12%
Combined	306,522	100.00%	111,695	100.00%

Notes: Matched = VATraffic ∩ ATMS; Combined = VATraffic + ATMS − Matched. SSP = Safety Service Patrol

Table 4 presents the data for detection source and response agency for incidents along the SSP corridors. These data are generated based on the matched records in Table 3. Information about the agency responding to the incidents is extracted from the ATMS agent data. Some 6,518 incidents are excluded, since they did not have the agent information, which accounts for about 3.70% of the matched incidents in Table 3. Disabled vehicles, traffic crashes, disabled tractor-trailers, and vehicle fires constitute about 90% of all incidents in Table 3. As these four types of incidents make up the great majority of all incidents, only these four types are selected in developing models for incident frequencies and durations.

Table 4. Detection Source and Responding Agency for Incidents along Safety Service Patrol (SSP) Corridors

Incident Type	Incident Freq.	Detected by SSP		Responded by SSP	
		Count	Percentage (Count/ Incident Freq.)	Count	Percentage (Count/ Incident Freq.)
Disabled Vehicle	103,247	65,752	63.68%	99,399	96.27%
Traffic Crash	41,317	3,465	8.39%	27,673	66.98%
Disabled Tractor Trailer	6,831	3,452	50.53%	6,167	90.28%
Vehicle Fire	1,211	70	5.79%	752	62.15%
Weather	653	58	8.88%	58	8.88%
Brush Fire	349	22	6.30%	183	52.44%
Others	15,873	5,203	32.78%	10,952	69.00%
Total	169,481	78,022	46.04%	145,184	85.66%

Table 5 shows the breakdown of incidents by type, whether more than one SSP vehicle responded, and whether travel lanes are blocked. The results show that 93.38% of incidents were responded to by only one SSP vehicle, while only 6.62% needed multiple SSP vehicles for the four types of incidents. Given the relatively small percentage of incidents requiring multiple SSP vehicles, such scenarios are not considered in the SSP simulation logic.

Table 5. Travel Lane Status of Safety Service Patrol (SSP)-involved Incidents along SSP Corridors

Incident Type	Percentage of incidents responded to by SSP	Only One SSP involved (93.38%)		Multi-SSP Involved (6.62%)	
		Travel lanes not blocked	Travel lanes blocked	Travel lanes not blocked	Travel lanes blocked
Disabled Vehicle	67.66%	91.24%	5.22%	2.77%	0.77%
Traffic Crash	27.07%	49.82%	32.79%	5.52%	11.87%
Disabled Tractor Trailer	4.48%	84.30%	10.12%	3.10%	2.48%
Vehicle Fire	0.79%	24.43%	48.87%	4.98%	21.72%

Figure 8 shows the temporal distributions of SSP response rates for the selected incident types along the SSP corridors. SSP response rates for traffic crashes and vehicle fires have similar temporal patterns with significant temporal variations in the time of day. In contrast, SSP response rates for disabled vehicles and disabled tractor-trailers are also similar for different times of day but with higher SSP response rates and lower temporal variations than for traffic crashes and vehicle fires. Given these observations, in this study, disabled vehicles and disabled tractor-trailers are combined into one category called *Disabled* while crash and vehicle fire are combined into another category called *Crash.* This reduces the complexity of the simulation logic and the amount of output data generated by the SSP-OPT tool.

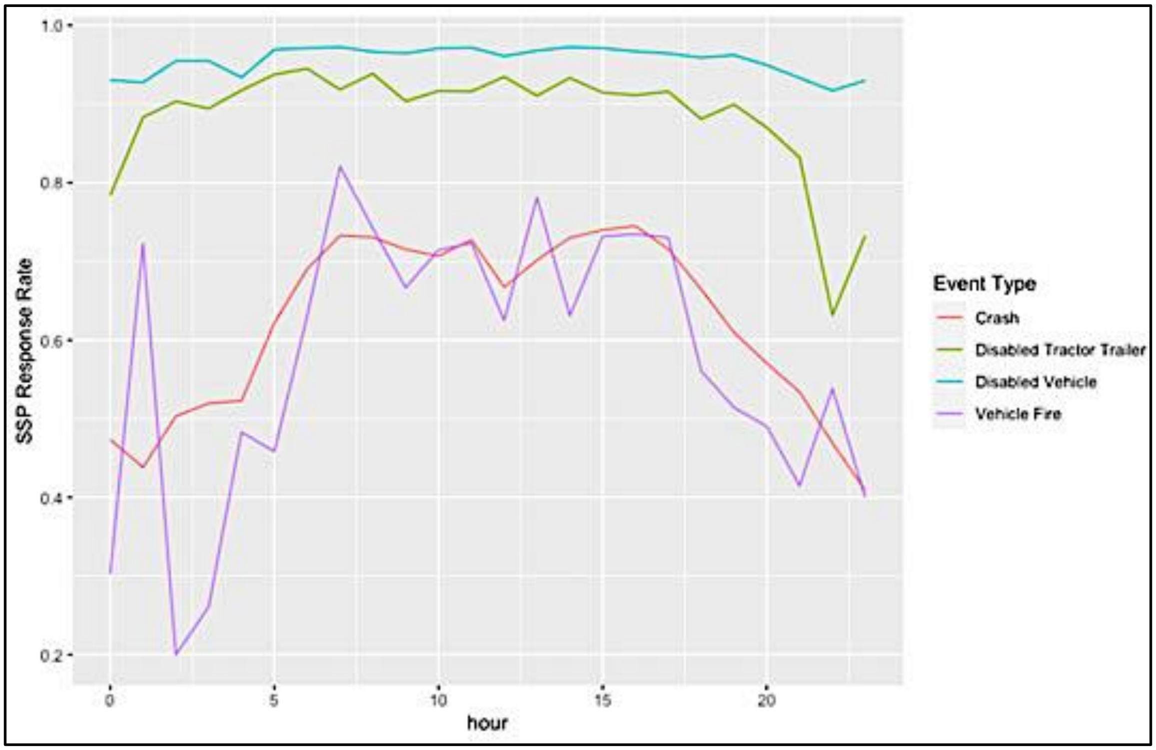


Figure 8. SSP Response Rates for the Selected Incidents along Safety Service Patrol (SSP) Corridors (2017-2019)

In addition to the observed temporal variations of SSP response rates during the day, the spatial variations of the SSP detection rates and response rates are also summarized. Figure 9 and Figure 10 present the SSP detection rates for crashes and disabled vehicles along SSP routes, respectively. Based on these maps, it can be observed that crashes have significantly lower SSP detection rates than disabled vehicles. SSP detection rates tend to be higher for both types of incidents in mountainous areas where alternative incident detection methods might be limited.

Figure 9. Detection Rates for Crashes along Safety Service Patrol (SSP) Routes

Figure 10. Detection Rates for Disabled Vehicles along Safety Service Patrol (SSP) Routes

Figures 11 and 12 depict the SSP response rates for crashes and disabled vehicles, respectively. The SSP response rates have fewer spatial variations.

Figure 11. Response Rates for Crashes along Safety Service Patrol (SSP) Routes

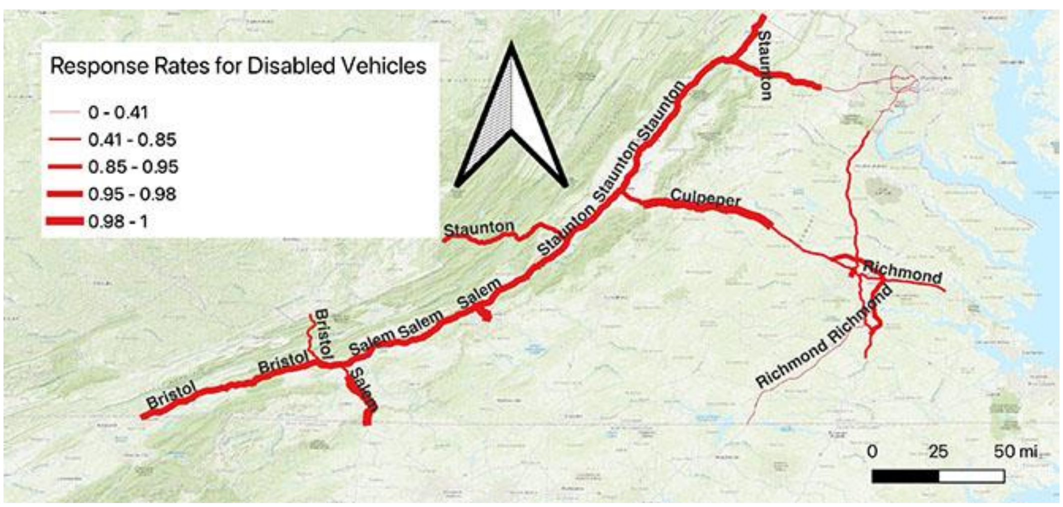


Figure 12. Response Rate for Disabled Vehicles along Safety Service Patrol (SSP) Routes

After the data were analyzed, it was discovered that there were a significant number of cases where the SSP response time was less than one minute for some incidents, although the detection source for these incidents was not listed as SSP in the database. When the SSP response time is less than one minute, it is plausible to assume that such incidents were also detected by SSP. Including these incidents (when SSP is not listed as the detection source, but SSP response time is under one minute) as part of those detected by SSP, significantly increased the rate of detection by SSP vehicles for some corridors. Figure 13 and Figure 14 show these updated detection rates, called patrolling detection rates, for crashes and disabled vehicles, respectively. In comparison to the detection rates in Figure 9 and Figure 10, the results in Figure 13 and Figure 14 show that some corridors (e.g., I-95 in Northern VA) have much higher detection rates for disabled vehicles.

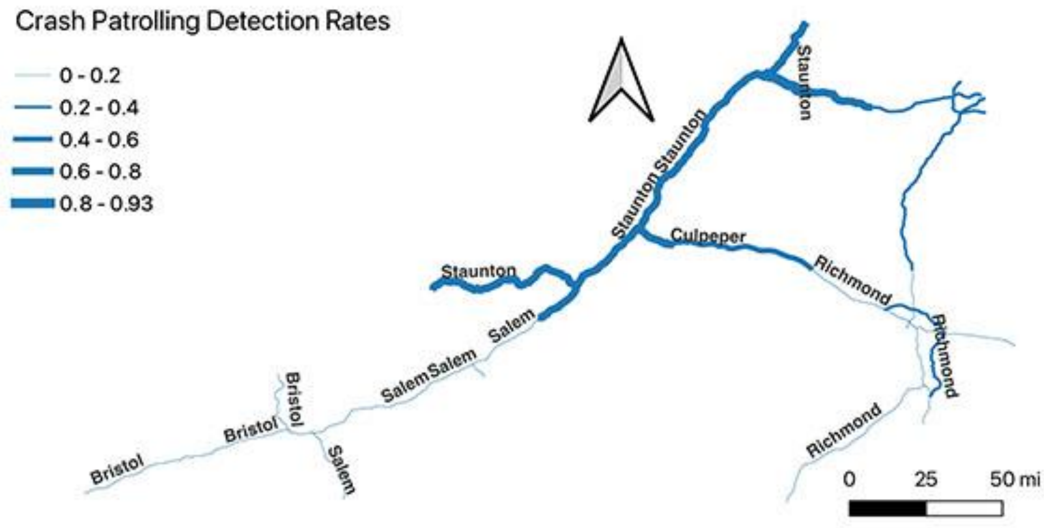


Figure 13. Patrolling Detection Rates for Crashes along Safety Service Patrol (SSP) Routes

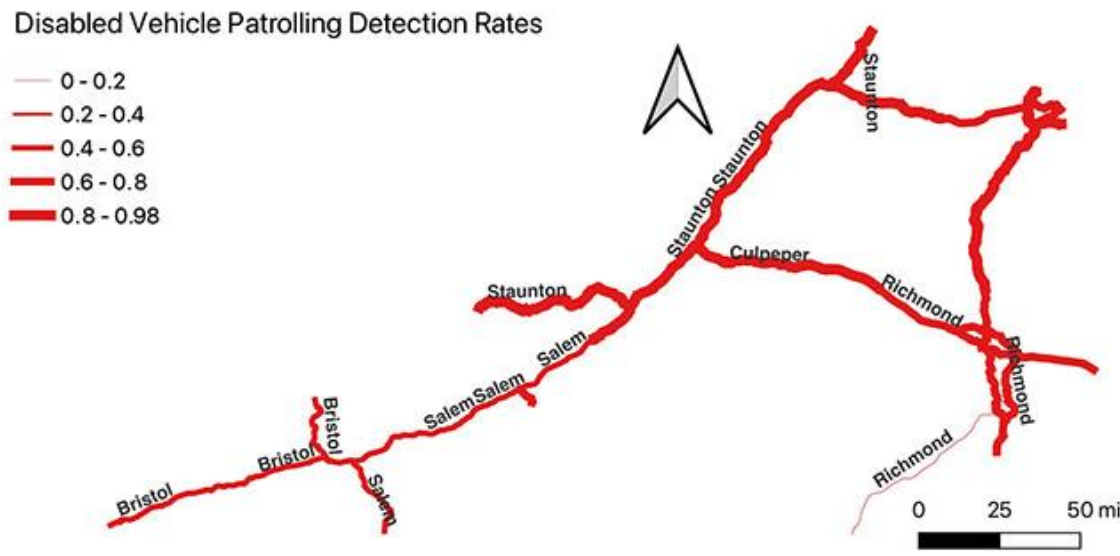


Figure 14. Patrolling Detection Rates for Disabled Vehicles along Safety Service Patrol (SSP) Routes

Analysis of Incident Duration

Figure 15 presents the flowchart for the incident management procedure used by Federal Highway Administration.[57] In general, it is difficult to get an accurate timestamp of when exactly an incident first occurred. The first time the incident is detected may be used as an approximation for the actual occurrence time. While accurately recording the exact time an incident occurs is important, this time is not needed for the SSP simulation program as the incidents are randomly generated. Instead, two important durations are needed for simulation calibration and validation: SSP response time and SSP service time. These times are obtained from the field data using various timestamps collected which are shown in Table 6.

