Simulating Incident Management Team Response and Performance

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Abstract

The abstract is a crucial component of any scientific paper, as it provides a summary of the research and its main findings. This paper provides guidelines for writing an effective scientific abstract. The first step is to identify the key elements of the research, such as the research question, methods, results, and conclusions. Next, the abstract should be written in a clear and concise manner, using simple language and avoiding technical jargon. The abstract should also be structured, with a clear introduction, methods section, results section, and conclusion. Additionally, the abstract should accurately and succinctly convey the main findings of the research, highlighting the significance and implications of the work. By following these guidelines, researchers can ensure that their abstract effectively communicates the key aspects of their research and attracts the attention of potential readers. - Written by ChatGPT

1. Introduction

Many regions have introduced Incident Management Teams (IMT) as a method to improve highway system operations, especially during peak periods when the user costs of incidents clogging roadways can be particularly high. IMT can respond quickly to incidents ranging from vehicle breakdowns to serious, multi-car collisions and aid other first response agencies to manage the traffic stream and return traffic to normal conditions CITE. Some studies have suggested that IMT can save a region as much as $X in user costs over the course of a year / peak period CITE.

In spite of the claimed benefits of IMT and the relative importance that many organizations are placing on their deployment, academic research into IMT is

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somewhat limited. This applies to both effectiveness studies, but especially to prospective attempts to study what effect an increase in system deployment may have, or how an increase in traffic incidents — caused by an increase in driver distraction, population growth, or any other exogenous cause — might strain the system deployment.

In this research, we explore a micro-simulation approach for representing IMT response to incidents in a highway network. This approach relies on adaptations to the MATSim transportation modeling framework to represent both incidents and the IMT response, and is implemented in a scenario representing the Wasatch Front (Salt Lake City) region of Utah. The simulation aims to demonstrate how IMT effectiveness varies with changes in allocated resources as well as the concentration of incidents.

The paper proceeds in a typical order. A discussion of previous research into IMT motivations, effectiveness, and optimization follows this introduction. **?@sec-methods** describes the simulation methodology and scenario construction, while **?@sec-results** presents the results of the analysis alongside a discussion of their implications. The paper concludes in **?@sec-conclusion** with an outline of future research motivated by this study's limitations.

2. Literature Review

Traffic incident management in general — and IMT in particular — are not strictly new innovations. The Federal Highway Administration (FHWA) publishes the *Traffic Incident Management Handbook* (FHWA, 2000), which defines traffic incident management as:

> *The systematic, planned, and coordinated use of human, institutional, mechanical, and technical resources to reduce the duration and impact of incidents and improve the safety of motorists, crash victims, and incident responders. (p. 1-1)*

The handbook details the process of how to implement a traffic incident management program as well as improve it. The manual covers various aspects of incident management, including the responsibilities of emergency medical teams, law enforcement, and other responding entities. For this research, we focus on the dedicated traffic incident management teams operated by departments of transportation or similar agencies and not other types of first responders.

The FHWA has established performance measures to develop a framework to quantify improvements to IMT operations and traffic (FHWA, 2000). Two specific measures related to this research are: first, roadway clearance time (RCT) is the time between the first recordable awareness of the incident to the time all lanes open for traffic flow; second, incident clearance time (ICT) is the time between the first recordable awareness of the incident and when the last responder has left the scene.

There is substantial evidence from numerous studies demonstrating the positive influence of TIM programs on traffic conditions, often measured using FHWA or similar performance indicators. One study of note, by (Schultz et al., 2019-04-01, 2019-04), highlights the substantial benefits of IMT implementations. The study took advantage of the interconnected data used by UDOT and the Utah Highway Patrol to estimate the reduction in traffic resulting from the rapid response of IMT units at crash sites. The findings were compelling: the deployment of IMT units notably decreased excess travel time, alleviated the user costs associated with congestion, and effectively reduced the volume of traffic affected by an incident BY HOW MUCH.

Kim et al. (2012-04-01, 2012-04), in a study of Maryland's Coordinated Highways Action Response Team (CHART) operations, devised a model using CHART's data to compute the costs associated with traffic delay. The team established a marginal cost-to-benefit ratio to discern the ideal fleet size. They first estimated the reduction in traffic delay under various highway response unit strategies. Subsequently, they calculated the costs of fuel consumption, emissions, and delay times and converted these into monetary values. These figures were then multiplied by the delay's duration to obtain the traffic delay's marginal costs. The research determined that each additional unit added provided a greater benefit than its associated cost until seven highway response units were deployed. This finding implies that while there is a significant cost-to-benefit ratio with the optimal number of response teams, the benefit diminishes when adding too many teams. Determining the ideal number of teams is a function of budget, network size, and incident frequency.

Skabardonis (1998) concluded in a study of the California Freeway Service Patrol (FSP) IMT service that, on average, total incident response time was 15 minutes longer when California Highway Patrol (CHP) units responded without the support of FSP units. Using a system to assign a cost per traveler per unit of time to vehicles in the observed area, the authors determined that FSP units had a cost-to-benefit ratio of 5:1. They also concluded that CHP officers spent less time on incidents (including vehicle breakdowns).

2.1. IMT Optimization

Given the compelling evidence that IMT programs improve traffic conditions and reduce costs for government entities and individuals, it becomes paramount to further research avenues to maximize these benefits. One effective strategy is the strategic placement of IMT units, optimizing their spatial effectiveness to enhance their impact.

Enhancing IMT programs often focus on the precise deployment of individual trucks and the strategic positioning of IMT depots—locations where inactive trucks await dispatch. For scenarios where IMT vehicles are actively on patrol, research often concerns designing an efficient service area or "beat." Various methodologies have been applied to tackle this allocation challenge. While some studies employ statistical models, incorporating a range of variables to maximize specific performance measures given constraints, others opt for digital modeling as a solution.

For instance, Lou et al. (2011-04-01, 2011-04) explored strategies aimed at minimizing IMT response time. They developed a mixed-integer nonlinear optimization model and proposed different algorithms to address this problem. The research modeled IMT units as roaming entities within specific freeway sections, aiming to determine the optimal unit locations for minimizing response times. Incident frequencies were generated randomly on the network, given mean and standard deviations of incident occurrence on each link in the network. The study focused on developing and optimizing these algorithms for broad implementation rather than focusing on any particular network or reducing response times in specific areas. They implemented a template "Sioux Falls" network into the model as a practical demonstration. Compared to the existing deployment plan in Sioux Falls, the algorithm-generated plans could potentially reduce total response time by 16.5-20.8%.

Ozbay et al. (2013-03-01, 2013-03) developed a model that provides information on resource allocation between "depots" or the staging areas of IMT units. A mixed-integer programming model with probabilistic constraints was developed in this research to approach the problem of IMT allocation within the various depots. Given that the probability of incident types on a network is known, IMT units are allocated to the incident scene, considering the future probabilities of incidents on the network. The model's objective is to minimize incident management costs while maximizing utility. The function is applied to a simplified South Jersey Highway network model to demonstrate the implementation of the model in IMT decision-making. Distribution of demand is based on traffic incident data from South New Jersey. In the test results, a number of depots and trucks assigned to each depot was found given a budget of $500,000 for the whole program. No comparison to existing depot and unit distribution was made; therefore, improvement because of the model was not quantified.

In his work, Ozbay et al. (2013-03-01, 2013-03) developed a model to inform resource allocation across New Jersey "depots," the designated staging areas for IMT units. This research employed a mixed-integer programming model with probabilistic constraints to address the challenge of IMT allocation within these depots. With known probabilities of different types of incidents occurring on a network, IMT units were strategically allocated to incident scenes while considering future probabilities of incidents on the same network. The goal of his model was twofold: to minimize incident management costs and to maximize utility. To demonstrate the model's practical applicability in IMT decision-making, it was implemented on a simplified South Jersey Highway network model. The model's demand distribution was based on traffic incident data from South New Jersey. The test results established an optimal number of depots and trucks assigned to each depot, given a program budget of $500,000. However, as no comparison was made to the existing depot and unit distribution, the precise improvement attributable to the model was not quantified.