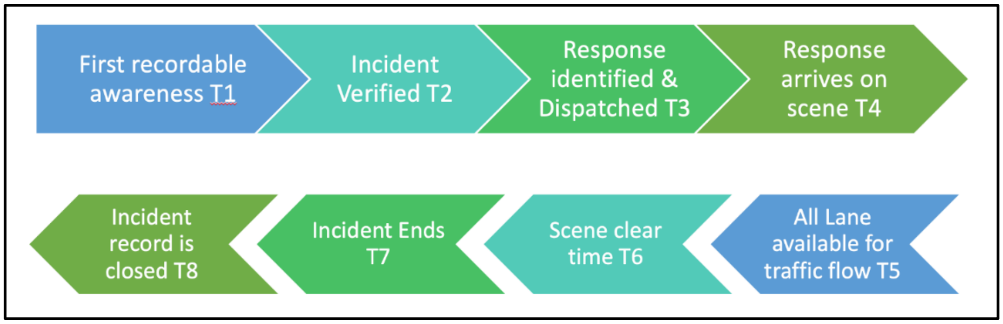


Figure 15. Flowchart for the Incident Management Procedure

Table 6. Incident Timestamps from Different Datasets

Dataset	T1	T2	T3	T4	T5	T6	T7	T8
VaTraffic		CREATED_DT			CLEARED_DT	SCENECLEAR_DT	CLOSED_DT	
ATMS	Time Created, Str Time Created, Event Date, Event Begin Time	Str Time Verified, Str Time Started			Actual Clear Time, Dt Actual Clear Time, Dt Est Clear Time, Time Start, Time Verified	Dt Scene Clear Time, Scene Clear Time	Dt End Time, Str Time End	Dt Final Time, Last Updated, Str Last Updated, Str Time Final, Time End, Time Final
ATMS Agent	Event Date	Time_Notified, Notified_Date, Str_Time_Notified, Str_Time_Responded		Time_On_Scence, Str_Time_On_Scene	Time_Departed, Str_Time_Departed			

Notes: T1: First recordable awareness; T2: Incident verified; T3: Response identified & dispatched; T4: Response arrive on scene; T5: All lanes are available for traffic flow; T6: Scene clear time; T7: Incident end; T8: Incident record is closed.

The SSP response time is calculated by Eq.14.

$$SSP\ response\ time = STR\ TIME\ ON\ SCENE(the\ first\ on\ scene\ SSP) - STR\ TIME\ NOTIFIED(the\ first\ notified\ SSP) \qquad [Eq. 14]$$

In some cases, one incident could be responded to by multiple SSP vehicles. For such cases, the expression above captures the total time, from the first notification sent out to the time when the first vehicle arrives at the scene. For example, the first notified SSP vehicle might not be able to arrive on scene before another SSP vehicle due to traffic congestion and availability of other SSP vehicles.

The SSP service time refers to the time interval between the departure time of the last SSP vehicle and the on-scene time for the first SSP, which is calculated by Eq.15,

$$SSP\ service\ time = STR\ TIME\ DEPARTED(the\ last\ SSP) - STR\ TIME\ ON\ SCENE\ (the\ first\ SSP) \qquad [\text{Eq. } 15]$$

Figure 16 shows the SSP response times for different types of incidents that are detected by SSP vs other detection methods. The results indicate that the SSP response time for incidents that are responded to by SSP is significantly shorter for incidents detected by SSP. In addition, disabled vehicles and disabled tractor-trailers were found to have higher SSP response priority than traffic crashes and vehicle fires once detected by SSP due to significantly lower response time. As shown in Figure 17, disabled vehicles and disabled tractor-trailers have similar SSP service times, while traffic crashes and vehicle fires also have similar SSP service times. Therefore, the study combined disabled vehicles and disabled tractor-trailers into one new type of incident as opposed to the other new type of incidents (traffic crashes and vehicle fires) when modeling SSP service time.

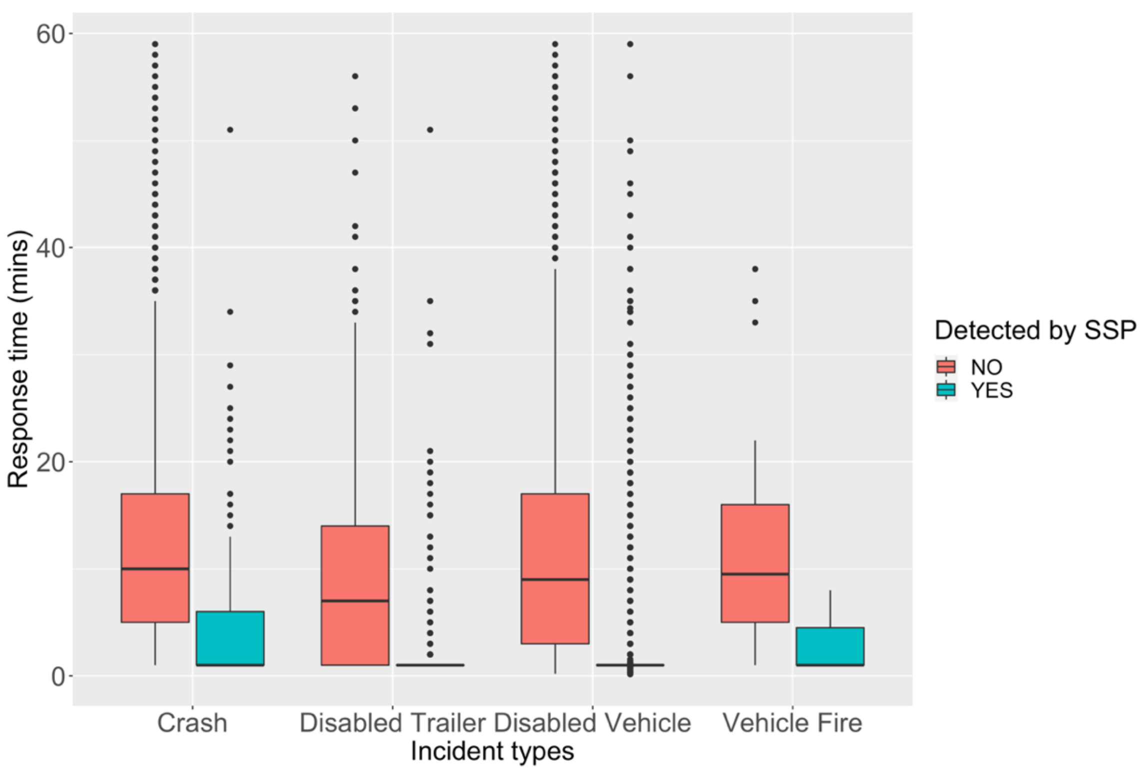


Figure 16. Safety Service Patrol (SSP) Response Time by Incident Type for Incidents Detected by SSP vs. Other Detection Methods

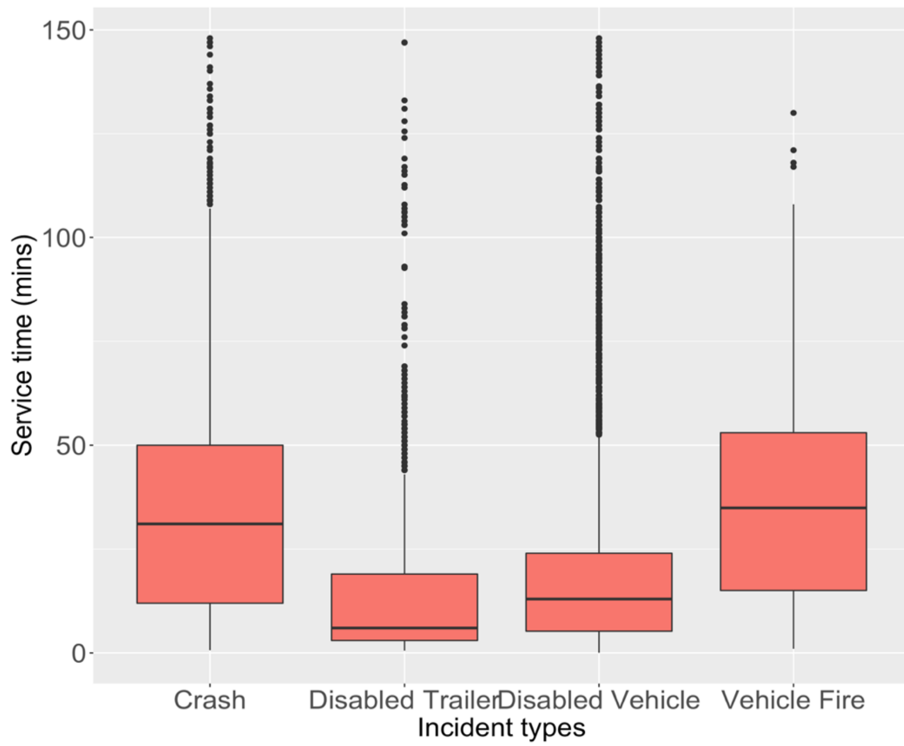


Figure 17. Safety Service Patrol (SSP) Service Time for Incidents Responded to by SSP

Incident Prediction Models

This section describes the incident frequency and incident duration prediction models, which are required for incident simulations. More specially, incident frequency models and SSP service time models make generating incident frequencies and SSP service time possible after the user provides the basic input variables (e.g., AADT, road length).

Incident Frequency Prediction

To clean the data and remove potential erroneous entries, spatial filters are applied to the VATraffic data. Some data points were found to be outside VA, based on the longitude and latitude data, and these are eliminated. In addition, incidents outside the SSP corridors are omitted from the analysis. As indicated earlier, incidents from the Hampton Roads region are also excluded.

After data cleaning, a Hierarchical Negative Binomial (HNB) model is fit to the 2017-2019 data. Table 7 presents the input variables and their coefficients and standard deviations. The coefficients for the random effect terms (44 of them) are included in a csv file as part of the SSP-OPT program. These coefficients capture heterogeneity among different corridors and districts as defined by the route names and VODT districts in Appendix C. The incident records from VATraffic include route names and VODT districts. The fixed effects for AADT and road length are found to be positively associated with incident frequencies.

In addition to the HNB, an NB model is fit to the same data. The prediction performance of both HNB and NB are shown in Table 8, as well as those from HIF approach. For a given segment, the HIF method uses the incident count from a previous year as the prediction. For example, it uses the 2017 count as the prediction for 2018 and 2018 for 2019.

As reported in Table 8, the performance of the HNB model is found to be significantly better than that of NB based on Mean Absolute Error, Mean Absolute Percentage Error, and pseudo-R squared. Furthermore, Figure 18 shows better agreement of the HNB predictions with the observed data – points are closer to the dashed diagonal. The HIF approach has lower error rates, but it requires access to (historical) incident data from a previous year, which may not be available for all corridors. Moreover, it is not sensitive to any changes in traffic volumes. Therefore, for incident frequency modeling, the HNB model is selected. While the majority of the SSP corridors are covered in the 44 group identifiers, some interstates in the Commonwealth are not. For such cases, incident frequencies will be estimated by using the fixed effects.

Table 7. Results of Hierarchical Negative Binomial Models

Variables	All Periods	
	Coefficient	Standard Error
Fixed effects		
Intercept	-4.70	0.98
Log (AADT)	0.77	0.09
Log (Road Length)	0.75	0.03
Random effects that vary by group ID (N= 44, based on VDOT districts and routes).		
Intercept	Varies by group ID	5.21
Log (AADT)	Varies by group ID	0.47
Log (Road Length)	Varies by group ID	0.14

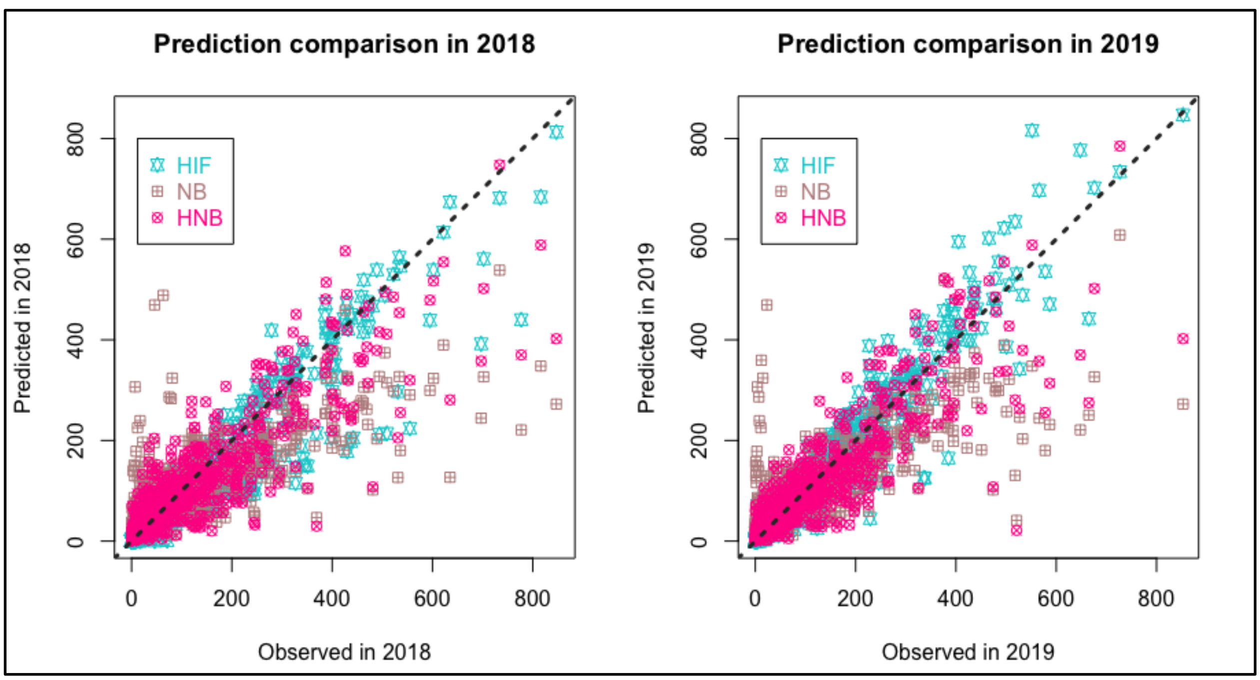


Figure 18. Comparisons of Incident Frequency Prediction Performance for All Time Periods. HIF = Historical Incident Frequency, NB = Negative Binomial, HNB = Hierarchical Negative Binomial.

Table 8. Comparisons of Incident Frequency Prediction Performance for All Models and All Time Periods. HIF = Historical Incident Frequency, NB = Negative Binomial, HNB = Hierarchical Negative Binomial.

Metrics	Year	HIF	NB	HNB
Mean Absolute Error	2018	23.15	48.47	30.95
	2019	18.87	43.66	29.60
Mean Absolute Percentage Error	2018	25%	53%	33%
	2019	21%	48%	38%
Pseudo R-squared	2018	0.87	0.59	0.81
	2019	0.92	0.62	0.80

Incident Duration Prediction

To prepare the data for duration modeling, the same dataset used previously for incident frequency modeling is used. However, additional screening is applied to further clean the data. For example, some timestamps were inconsistent (e.g., on-scene time < notification time, departure time < on-scene time, and end time < time departure) and such records were excluded from the dataset. In addition, outliers in SSP response times and SSP service times are removed by INLA package of R.[10]

Table 9 presents the results of the hierarchical Weibull models for SSP service time. Time of day, seasons, and incident types are found to be significant factors in estimating SSP service time. The duration of incidents that occurred at the MD, PM, and NT periods is found to be positively associated with the SSP service time. The AM period is taken as the base or reference period. Incidents that occurred in the fall and winter season are found to have a longer service time compared to the spring and summer. Crashes are also found to have a longer service time than disabled vehicles. In addition, a large variation of random effects for the intercept, the PM period, winter season, and incident types indicate the importance including spatial heterogeneity as defined by group identifiers based on routes and VDOT districts – these groups are in Appendix D.

Table 10 compares the prediction performance of two SSP service time models: Weibull and hierarchical Weibull models. The estimates of the hierarchical Weibull models outperform the Weibull model as demonstrated by the lower MAE value and both have similar Pseudo R-squared and MAPE values.

Table 9. Results of the Hierarchical Weibull Model for Safety Service Patrol (SSP) Service Time

Variables	Fixed effects			Random effects
	Coefficients	Standard Error	Change (%)	
Intercept	2.59	0.02	-	0.02
MD (9 AM-3 PM)	0.03	0.02	3.05	< 0.01
PM (3 PM-7 PM)	0.03	0.02	3.05	0.02
NT (7 PM-7 AM)	0.07	0.02	7.25	<0.01
Fall (No = 0, Yes = 1)	0.02	0.01	2.02	< 0.01
Winter (No = 0, Yes = 1)	0.03	0.01	3.05	0.02
Incident type (Disabled vehicle = 0, Crash =1)	0.96	0.01	161.17	0.21

Table 10. Prediction Performances of Safety Service Patrol (SSP) Service Time Models

Prediction Metrics	SSP Service time for incidents responded to by SSP	
	Weibull	Hierarchical Weibull
Mean Absolute Error (minutes)	12.41	12.17
Mean Absolute Percentage Error	56%	55%
Pseudo R-squared	0.31	0.32

Development of the SSP-OPT Tool

SSP Model Calibration

For model calibration, seven beats on I-95 and three beats on I-81 were selected as a sample to calibrate the SSP model. Data from 2019 for these ten beats were used for the model calibration. Incidents for each day were generated in the simulation with their observed occurrence times, locations, and service times. All 10 beats were simulated for one year, and the results were collected and analyzed for parameter calibration. The field data used in calibration from these 10 beats are summarized in Table 11. It should be noted that the number of samples (incidents) observed on beats 8, 9, and 10 are smaller than those from the other beats.

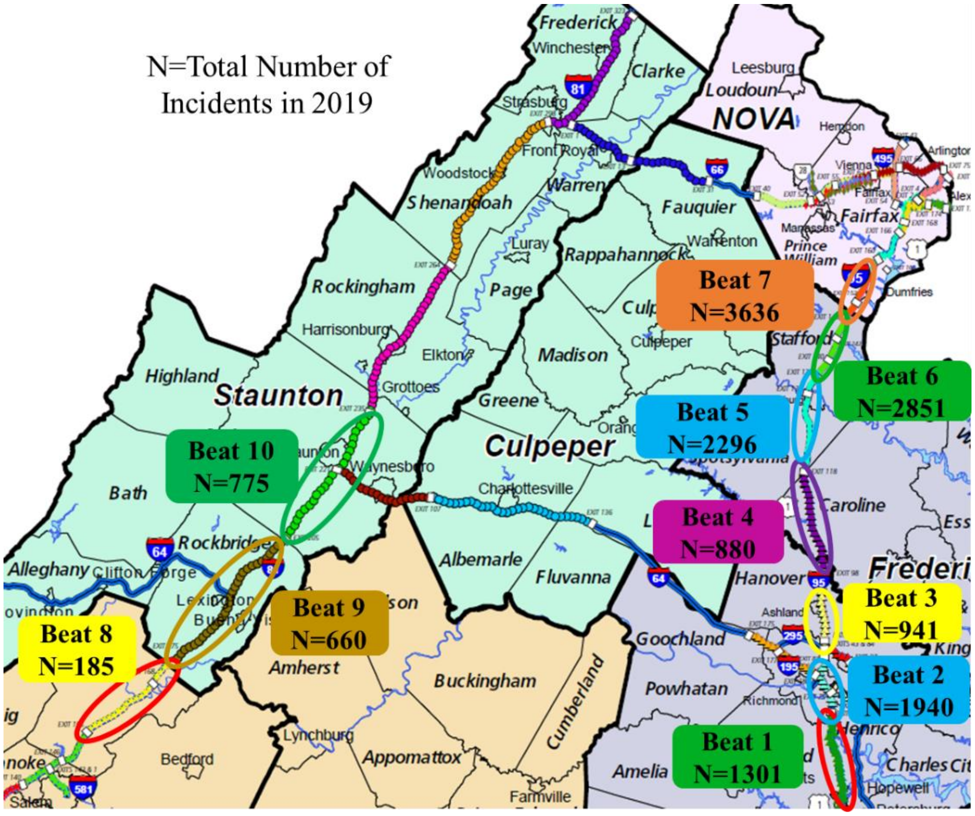


Figure 19. Ten Selected Beats for Model Calibration

There are three key model parameters to be calibrated: (1) thresholds for notification time, (2) SSP vehicle speed, and (3) waiting time threshold. The process followed in calibrating these parameters is described below.

Notification Time Calibration

The notification time primarily affects the SSP detection rates. The detected incidents can be classified into two groups: one represents incidents detected by SSP and the other includes incidents detected by any other sources. However, those incidents detected by other resources with SSP response times are less than 1 minute are also treated as detected by SSP in the simulation. If an incident is detected by SSP, the response time is expected to be close to be zero, which is generally the case in the field data.

Table 11. Incident Information for 10 Calibration Beats

Beat	Total Observed Incidents (2019)	Incidents Responded by SSP	Beat Length (mi)_	Response Rate (RR)	SSP Response Rate		SSP Detection Rate		Incidents Responded by SSP with Response Time >1min	
					Disabled Vehicle	Crash	Disabled Vehicle	Crash	Number of Incidents	%
1	1301	1154	45	0.89	0.94	0.78	0.61	0.13	541	47%
2	1940	1844	21.4	0.95	0.97	0.92	0.52	0.17	1002	54%
3	941	871	29.8	0.93	0.96	0.85	0.69	0.14	353	41%
4	880	806	41.4	0.92	0.96	0.78	0.69	0.21	251	31%
5	2296	2073	29.8	0.90	0.98	0.63	0.72	0.57	200	10%
6	2851	2528	29	0.89	0.98	0.61	0.75	0.52	292	12%
7	3636	3273	25	0.90	0.98	0.66	0.79	0.62	346	11%
8	185	185	38	1.00	1.00	1.00	0.52	0.10	95	51%
9	660	655	60	0.99	1.00	0.95	0.84	0.59	35	5%
10	775	771	60	0.99	1.00	0.98	0.82	0.57	35	5%

Since the detection rates for the two incident types, i.e., disabled vehicles and crashes, are significantly different (see Figures 13 and 14), the thresholds for notification times need to be set to different values. The simulation models were run under varying notification times, and the SSP detection rates were recorded for the two incident types and compared to the field observations. The goal is to match the observed detection rates as much as possible. An example is presented in Figure 20 for beat number two. As the notification threshold (x-axis) is increased, the detection rate also increases as expected, eventually approaching 100%. The field observations are marked with the horizontal dash lines. The notification times that produce the closest values to the field data are indicated on the figures for this beat, and this process is repeated for all the other beats.

The notification times for disabled vehicles and crashes are calibrated for all ten beats. Figure 21 shows these calibrated values versus beat lengths. Given the relatively strong correlation between the calibration values and beat length, a simple linear regression line with zero intercept is fit to the data. The respective regression equations are included in Figure 21. These equations are coded in the simulation to set the notification time thresholds for each beat.

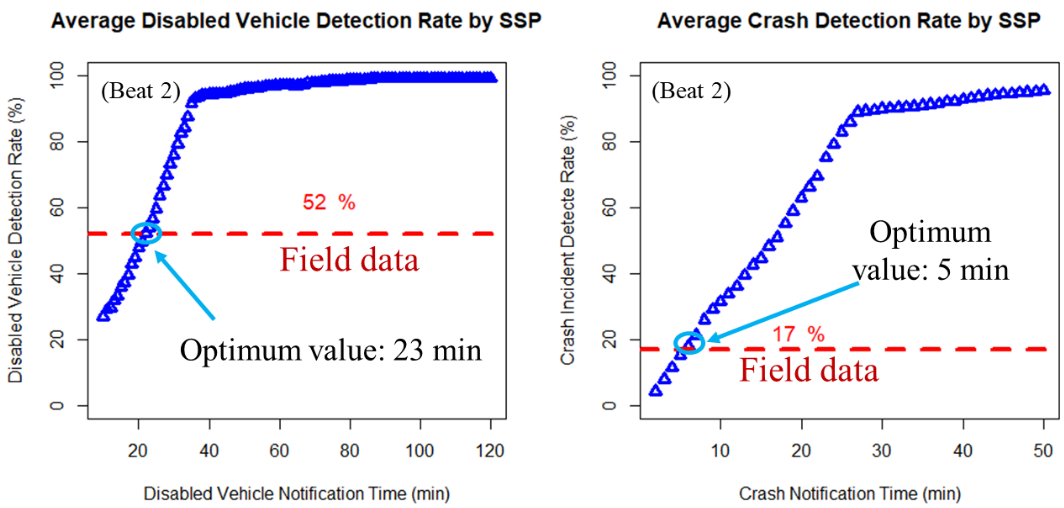
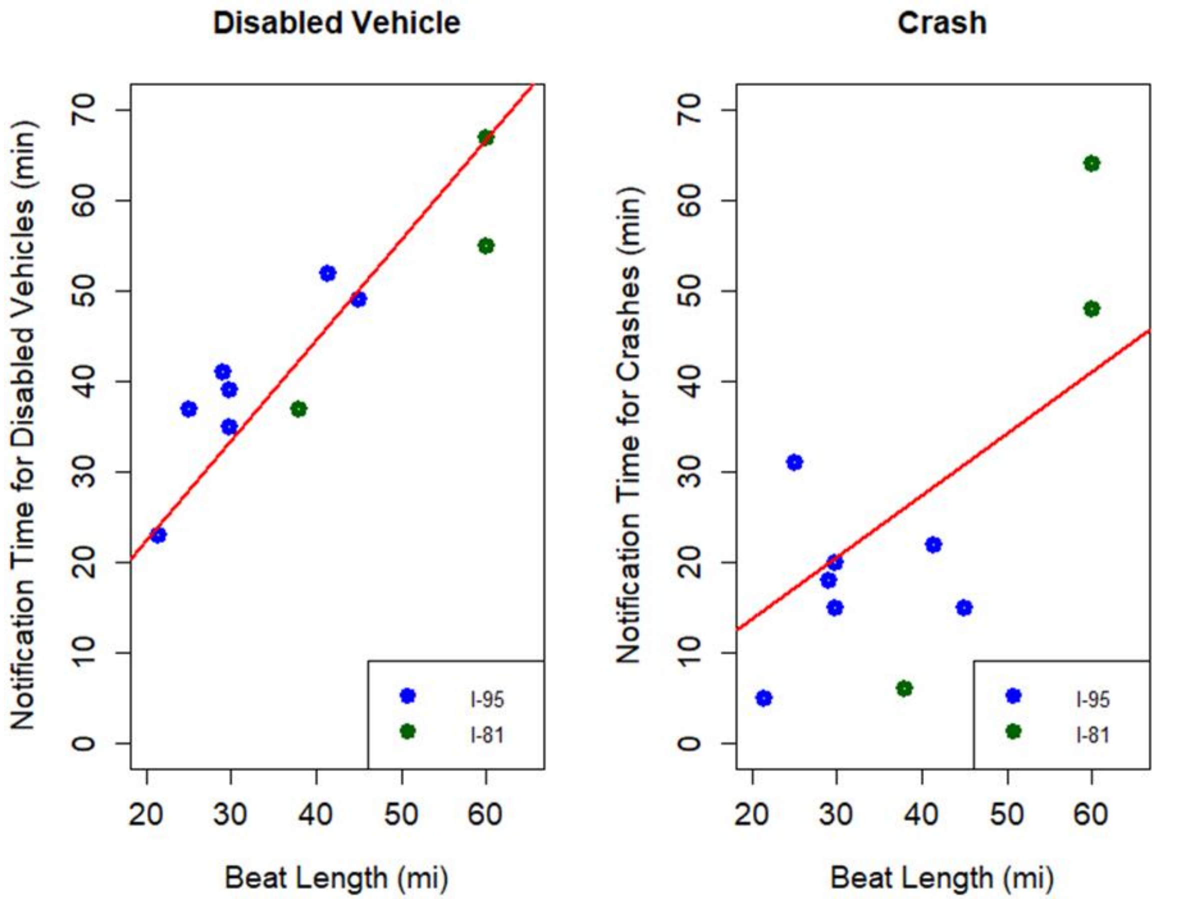