Digital models of IMTs have been developed in the past with various software packages. Pal and Sinha (2002) developed a digital model to replicate IMT impacts on traffic conditions. Overall traffic time in the system was used as the performance indicator of the units. The software program was developed from scratch as existing programs at the time used in mesoscopic traffic simulation could not simulate incident response units. Various configurations of response vehicles were simulated using probability distributions of crash data, vehicle speed, and carrying capacity. Given the study results, suggestions were made regarding fleet size, hours of operation, patrol area design, and improvements regarding the dispatching policy.

These models, whether simulations or optimization problems, have been effective for what they were, but they fail to replicate real-world scenarios in the way that a MATSim simulation can. Simulations like MATSim provide the opportunity to incorporate real-world data and create more realistic networks and model drivers with tools like within-day replanning, which will be discussed in later chapters.

An important consideration in determining the optimal location for the IMT units to be stationed is the metric by which the IMT is judged. The FHWA has established performance measures by which IMTs were evaluated; however, some researchers have felt that other metrics proved helpful in specific scenarios. Pal and Sinha (2002) use a metric of total traffic time to analyze the model. Total traffic time is a practical approach as traffic slowdowns incur financial costs and other burdens on the individual and community (Bivina et al., 2016-01-01, 2016-01). An economic cost-based model is implemented in some research on incident management programs. Kim et al. (2012-04-01, 2012-04) use assumed values of fuel price and pollution externalities gathered from previous research to assign a monetary value to consequences of traffic delay in time and environmental costs. The study focuses on optimizing IMT programs in general based on specific budgets. Kim and Chang do not implement IMT units directly in their traffic simulation. The total traffic time and financial costs are similar in their fundamental nature in that financial costs are a function of the traffic delay. From another perspective, Ozbay et al. (2013-03-01, 2013-03) developed a statistical model where the costs associated with response times are minimized to meet budget constraints. Deciding what factors are most important to measure in the traffic simulation, like costs or response time, will help the decision-making process behind IMT allocation.

2.2. Incident Modeling

As outlined in the preceding section, previous attempts to understand optimal IMT deployment have been primarily based on ad-hoc models, specially constructed utility functions, or similar stand-alone efforts. Rarely has there been an explicit attempt to model traffic delay associated with incident management, at least partially because research modeling the effects of incidents on region-scale traffic networks is a recent innovation.

Traffic models are based on static assignment, dynamic assignment, or sometimes a combination of both. Static traffic assignment (STA) and dynamic traffic assignment (DTA) make the same behavioral assumption: drivers want to reach their destination in the shortest time possible. A static model achieves optimization by calculating route travel times, finding the shortest path, and adjusting routes toward equilibrium. The issue with static models is that they assume that all vehicles experience the same delay – in particular, traffic flow is anisotropic and obeys causality (Boyles, 2018-01-22, 2018-01).

Dynamic modeling also aims to achieve equilibrium through route choice. Dynamic modeling shows how congestion varies over time, and it bases equilibration on experienced travel times, not instantaneous travel times. According to Boyles (2018-01-22, 2018-01), "DTA is best applied when the input data are known with high certainty, only a few scenarios are needed, and detailed congestion and queueing information are critical" (Boyles, 2018-01-22, 2018-01, p. 28). A study on the effects of congestion conducted by Sisiopiku et al. (2007-01-01, 2007-01) highlighted the applications of simulation-based DTA modeling on incident management. Her study argues that dynamic assignment is preferred over static when considering incident modeling. Sisiopiku describes her methodology as follows:

> *The overall approach in this study is to use the DTA capabilities to support decision-making for incident management. Unlike static assignment methods, which are based on average daily traffic and fail to capture the dynamic process of an incident, DTA is particularly appropriate for studying short-term planning applications such as evaluating various incident management options (p. 111).*

In this study, Sisiopiku used a simulation-based DTA model to assess the impacts of designed incident scenarios. She evaluated the effectiveness of candidate incident management plans and the impacts of traffic operations and control strategies for the analysis period.