Figure 20. Example of Notification Time Calibration for Disabled Vehicle and Crash (Beat 2)



Disabled Vehicles:
$y = 1.1126 * x$
Adjusted $R^2 = 0.978$,
$p = 5.59\,e - 09$

Crashes:
$y = 0.6828 * x$
Adjusted $R^2 = 0.806$,
$p = 0.0001077$

Figure 21. Notification Time Regression Results for Disabled Vehicles and Crashes

SSP Speed and Waiting Time Calibration

For calibrating the speed of the SSP vehicle and the waiting time threshold, the SSP operations are tested on the ten beats with different speed and waiting time values. The differences between field data and simulation results, in terms of response time and response rate, are used as the error measure. The results are summarized as heatmaps shown in Figures 22 and 23. The values in the cells are computed by Eq. 16.

$$Cell\ Value = Field\ Value\ - Simulation\ Value \qquad \text{[Eq. 16]}$$

In Figures 22 and 23, the rows represent the speed (mile/min), and columns the waiting time (in minutes). The speed values yielding the lowest errors are indicated by red rectangles. It is evident that no single speed value is optimal for all beats. After considering the geographic location of the ten selected beats (Figure 19) and analyzing the errors in Figure 22 and Figure 23, three speed categories are recommended for the SSP vehicle speed in simulation as follows:

- Urban or congested corridors: 35 mph (0.58 miles/min)
- Rural corridors: 60 mph (1.0 miles/min)
- Suburban corridors: 45 mph (0.75 miles/min)

The waiting time does not show a strong trend based on the results in Figures 22 and 23. Setting the waiting time to a very low value, e.g., 10 minutes, worsens the response rates, as more incidents will be omitted from the SSP service. A value too large is not optimum either, as the errors in response times become too large. Therefore, the waiting time threshold in the simulation is set to a default value of 30 minutes. This can be replaced by the user if needed.

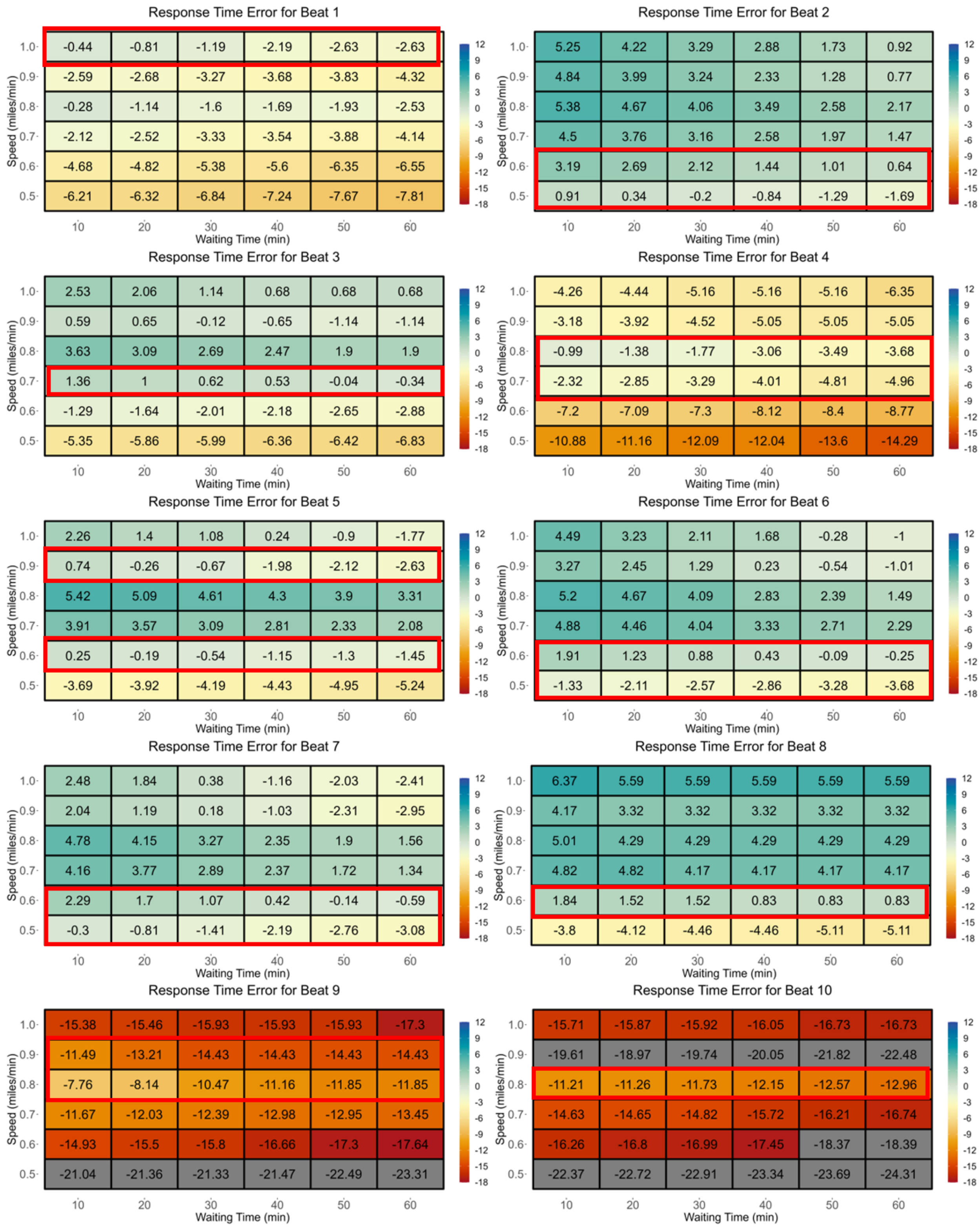


Figure 22. Heat Maps of Response Time Error for 10 Beats

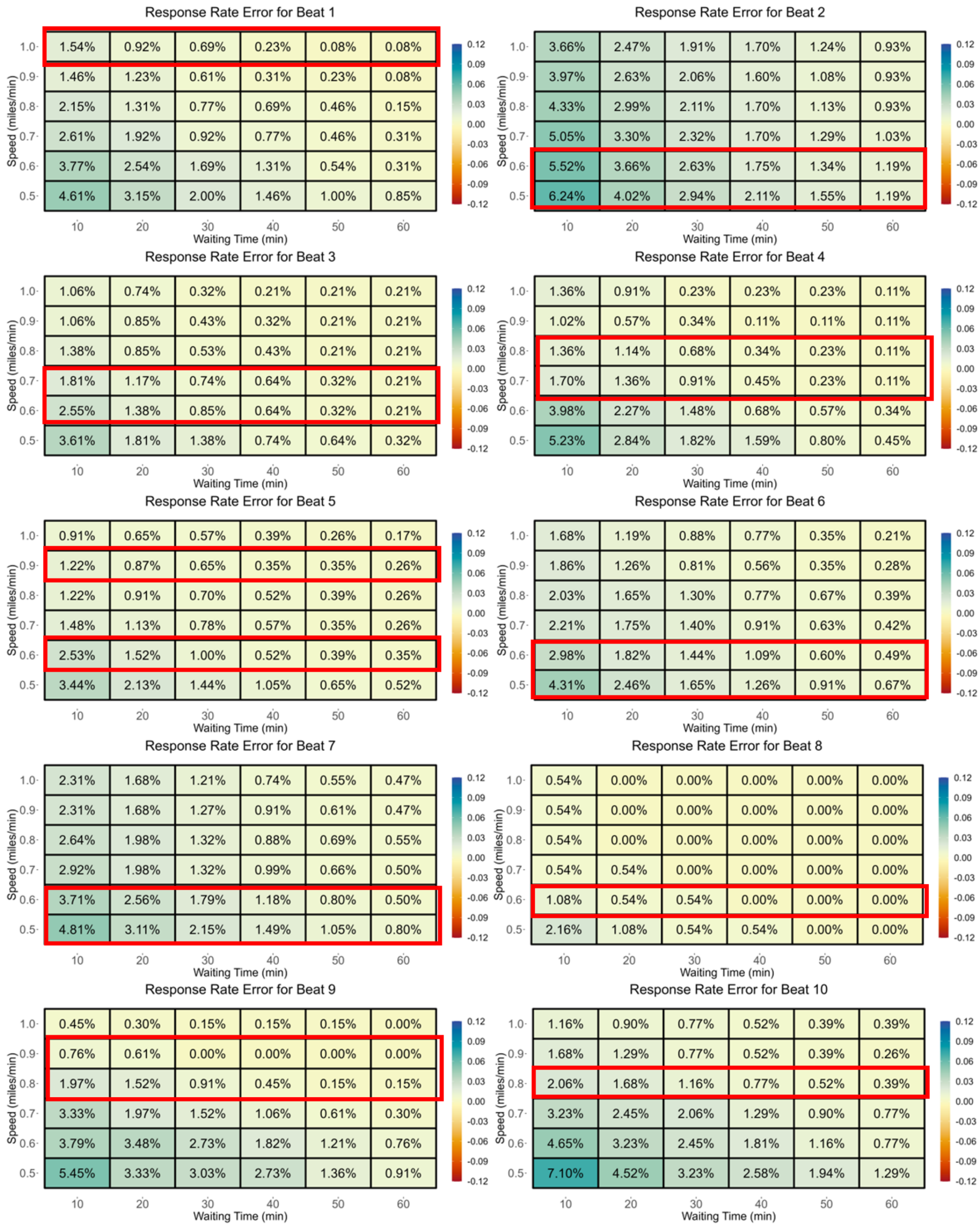


Figure 23. Heat Map of Response Rate Error for 10 Beats

SSP Model Validation

For model validation, a corridor consisting of two SSP beats on I-95 (beats 1 and 2 in Figure 19) is selected. The segment includes 20 interchanges between the start and end mileposts. Incident data generated from the incident frequency and duration models (i.e., HNB and Hierarchical Weibull models) are used as input to the simulation model. The incident data are synthesized for 40 weekdays to reach a stable generation of incident frequencies, and the simulation period is set to 24 hours. The calibration parameters are set as described in the previous section.

For this selected I-95 corridor, the beat lengths are restricted to between 7 and 30 miles. With this constraint, the total number of all feasible beats is found to be 36 by the SSP-OPT tool. These beats are listed in Table 12. The "*Start*" and "*End*" columns contain the mileposts representing the beginning and end of the corridor. The mileposts recorded in columns starting with an “X” demarcate the boundary between two beats within the corridor. These generally correspond to interchanges where the SSP vehicle can make a U-turn. For example, beat configuration C7 has two beats: one from milepost 50 to 72.5 and another from milepost 72.5 to 83.2. In these columns, a "-1" indicates an inapplicable value.

The results of the simulation are presented in Figure 24, which comprises three types of charts for three different simulation runs. The first row of charts displays the RT and RR performance metrics, the second row the TU and RT, and the third row RT2 and RR. The chart axes are labeled accordingly, and different beat configurations are annotated. The red dots represent two beat configurations, the green triangles three beats, and the blue squares four beats.

It is evident that the performance of a beat configuration improves as the number of SSPs assigned to the corridor increases. This is indicated by a decrease in both RT and $RT2$, along with an increase in RR as the number of beats is increased from two to three or four.

The field observations are indicated by the red diamond for the existing two-beat configuration. The two-beat configuration C7 is identical to the existing SSP beat configuration in the field. The simulation results for this beat are circled in the charts. The results show good agreement with the field data. As shown in Figure 24, performance metrics fluctuate from one simulation run to another. To obtain more stable results, the simulations can be repeated multiple times. Figure 25 shows the outputs for individual runs, as well as the average of RR and RT when the number of simulations increases. The results become quickly stable after only ten or so runs. For this beat configuration, the RR and RT values from the field observations are 0.92 and 12.66 minutes, respectively. Running the simulation ten times and averaging the results yields 0.95 and 13.56 minutes for RR and RT, respectively. The RR and RT from the simulation are 4% and 7% higher than the field values. These small differences indicate the SSP-OPT can produce relatively accurate results.

To determine the optimum beat configuration, performance metrics from the tool could be analyzed. Since there are multiple criteria (e.g., RR, RT), the best option would depend on the user’s preferences or on how much importance is placed on different metrics. The SSP-OPT tool also computes a composite score by combining normalized metrics for RR and RT as shown previously in Eq. 13. The SSP-OPT tool also displays a subset of the solutions that perform best in terms of one metric. Figure 26 shows this subset for the analyzed I-95 corridor where top two performing beat configurations are displayed when only one metric is considered.