Sisiopiku initially conducted a base scenario under non-incidental conditions, which served as a benchmark for comparison. The follow-up scenario introduced an incident simulation, with the key caveat that drivers were kept uninformed about the incident. The duration and severity of the incidents were manipulated between different iterations of this second scenario. The third scenario mirrored the second but introduced information provision to the drivers. In this scenario, drivers were empowered to optimize their route through the incident zone and given access to information about pre-planned diversion paths. This information was relayed to the drivers through Variable Message Signs (VMS) strategically positioned upstream of decision points, as detailed in Sisiopiku's 2007 study.

The scenarios Sisopiku ran in Birmingham and Chicago revealed that travel time savings and traffic delay reduction could be achieved if information was provided to the agents following an incident. The study also shows how a simulation-based DTA model can simulate the impact of incidents on congestion and the impacts of different traffic operation and control strategies. The DTA tool Sisiopiku uses is Visual Interactive System for Transport Algorithms or VISTA, a tool commonly used in traffic modeling.

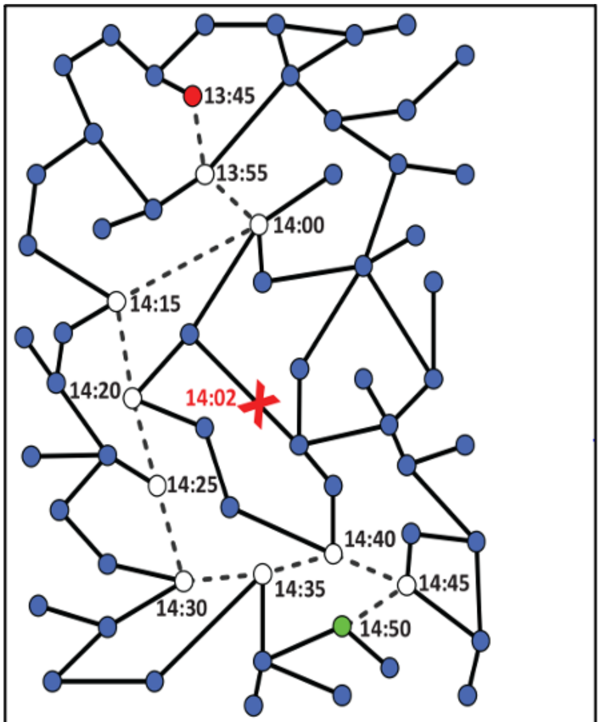
Echoing Sisiopiku's usage of VISTA, Wirtz et al. (2005-01-01, 2005-01) also undertook an in-depth analysis of this tool in his 2005 traffic incident simulation study. Wirtz elaborated on the limitations of both VISTA and DTA systems. As part of their route adjustment towards equilibrium, these systems presume all drivers possess flawless travel time information for routing to the user-optimal path. For instance, Sisiopiku, in her 2007 study, presumed a 100% compliance rate for the diversion routes provided to the drivers in her model. The validity of this assumption of perfect travel time information is partially contingent on the communication medium—radio traffic reports, the internet, or VMS. Wirtz's 2005 study revealed that "less-informed drivers spend more time traveling than necessary, representing a departure from the user-optimal traffic conditions simulated by VISTA." With the advancements in personal GPS information and its increased accessibility, drivers are more likely to identify an optimal path post-incident. It is critical to acknowledge that the assumptions embedded in a model, along with its scope and scale, significantly influence its functionality.

DTA models generally fall into two camps: microscopic and mesoscopic. Microscopic models run on small scales and track the trajectories of individuals. In contrast, mesoscopic models are more aggregated and simplify variations in behavior; they involve elements of both static modeling and dynamic microscopic models (Boyles, 2018-01-22, 2018-01). The level of detail in microscopic models makes them highly realistic but impractical for modeling large regions. A mesoscopic model that shows the paths of individual vehicles but ignores traffic flow issues like turn conflicts and lane changes would work well for modeling traffic flow over a greater area (Boyles, 2018-01-22, 2018-01).

VISTA is an example of a mesoscopic model which showcases DTA's capability for incident modeling. Microscopic models, like VISSIM, can also be used for incident modeling. Microscopic models can track precise locations of vehicles, driver behavior, and even vehicle characteristics; this makes the models extraordinarily realistic but impractical for modeling large regions (Boyles, 2018-01-22, 2018-01). In Australia, Dia and Cottman (2006-10-01, 2006-10) used VISSIM to evaluate incident management impacts on two arterial routes (Coronation Drive and Milton Road) connecting the western suburbs of Brisbane and the Central Business District. Another framework used for incident modeling is the traffic simulator JDSMART. This model was used by van Lint et al. (2012-01-01, 2012-01) for incident simulation and to study how roadway policies influence congestion.