Table 12. Feasible Beat Configuration

Beat Config	Total Beats	Start	X1	X2	X3	End
C1	2	50	57.2	-1	-1	83.2
C2	2	50	60.3	-1	-1	83.2
C3	2	50	62	-1	-1	83.2
C4	2	50	63.9	-1	-1	83.2
C5	2	50	66.9	-1	-1	83.2
C6	2	50	68.5	-1	-1	83.2
C7	2	50	72.5	-1	-1	83.2
C8	2	50	73.3	-1	-1	83.2
C9	2	50	74.7	-1	-1	83.2
C10	2	50	75.6	-1	-1	83.2
C11	3	50	57.2	66.9	-1	83.2
C12	3	50	57.2	68.5	-1	83.2
C13	3	50	57.2	72.5	-1	83.2
C14	3	50	57.2	73.3	-1	83.2
C15	3	50	57.2	74.7	-1	83.2
C16	3	50	57.2	75.6	-1	83.2
C17	3	50	60.3	68.5	-1	83.2
C18	3	50	60.3	72.5	-1	83.2
C19	3	50	60.3	73.3	-1	83.2
C20	3	50	60.3	74.7	-1	83.2
C21	3	50	60.3	75.6	-1	83.2
C22	3	50	62	72.5	-1	83.2
C23	3	50	62	73.3	-1	83.2
C24	3	50	62	74.7	-1	83.2
C25	3	50	62	75.6	-1	83.2
C26	3	50	63.9	72.5	-1	83.2
C27	3	50	63.9	73.3	-1	83.2
C28	3	50	63.9	74.7	-1	83.2
C29	3	50	63.9	75.6	-1	83.2
C30	3	50	66.9	74.7	-1	83.2
C31	3	50	66.9	75.6	-1	83.2
C32	3	50	68.5	75.6	-1	83.2
C33	4	50	57.2	66.9	74.7	83.2
C34	4	50	57.2	66.9	75.6	83.2
C35	4	50	57.2	68.5	75.6	83.2
C36	4	50	60.3	68.5	75.6	83.2

Notes: C (Configuration); X (Milepost demarcating the boundary between two beats within the corridor)

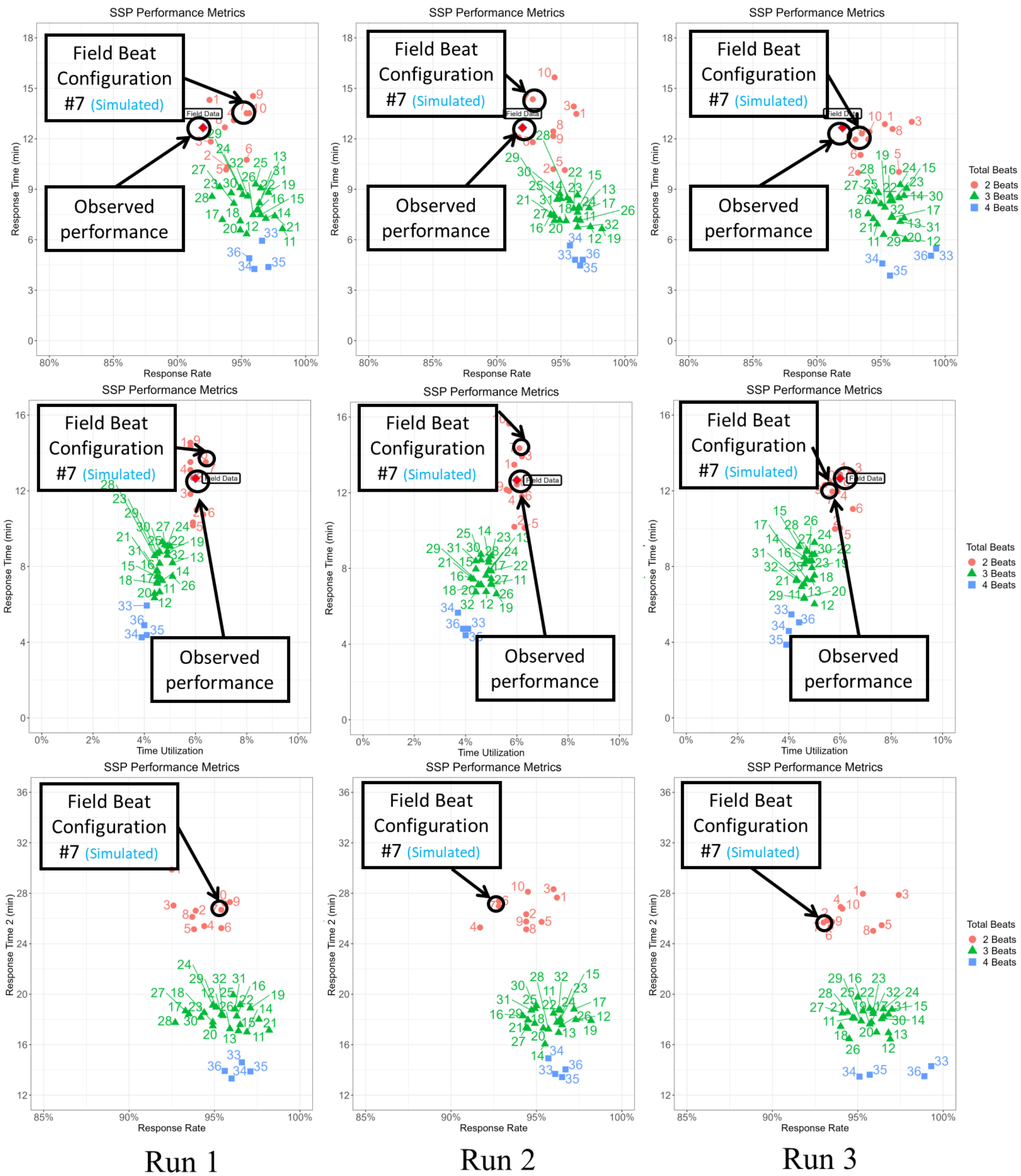


Figure 24. Performance Metrics of Safety Service Patrol (SSP) Simulation

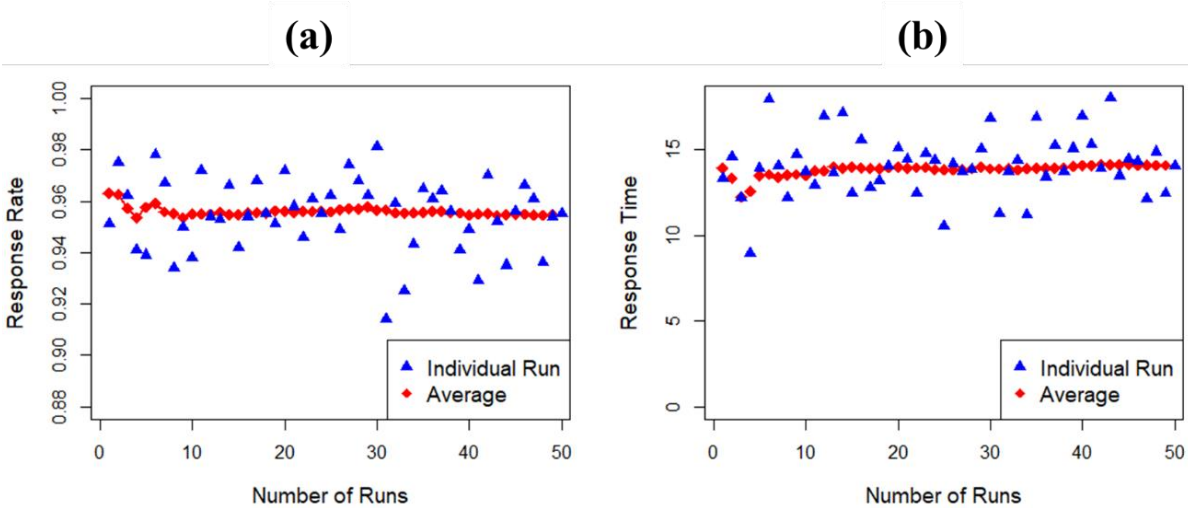


Figure 25. Average Response Rate (a) and Average Response Time (b) as the Number of Runs Changes

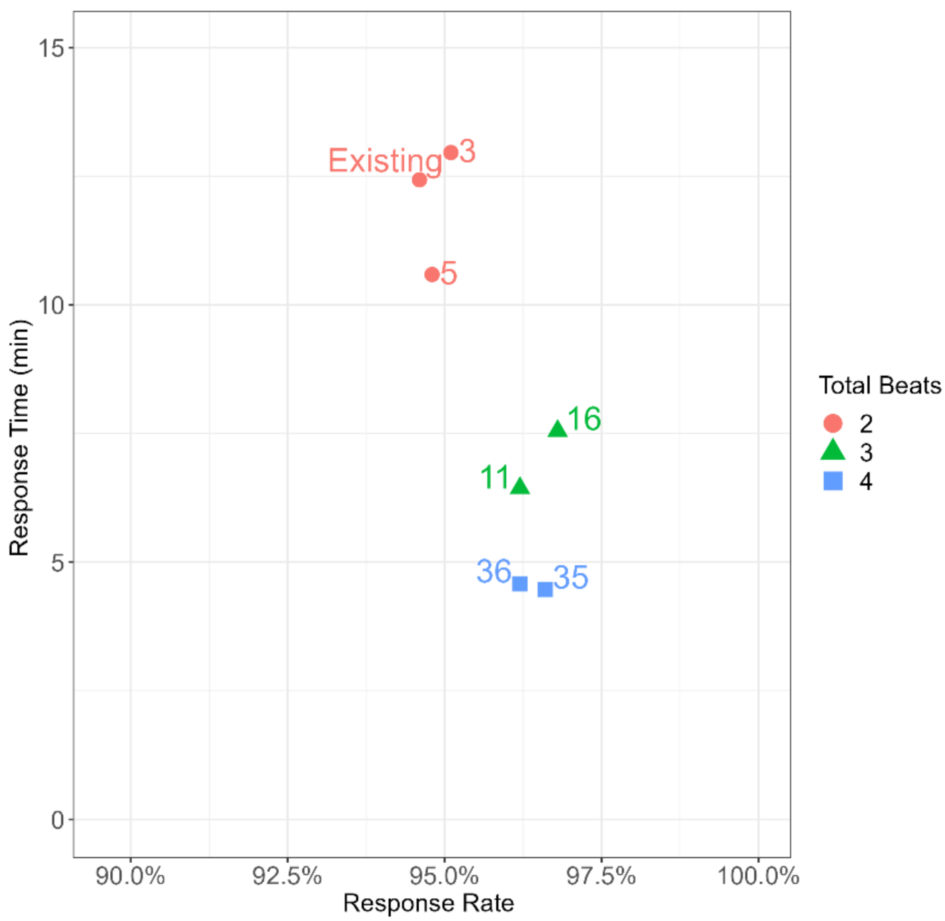


Figure 26. Performance Metrics for Recommended Beat Configurations

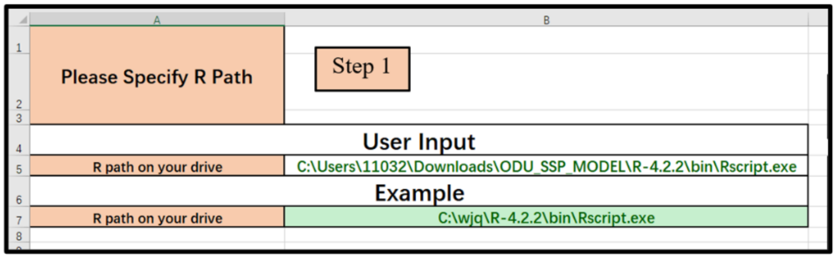
User Interface for the SSP-OPT Tool

A user interface for the SSP-OPT tool is developed in the Visual Basic for Applications (VBA) programming language within MS Excel – see Figure 27. The main algorithms behind the tool are coded in the R programming language. R offers a wide range of statistical models, data processing libraries, and data structures enabling efficient computation and code development. VBA Macros within MS Excel call the R programs to generate the incident data and perform the simulation runs. The user can set various input parameters within Excel that are then read by the R program as input in the SSP simulation logic.

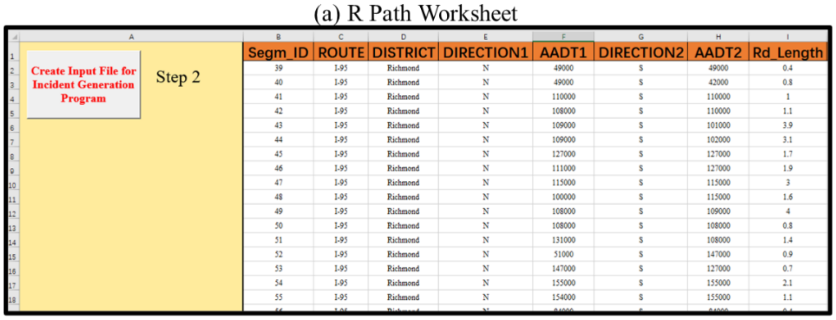
The SSP-OPT tool interface has six worksheets, and a detailed user guide (see Appendix A). The first worksheet requires the user to input the path for Rscript.exe (executable R). The ODU team prepared a zip file containing an installation of the R along with all the necessary libraries. The user, therefore, does not need to directly install R or interact with R, but will simply unzip the provided files. However, this is a relatively large file (387MB).

The second worksheet allows the user to enter corridor geometry and traffic volume data. The third and fourth worksheets contain key parameters and constraints for incident generation and simulation. If the user chooses to optimize or analyze an existing SSP corridor, the existing beat configuration data can be entered on the *"Existing_Beat_Config"* worksheet. The users can choose to perform the analysis for weekdays or weekends, adjust SSP operations shifts or hours, specify desired minimum and maximum beat lengths, and customize various parameters governing the simulation logic such as SSP speeds, waiting time threshold, and notification time functions in the simulation. The total number of simulation runs can be controlled as well.

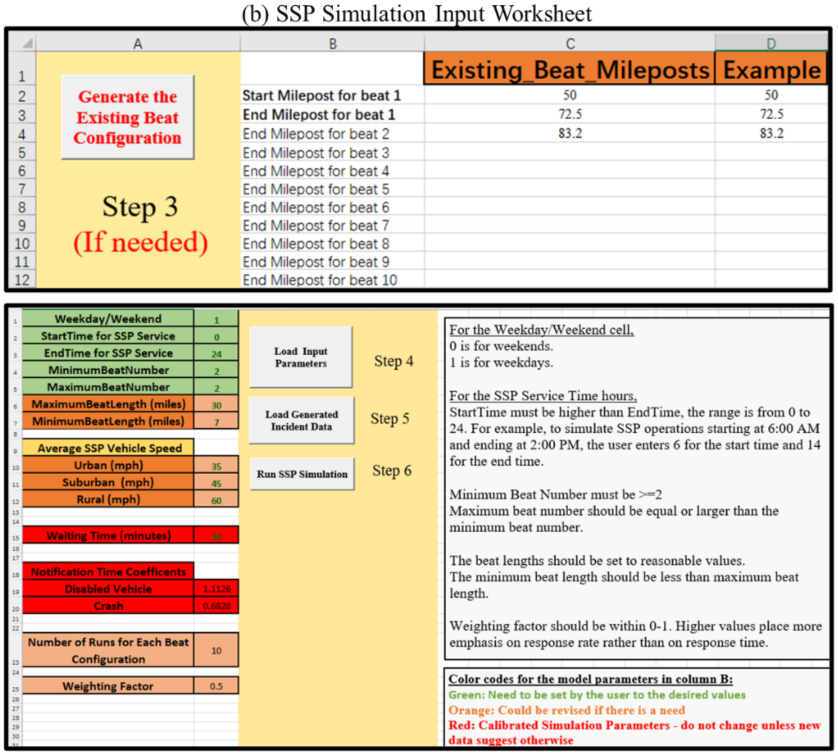
Based on the simulation results, the model generates the recommended beat configurations and output the data for all possible beat configurations in csv files. The last two worksheets are used to load the output files and display the performance metrics.



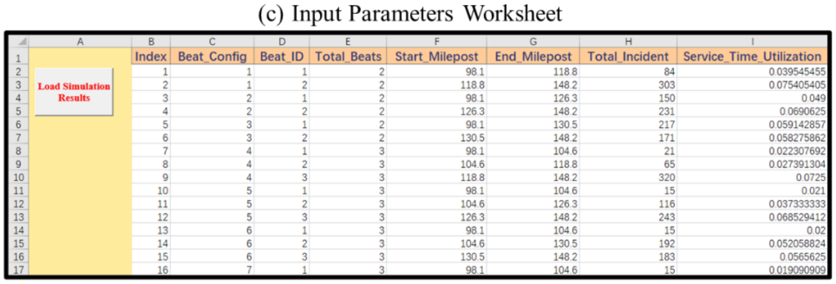
(a) R Path Worksheet



(b) SSP Simulation Input Worksheet



(c) Input Parameters Worksheet



(d) Load Simulation Result Worksheet

Figure 27. SSP-OPT Interface

DISCUSSION

- The incident prediction models developed here are based on 2017-2019 statewide incident data from Virginia SSP corridors (except for those in Hampton Roads District). As traffic patterns change, and traffic monitoring technologies (e.g., surveillance cameras) and SSP programs evolve, such changes may affect incident data and SSP performance characteristics (e.g., response time). In addition, construction projects like the expansion of Hampton Roads Bridge Tunnel could also affect incident occurrence patterns. Consequently, the prediction models may need to be recalibrated in the future to accommodate significant deviations from the conditions reflected in 2017-2019 data.

- The output from the SSP-OPT tool includes multiple performance metrics (e.g., RR, RT). However, benefits to the traveling public in terms of dollar amounts or travel time savings are not computed within the tool. If needed, the total benefits could be estimated by using the FHWA's TOPS-BC (Tool for Operations Benefit-Cost Analysis) tool adopted by VDOT. TOPS-BC tool for SSP benefits has various input parameters including the number of incidents, the percentage of incidents serviced by SSP, lane blocking incidents, and average incident duration reduction due to SSP. The SSP-OPT tool directly provides the percentage of incidents serviced by SSP and SSP response time. These metrics can be incorporated into the TOPS-BC tool to estimate the benefits of SSP operations improvements.

- The SSP-OPT tool is currently not optimized to handle large networks, e.g., corridors longer than 100 miles. Since SSP operations are planned at the VDOT district level, most SSP corridors within the districts are shorter than this limit. The computation time for the simulation depends on the number of turnaround points/interchanges, user preferences for beat size, and the selected number of simulations, as well as the specifications of the computer (i.e., processing speed and memory) running the program. Computation times from several tests are listed in Appendix C.

- MS Excel was selected to create the user interface for the SSP-OPT tool since it is commonly available on VDOT computers. As explained earlier, the main algorithms are coded in the R programming language which are called from the Excel interface. As explained in the Implementation and Benefits section, some difficulties were encountered in installing the tool on the VDOT computers (e.g., security restrictions for VBA macros). An alternative platform for the user interface might be considered to improve the usability of the tool as discussed in the Implementation and Benefits section.

CONCLUSIONS

- *The SSP simulation model incorporates a hierarchical negative binomial model for incident frequencies and a hierarchical Weibull model for incident duration. These models were found to be effective in simulating the spatiotemporal distributions of incidents along the highway corridors and for generating their attribute data (e.g., incident type, SSP service duration).*

- *The simulation-based approach proposed in this study for modeling SSP operations is shown to produce realistic performance measures (e.g., response time, response rate) that are consistent with field observations.* The simulation program employs a discrete event-based approach using a few calibration parameters (e.g., SSP vehicle speed, thresholds for waiting and notification times). After calibrating the model, the validation results show good agreement with field observations when applied to two sample SSP corridors from I-95.

- *The proposed SSP optimization model could be applied to corridors with or without existing SSP service.* However, it should be noted that the models are calibrated based on historical incident and SSP operational data from existing SSP corridors. The model outputs for future scenarios will be valid insofar as those scenarios are consistent with the historical data.

RECOMMENDATIONS

1. *The Virginia Transportation Research Council (VTRC) should conduct a pilot project on integrating the SSP-OPT tool into the planning process of SSP beat design and vehicle scheduling.* The pilot project will be helpful in demonstrating how effective the SSP-OPT tool is in supporting real-word decision making. The feedback from the pilot may identify potential revisions and improvements that could be made to enhance its useability and functionality in practical scenarios. Based on the feedback from the TRP, the SSP-OPT tool could be revised and customized to streamline its integration into the design process of SSP beats and schedules.

IMPLEMENTATION AND BENEFITS

The researchers and the technical review panel (listed in the Acknowledgments) for the project collaborate to craft a plan to implement the study recommendations and to determine the benefits of doing so. This is to ensure that the implementation plan is developed and approved with the participation and support of those involved with VDOT operations. The implementation plan and the accompanying benefits are provided here.

Implementation

To implement the recommendation above, the SSP-OPT tool needs to be tested and evaluated on VDOT computers and revised as needed to ensure a positive end user experience. In this project, MS Excel and macros written in VBA are used to create the user interface and facilitate interactions with the SSP simulation coded in R. Based on several initial tests of the tool on VDOT computers, some difficulties were encountered in program installation including security restrictions with MS Excel Macros and unzipping the large number of R files needed for the program to run. While the program functions and produces the desired performance metrics, alternative options for program installation (e.g., cloud-based services, access through virtual machine) could be considered and pursued to streamline the user experience. In addition, the outputs from the tools can be further enhanced and customized to the needs and preferences of the VDOT staff responsible for SSP route planning.

To conduct the pilot project, VDOT would need to identify a suitable pilot site (i.e., an interstate corridor with or without SSP service) and coordinate with the respective TOC and staff to determine the scope of the pilot project. The scope of the study will include specifying the corridor length to be covered by the SSP service, preparing the input data, defining scenarios to be tested, and analyzing the scenarios with the SSP-OPT tool. If there is already SSP service in place along the corridor, the pilot project could entail a comparison of the tool's output (i.e., performance metrics) with ground truth data. In addition, the optimal beat configurations produced by the tool could be considered as alternative options for revisions to the beat lengths and SSP vehicle schedules. The pilot project will help identify potential revisions that can be made to the tool for better integration within the SSP planning processes. The pilot will also pave the way for a broader adoption of the tool across the VDOT districts and will serve as an example of how the tool can be used to identify alternative beat designs that optimize SSP resources while maximizing the quality of the service to the traveling public.

After revising the SSP-OPT tool and conducting the pilot project, the research team, in coordination with VTRC, will provide written instructions on using the SSP-OPT tool and will conduct a webinar for interested VDOT staff to demonstrate the application of the SSP-OPT tool in identifying candidate beat configurations and generating their performance metrics. The webinar will be scheduled by the VTRC in consultation with ODU and participants from VDOT. Invitees may include TOC managers and staff who engage in SSP scheduling and operations from different VDOT districts. Implementation funds will be requested to undertake this effort within one year of the publication of this report.

Benefits

The operational and safety benefits of SSPs have been studied and documented by many states including Virginia. VDOT's SSP service covers approximately 926 miles of roadway. Planning and managing the SSPs effectively across the state requires robust and practical tools that can help in optimally allocating SSP resources. This entails determining the best beat designs and SSP shifts for a corridor, given a limited number of SSP vehicles. The SSP-OPT tool created within this project is expected to meet this need. The tool generates all feasible beat configurations and evaluates them one by one in a simulation model to produce accurate performance metrics, including response rate and average response time. The output from the tool will help decision makers select the best possible beat configurations that meet the desired criteria. Overall, the tool will have benefits both for the motorists as well as the VDOT districts operating SSP services:

- The tool will help identify optimal beat configurations that minimize SSP response times and maximize the SSP response rates that can be attained with a given number of SSP vehicles on a corridor. Implementing these solutions in the field will result in travel time savings and will improve highway safety since SSP resources will be more efficiently utilized in reducing the impacts of incidents on traffic flow.

- The SSP-OPT tool will help VDOT staff quickly evaluate alternative beat designs before implementing them in the field. Once widely adopted, the tool can become an integral part of the SSP planning process to consistently determine beat configurations across the state based on quantitative performance metrics generated by the tool. The tool can also be used to evaluate existing SSP operations, identify inefficiencies, and support decisions in reallocating resources where most needed.

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APPENDIX A: SSP-OPT USER GUIDE

This Appendix provides instructions for using the SSP-OPT tool. To facilitate data entry and interactions with the tool, a user interface is created in MS Excel. The Visual Basic for Applications (VBA) programming language is used to read, load, and write data files needed for the core components of the SSP-OPT tool, which are coded in the R programming language. These core components include incident data generation, generating alternative beat configurations, simulating SSP operations, and computing performance metrics. After the user enters the needed input data, the SSP-OPT tool computes performance metrics (e.g., average response time, response rate) for numerous SSP beat configurations and identifies a few beats that perform the best in terms of these metrics.

All files needed to run the program are packaged in a zip file named "SSP_SIMULATION_MODEL." In addition to the code written for the SSP-OPT tool, this zip file also contains an installation of R programming language and all libraries needed for the code to run. Simply unzipping the files as explained in this Appendix is sufficient and there is no need to download or install R from its website.

The R scripts need to read various csv input files from a working directory. The R scripts are written to look for input files under a folder named "SSP" in C drive. Therefore, the user needs to create a folder named "SSP" under C drive and unzip SSP_SIMULATION_MODEL to this new folder as shown in Figure A1. After unzipping this file, the following two folders will be created that contain all the necessary files:

- SSP_SIMULATION_MODEL
- R-4.2.2

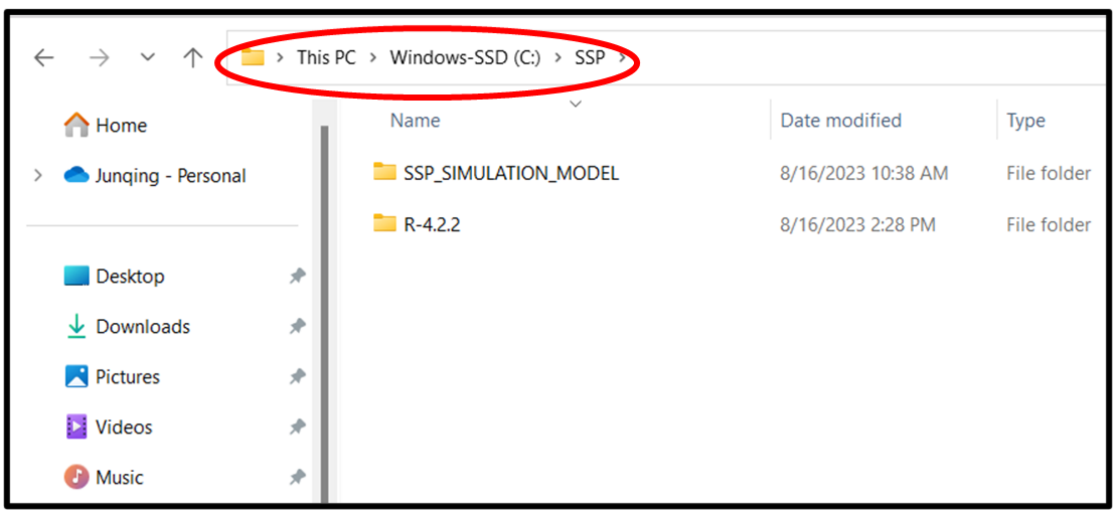


Figure A1. The SSP Folder in C Drive Containing "SSP_SIMULATION_MODEL Folder.

The first folder, SSP_SIMULATION_MODEL, which is also referred to as "working folder," contains the R source code and Excel files needed, while the second one is the installation of R programming language. The user does not need to modify any files directly as all data and parameter entry can be done through the main Excel file named "*VDOT_ODU_SSP-OPTIMIZER.xlsm*" as discussed below. This Excel file is also referred to as the User Interface or simply UI. This file is in "C:\SSP \SSP_SIMULATION_MODEL."

After unzipping the files, the user can start the program by opening *VDOT_ODU_SSP-OPTIMIZER.xlsm*. It should be noted that this file contains a VBA macro and, therefore, Windows may block its running. In that case, the user needs to enable macros in Excel. The are two ways to unblock the macros. The following steps might be helpful in unblocking the macro:

Method 1:

1. Close the workbook containing the blocked macro.
2. In File Explorer, browse to the location where the workbook is saved.
3. Right-click the file and select Properties from the context menu.
4. In the Properties dialog box, check the Unblock box, and then click OK.

Method 2 (this is the method found to work on VDOT computers during testing):

1. Open the workbook containing the blocked macro.
2. Click File→Options→Trust Center→Trust Center Settings→Trusted Locations.
3. Click Add new location, and copy & paste the path "C:\SSP\SSP_SIMULATION_MODEL" in the path box, and then click OK.

A few steps need to be followed to load the necessary input data and execute the source code to generate the output. These steps are listed below and explained in detail in the following sections.

- Step 1: Specify the path for R program.
- Step 2: Enter information for incident generation.
- Step 3: Type existing beat configuration (if needed).
- Step 4: SSP simulation parameters input.
- Step 5: Load generated incident data.
- Step 6: Run the SSP simulation.
- Step 7: Load the simulation results into the output worksheets.