MATSim, the Multi-Agent Transport Simulation Toolkit, has recently gained recognition as a helpful software for incident modeling, demonstrating a capacity for producing microscopic and mesoscopic models. Operating as an open-source framework, MATSim is designed to implement large-scale agent-based transport simulations. Using a mesoscopic queue-based strategy, agents representing individuals seek the shortest routes connecting their activities.

In his 2016 chapter of the MATSim manual, Dobler and Nagel (2016) emphasized the necessity and application of a within-day replanning tool within the MATSim context. He elaborated that while MATSim's iterative modeling approach fares well under ideal conditions and in achieving user equilibrium, it falls short when dealing with unexpected occurrences. This deficiency manifests as illogical behavior, such as pre-emptive route changes before the incident's actual occurrence. For example, Figure 1 illustrates a MATSim routing problem featuring within-day replanning. It depicts an agent (a simulated individual) navigating from the red dot to the green dot. A crash ensues along the agent's assigned route at 14:02. Due to the iterative approach; however, the agent switches to a different route at 14:00, two minutes before the crash. This inconsistency exposes the limitations of an iterative approach in modeling unanticipated behavior, underscoring the need for a within-day replanning method, which utilizes a single iteration for replanning rather than multiple.



(d) Network with exceptional event and adapted route.

Figure 1: Figure 1: Within-day replanning approach for a MATSim routing problem.

While iterative systems leverage best-response modules, within-day systems necessitate using a best-guess module. This approach means that travel times can be optimized to a stable state with an iterative approach, but this is not the case with a within-day approach. An inherent attribute of within-day replanning is that it does not converge to a user equilibrium, unlike an iterative process. Decisions, appearing optimal in the heat of the moment, often reveal themselves as suboptimal upon retrospective evaluation. Given the limited information available to the agents in a within-day system, they may not necessarily choose the path with the shortest travel time post-incident, as discussed by Dobler in 2016.

Replanning contains two categories: replanning an element of the activity and executing the replanned elements. Elements include the trip's start and end times, location, route, mode choice, or dropping of a trip entirely. The system can execute plans for in-the-moment events or those performed in the future. In a presently performed procedure, we cannot conduct all replanning actions (e.g., we can no longer alter the start time of an activity or the transport mode of a trip currently being performed) (Dobler and Nagel, 2016). Figure 2: Iterative and within-day replanning MATSim loop illustrates where within-day replanning fits within a MATSim loop.

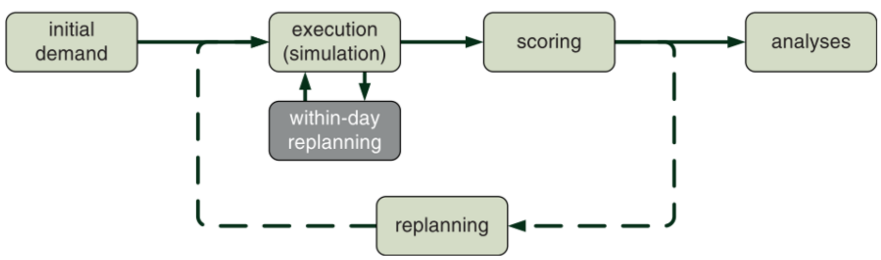


Figure 2: Figure 2: Iterative and within-day replanning MATSim loop.

An alternative to iterative or within-day replanning only approaches is to combine them. For example, we cannot thoroughly plan situations like parking or car-sharing, requiring iterative and within-day replanning methods. An agent can arrange a parking activity but cannot predict which parking spots will be available when they arrive. Thus, we use within-day replanning when the agent starts their parking choice.