These steps are explained in detail below. Also, the UI file is populated with data for a corridor on I-95 from Exit 50 to Exit 83.

Step 1: Specify the Path for the R Program

In this step, the user sets the environment by entering the path address to the R installation. To begin with this step, open *"VDOT_ODU_SSP-OPTIMIZER.xlsm"* which is in the working directory (i.e., SSP_SIMULATION_MODEL). Go to "R_PATH" worksheet to enter the path name as shown in Figure A2. The entry in cell B5 is for the R program and the path name needs to include "Rscript.exe" as shown in the figure.

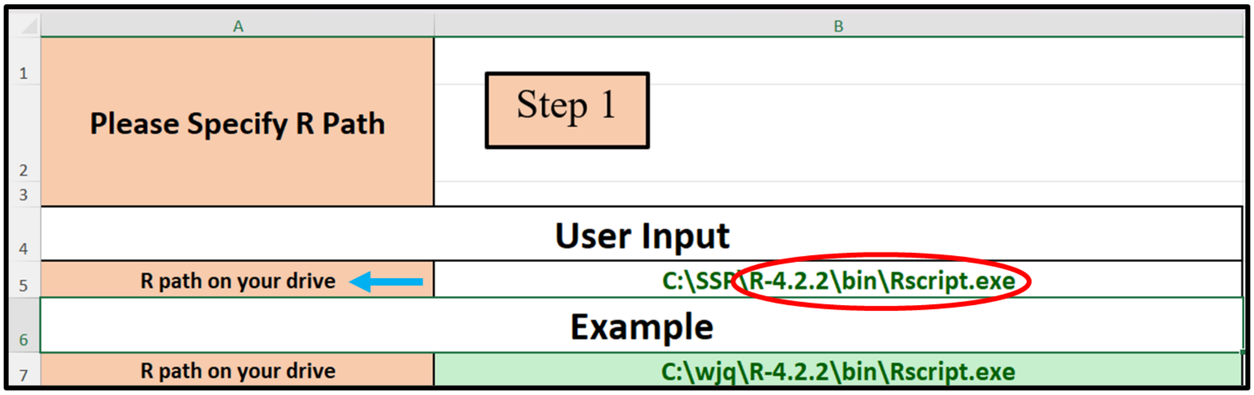


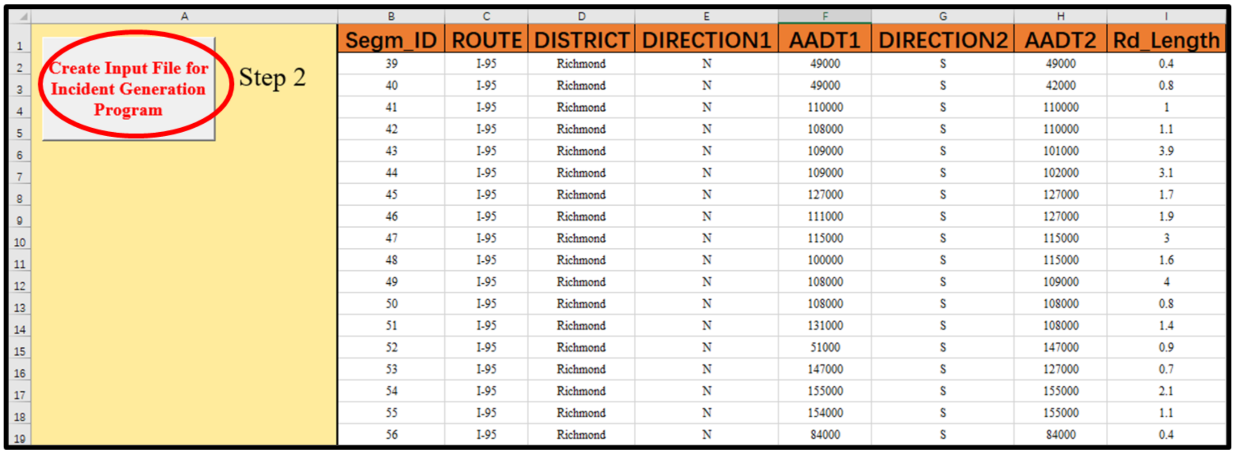
Figure A2. Identify Path for R Program and Working Folder

Step 2: Road Geometry for the Incident Models.

This step is about entering the road geometry for the corridor and other pertinent data in "*Simulation_Input"* worksheet. This information is organized by road segments. Each segment represents a section of a highway between two turnaround points (e.g., interchanges) where the SSP vehicle can make a U-turn. The "*Simulation_Input"* worksheet has eight columns to be completed for each road segment as shown in Figure A3. While entering the data, the following details need to be observed:

- Segment IDs in column B are just consecutive integers denoting the sequence of segments making up the corridor to be analyzed. The numbers could be any consecutive integers.
- Route IDs in column C denote the interstate name and number. There needs to be "-" between the number and the capital letter I. (e.g., I-95, I-64, I-81, etc.)
- District IDs in column D represent the VDOT district name. The first letter should be capitalized.
- Columns E and F are, respectively, for specifying the cardinal direction (e.g., N, S, E, W) and AADT for one of the directions of the highway. Columns F and G are for the opposing direction of the road.
- Road length in miles will be entered in column I.
- Start and end mileposts for each segment are typed into columns J & K.
- The Region variable column L should be selected from the three alternatives from the pulldown options. ("Rural," "Suburban," and "Urban."). Urban can be used for congested corridors that may not be necessarily in urban areas. This variable is used to determine the SSP vehicle's speed in the simulation.

After completing the data entry, click *"Create Input File for Incident Generation Program"* button to generate the data and save the input file needed for the statistical models for generating incidents along this corridor. These incidents will be used later in the simulation. The generated file called *"Incident_Input.csv"* can be found in the "C:\SSP \SSP_SIMULATION_MODEL\Input\User Input" folder. This csv file will be displayed for verification, the user will simply close it after reviewing it for accurate data entry as needed.



Segm_ID	ROUTE	DISTRICT	DIRECTION1	AADT1	DIRECTION2	AADT2	Rd_Length
39	I-95	Richmond	N	49000	S	49000	0.4
40	I-95	Richmond	N	49000	S	42000	0.8
41	I-95	Richmond	N	110000	S	110000	1
42	I-95	Richmond	N	108000	S	110000	1.1
43	I-95	Richmond	N	109000	S	101000	3.9
44	I-95	Richmond	N	109000	S	102000	3.1
45	I-95	Richmond	N	127000	S	127000	1.7
46	I-95	Richmond	N	111000	S	127000	1.9
47	I-95	Richmond	N	115000	S	115000	3
48	I-95	Richmond	N	100000	S	115000	1.6
49	I-95	Richmond	N	108000	S	109000	4
50	I-95	Richmond	N	108000	S	108000	0.8
51	I-95	Richmond	N	131000	S	108000	1.4
52	I-95	Richmond	N	51000	S	147000	0.9
53	I-95	Richmond	N	147000	S	127000	0.7
54	I-95	Richmond	N	155000	S	155000	2.1
55	I-95	Richmond	N	154000	S	155000	1.1
56	I-95	Richmond	N	84000	S	84000	0.4

Figure A3. Interface for Entering Road Geometry and AADT Data

Steps 3 and 4: Simulation Input Parameters

These two steps are about defining input parameters needed for the simulation program. These two steps are organized for easy referencing – see Figure A4.

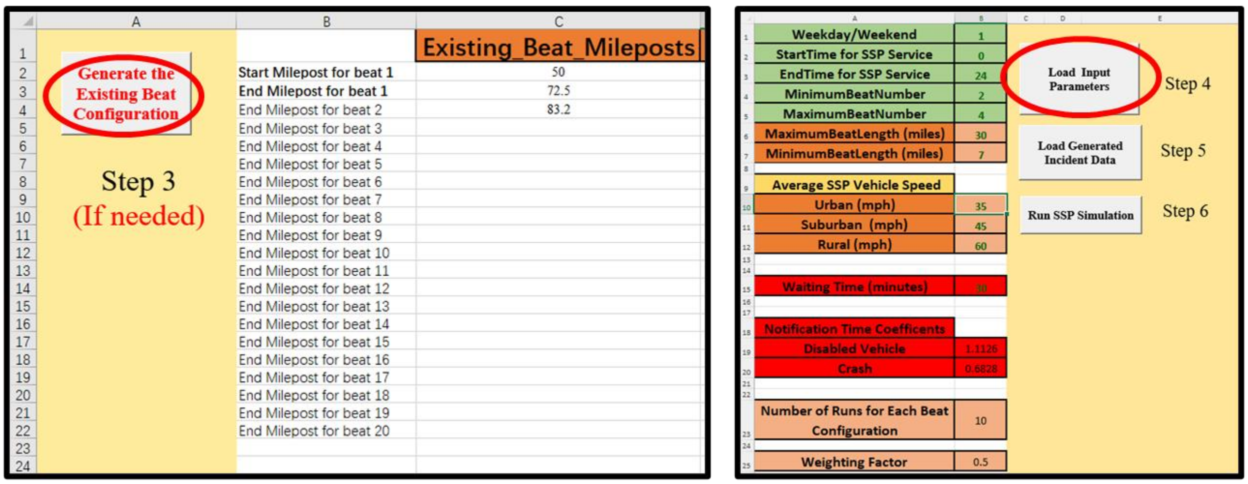


Figure A4. Load Road Segments and Input Parameters

In Step 3, information for existing beat configuration is entered in worksheet *"Existing_Beat_Config."* This step is optional as there may not be SSP service for the corridor being studied. Specify the existing beat configuration by entering the mileposts for each beat.

- Type the Start Milepost in cell C2. Then type the end milepost for each beat in this corridor in the subsequent cells under Column C. (e.g., if the corridor is from milepost 50 – 83.2 and the beat configurations are 50 – 72.5 and 72.5 – 83.2, the user should type 50, 72.5, and 83.2 in column C). These mileposts should correspond to (or be selected from) mileposts values typed in the "Simulation_Input" worksheet.
- Click the button "Generate the Existing Beat Configuration" to save the existing beat configuration to a csv file that will be used in the simulation. This file is named "*Existing_Beat_Config.csv*". This csv file will be displayed for verification, the user will simply close it after reviewing it for accurate data entry as needed.

In Step 4, important simulation model parameters are specified. These parameters are listed in columns A and B in the worksheet titled "Input_Parameters," and are explained below:

- The Weekday/Weekend option can be specified in cell B1. This allows simulating either weekday or weekend operations. Enter 0 for the weekend and 1 for weekdays.
- SSP service start and end times in simulation can be set in cells B2 and B3. Use a number from 0 to 24 to indicate the starting and ending hour of operations. Hour 0 corresponds to midnight to 1:00AM whereas 23 to 11:00PM to midnight. The hour entered for the end time is not included within the SSP operations period. For example, to simulate SSP operations starting at 6:00 AM and ending at 2:00 PM, the user enters 6 for the start time and 14 for the end time.
- The program allows the user to set the maximum and minimum number of beats to be considered for the corridor being studied. These are set in cells B4 and B5. The minimum beat number must be ≥ 2. The maximum beat number should be equal or higher than the minimum beat number.
- The beat length range can be set in cells B6 and B7. Minimum/Maximum beat lengths are used in creating feasible beat configurations.
- SSP vehicle speeds for different regions are found in cells B10-12. In the simulation, the SSP vehicle patrols the beat and responds to incidents at these speed values.
- Not all incidents could be responded to within a reasonable time as the SSP vehicle may be servicing other incidents. If the wait time (to respond to an incident) exceeds a threshold, that incident is labeled "unable to respond" and ignored for the rest of the simulation. The threshold is set in cell B15, and the default value is 30 minutes.
- Notification time coefficients can be adjusted in cells B19 (for disabled vehicle incidents) and B20 (for crash incidents). These parameter values define the linear regression functions for the notification times. They should not be modified unless there is a need to recalibrate these parameters.
- The number of runs for each beat configuration in the simulation can be adjusted in cell B23. The default value is set to 10.
- The weighting factor for the composite score, it can be adjusted in cell B25. The default value is set to 0.5. Higher values place more emphasis on response rate rather than on response time.
- The parameters are color coded to guide the user. The ones in red should not be modified unless a new calibration study is conducted to update these simulation parameters. The values in orange could be revised if the user believes that the default values may not represent the field conditions or preferred simulation settings. The ones in green need to be set by the user depending on the type of analysis being conducted. They pertain to the SSP operations hours and days and the number of beats to be considered for the corridor.

After entering the input parameters, the user can click the button *"Load Input Parameters"* to generate the input parameters file needed for the simulation. This file called *"Parameter_Input.csv"* can be found in "C:\SSP \SSP_SIMULATION_MODEL\Input\User Input" folder. This csv file will be displayed for verification, the user will simply close it after reviewing it for accurate data entry as needed.

Step 5: Load Generated Incident Data

This step generates the incident data or profile for the corridor using the statistical models developed. The user can click the button *"Load Generated Incident Data"* to generate and load the incidents to be simulated in the SSP tool. The generated file called *"Incident_Profile.csv"* can be found in the \SSP_SIMULATION_MODEL\Output\Incident_profile.

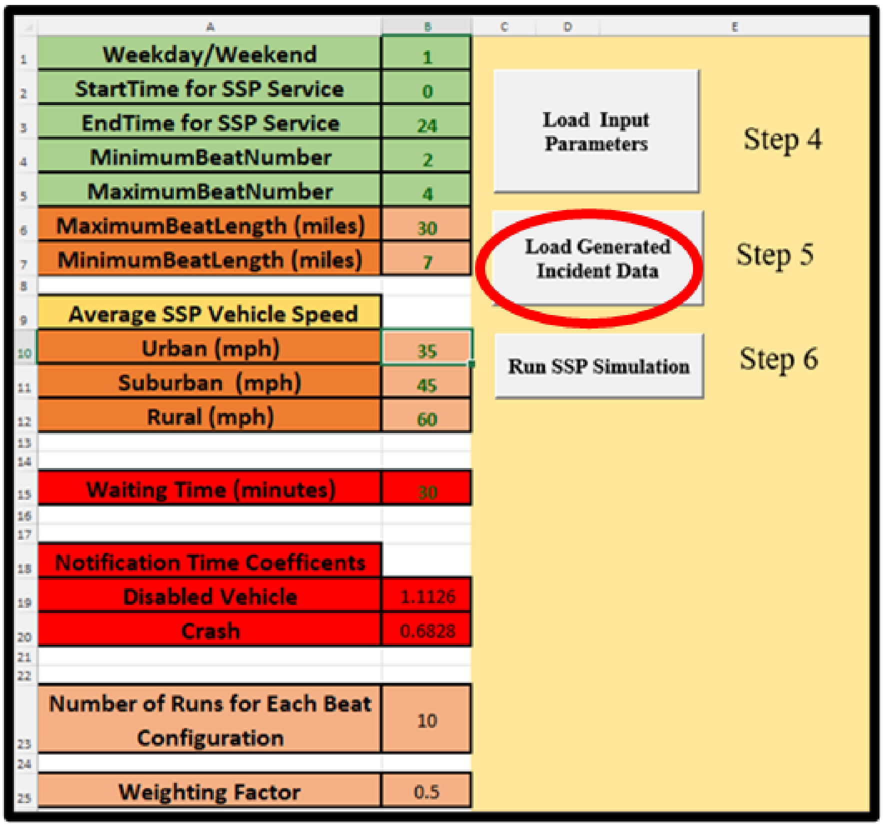


Figure A5. Load Generated Incident Data

Step 6: Run SSP Simulation

Once all input data is ready, the simulation program can be run to generate all feasible beat configurations and their performance metrics. Execute the R program by clicking the *"Run SSP Simulation"* button. This will generate output files that are stored in "*Output*" folder. The computation time in this step will vary depending on the corridor length and other parameters.

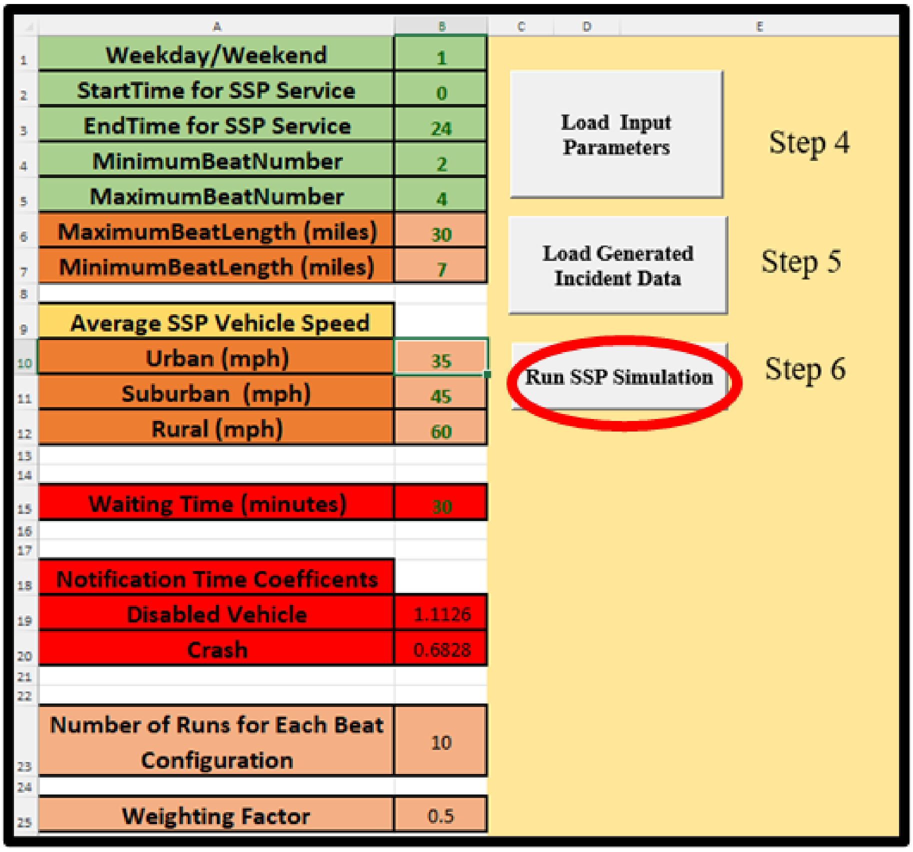


Figure A6. Run SSP Simulation

Step 7: Load the Simulation Data into the Output Worksheets

After the simulation is completed, four CSV files are generated and stored in "*Output*" folder:

1. *Beat_Configuration.csv*: This contains the list of all feasible beats meeting the specifications, e.g., maximum and minimum beat lengths and beat number.
2. *SSP_Performance_Metric(Beat-View).csv*: This file provides performance metrics for each beat within each feasible beat configuration. Each beat configuration can have two or more beats. The data from this file can be loaded to the UI by pressing the button in "Output_All" worksheet and navigating to the output folder to select *SSP_Performance_Metric(Beat-View).csv.*
3. *SSP_Performance_Metric(Config-View).csv*: This file provides performance metrics for each feasible beat configuration. The values for individual beats for a given configuration are aggregated in generating this file.
4. *SSP_Project_Best_Beat_Config.csv*: This file is a subset of the previous file and reports results only for those configurations that are found to perform better/best in terms of the key objectives (minimum response time and maximum response rate). The data from this file can be loaded to the UI by pressing the button in "Best_Configurations" worksheet and navigating to the output folder to select *SSP_Project_Best_Beat_Config.csv*.

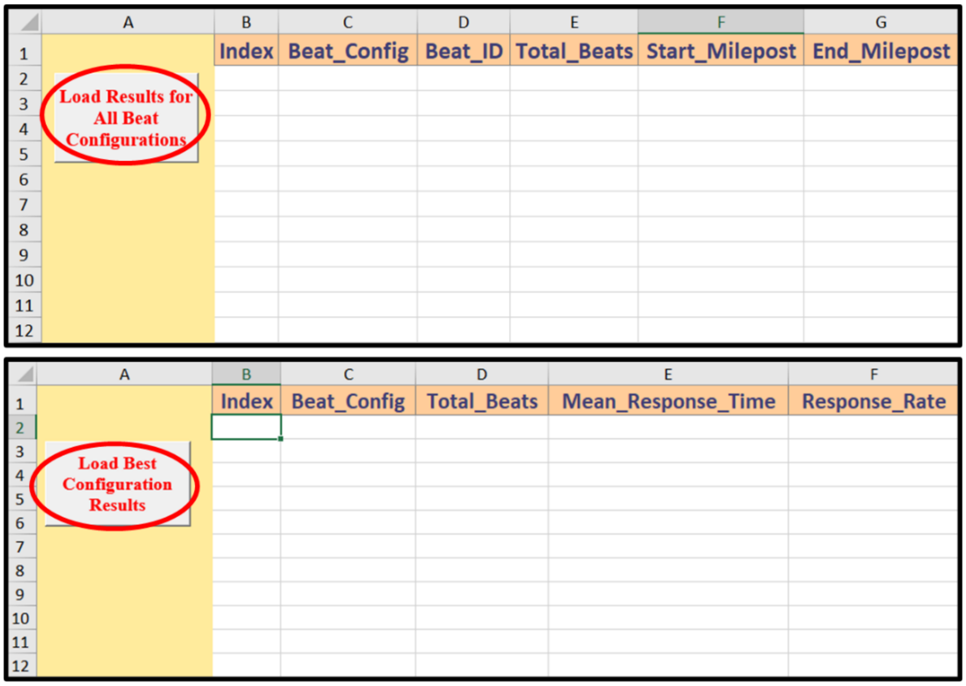


Figure A8. Worksheets for Loading Results for All Beat Configurations & Best Configuration

In addition to tabular results, the program automatically generates a scatter plot for response time and response rate (Figure A9), based on the composite score calculated, two of the key performance metrics. This plot is saved under "Output" folder.

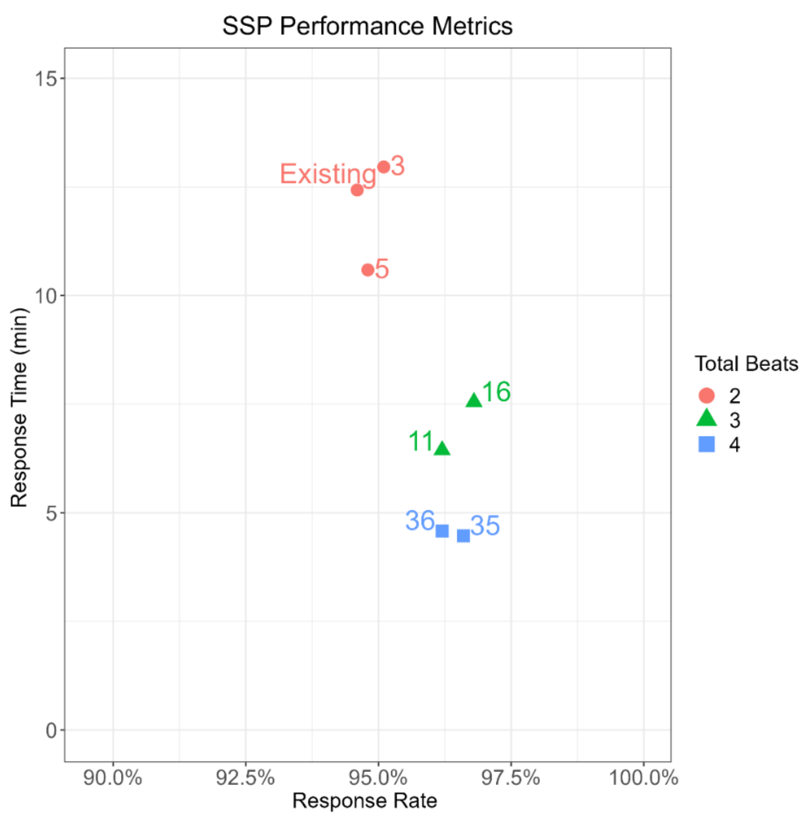


Figure A9. Sample Plot Showing the Results from the Best Beat Configuration Table

APPENDIX B: COMPUTATIONAL TESTS

Table B1. Results of Computational Tests

Hardware	Operating System	CPU	Memory	Test Scenario	Total number of beat configura-tions	Total beats	Total time to simulate 40 days for each configura-tion	Rate
Laptop	Microsoft Windows X	Intel®-Core™-i5-7300HQ CPU @ 2.50GHz	16GB	(I-95 from MM 98.1 to 148.2 mi)	133	432	3.58 minutes	37 beat configurations/ minute/run
Laptop	Microsoft Windows XI	Intel®-Core™-i7-12700H CPU @ 2.30GHz	16GB	(I-95 from MM 98.1 to 148.2 mi)	133	432	0.59 minutes	255 beat configurations/ minute/run
Workstation	Microsoft Windows X	Intel®-Core™-i7-9800X CPU @ 3.80GHz	32GB	(I-95 from MM 98.1 to 148.2 mi)	133	432	0.92 minutes	144 beat configurations/ minute/run

APPENDIX C: GROUP IDENTIFIERS FOR INCIDENT FREQUENCY PREDICTION

Table C1. Group Identifiers for Incident Frequency Prediction

Group Identifiers	Route Name	VDOT District	Group Identifiers	Route Name	VDOT District
1	I-195N	Richmond	23	I-66W	Culpeper
2	I-195S	Richmond	24	I-66W	Northern Virginia
3	I-295N	Richmond	25	I-66W	Staunton
4	I-295S	Richmond	26	I-77N	Bristol
5	I-381N	Bristol	27	I-77N	Salem
6	I-381S	Bristol	28	I-77S	Bristol
7	I-395N	Northern Virginia	29	I-77S	Salem
8	I-395R	Northern Virginia	30	I-81N	Bristol
9	I-395S	Northern Virginia	31	I-81N	Salem
10	I-495N	Northern Virginia	32	I-81N	Staunton
11	I-495S	Northern Virginia	33	I-81S	Bristol
12	I-581N	Salem	34	I-81S	Salem
13	I-581S	Salem	35	I-81S	Staunton
14	I-64E	Culpeper	36	I-85N	Richmond
15	I-64E	Richmond	37	I-85S	Richmond
16	I-64E	Staunton	38	I-95N	Fredericksburg
17	I-64W	Culpeper	39	I-95N	Northern Virginia
18	I-64W	Richmond	40	I-95N	Richmond
19	I-64W	Staunton	41	I-95R	Northern Virginia
20	I-66E	Culpeper	42	I-95S	Fredericksburg
21	I-66E	Northern Virginia	43	I-95S	Northern Virginia
22	I-66E	Staunton	44	I-95S	Richmond

APPENDIX D: GROUPS IDENTIFIERS FOR INCIDENT DURATION PREDICTION

Table D1. Group Identifiers for Incident Duration Prediction

Group Identifiers	Route Name	VDOT District	Group Identifiers	Route Name	VDOT District
1	I-195N	Richmond	23	I-66W	Staunton
2	I-195S	Richmond	24	I-77N	Bristol
3	I-295N	Richmond	25	I-77N	Salem
4	I-295S	Richmond	26	I-77S	Bristol
5	I-381N	Bristol	27	I-77S	Salem
6	I-395N	Northern Virginia	28	I-81N	Bristol
7	I-395S	Northern Virginia	29	I-81N	Salem
8	I-495N	Northern Virginia	30	I-81N	Staunton
9	I-495S	Northern Virginia	31	I-81S	Bristol
10	I-581N	Salem	32	I-81S	Salem
11	I-581S	Salem	33	I-81S	Staunton
12	I-64E	Culpeper	34	I-95N	Fredericksburg
13	I-64E	Richmond	35	I-95N	Northern Virginia
14	I-64E	Staunton	36	I-95N	Richmond
15	I-64W	Culpeper	37	I-95S	Fredericksburg
16	I-64W	Richmond	38	I-95S	Northern Virginia
17	I-64W	Staunton	39	I-95S	Richmond
18	I-66E	Culpeper			
19	I-66E	Northern Virginia			
20	I-66E	Staunton			
21	I-66W	Culpeper			
22	I-66W	Northern Virginia			