In general, within-day or en-route replanning means that travelers replan during the day or on their route, meaning that the simulation needs to influence the agent while the network runs. **?** that we influence agents' decisions through loops or by having users' routes dependent on the next link they choose. Because going through all links and nodes at every step would be computationally challenging, we may set certain links to be non-active and removed from the computation (Dobler and Nagel, 2016). The two implementation methods Dobler described are plan-based implementation and replacing the agent.

In a plan-based implementation, a loop is used where each agent can deliberate in every time step. The agent can decide that they have nothing to deliberate and return immediately. Because the number of links is typically much smaller than the number of agents in a scenario, massive optimization is necessary to make the loop computationally efficient. For this reason, we could ask each agent to choose a link only when they need to decide.

Such event-driven planning requires the agents to be re-programmed to have enough capabilities to be oriented about themselves (i.e., be able to compute plausible routes). Agents will only need to perform such computation when replanning is triggered by an event like an emergency warning or unexpected congestion; otherwise, they will follow their usual daily plans.

Re-programing agents and implementing within-day replanning, as shown in Figure 2: Iterative and within-day replanning MATSim loop., requires the implantation of a *MobsimEngine*, which can be plugged into the mobility simulator seen in the execution phase of Figure 2: Iterative and within-day replanning MATSim loop (Axhausen et al., 2016-08-10, 2016-08). Dobler and Nagel (2016) describes it this way, "in every simulated time step, the QSim iterates over all registered *MobsimEngines* and allows them to simulate the current time step. Besides simulation of the traffic flows, those engines can also let agents start or end activities" (Dobler and Nagel, 2016, p. 193). The engines contain within-day replanning logic called *WithinDayEngine*, which helps track agents and adapt their plans (Dobler and Nagel, 2016). Not all agents need to compute plausible routes at every turn, so an *AgentSelector* selects the agents to be replanned. *AgentFilters* assist them in narrowing the search population (Dobler and Nagel, 2016). Lastly, *TravelTimeCollectors* are part of the *WithinDayEngine* and provide actual link travel times to the replanners by collecting and averaging travel times of agents that have recently passed a link during a given time (Dobler and Nagel, 2016). The elements described above make up the plan-based system.

A significant incident modeling, plan-based system study used MATSim to simulate traffic incidents (Kaddoura and Nagel, 2018-01-01, 2018-01). Their research explains that MATSim models transport users as individual agents. MATSim is iterative and allows users to adjust travel plans during a single iteration, from iteration to iteration, or both (Kaddoura and Nagel, 2018-01-01, 2018-01). Kaddoura and Nagel accessed their incident data via the HERE application programming interface for traffic incidents. This incident data included Traffic Message Channel (TMC) information indicating an incident's cause and severity. With such robust data, Kaddoura and Nagel could categorize incidents as long or short-term and model each accordingly in MATSim. Long-term effects include multiple-day lane closures, whereas short-term incidents affect transport supply for less than a day. Their simulation was based on an inner-city network in Berlin, Germany. Figure 3: Traffic incidents mapped on the Berlin network illustrates the type of incidents modeled and their severity. In this example, a crash on the southern inner-city motorway ring road led to a full road closure, and several construction sites caused partial capacity reductions.

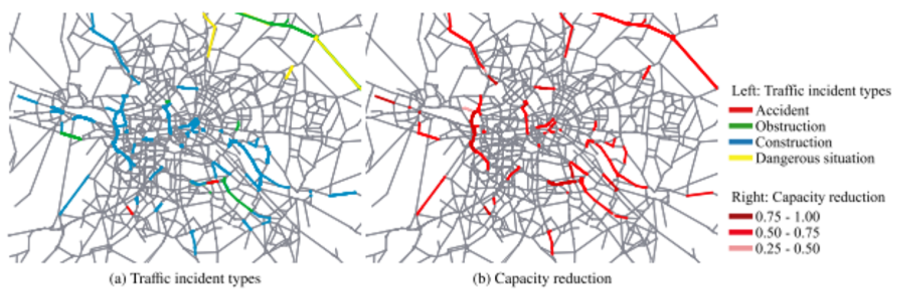


Figure 3: Figure 3: Traffic incidents mapped on the Berlin network.

Kaddoura and Nagel (2018-01-01, 2018-01) found that long-term traffic incidents increase traffic congestion and the average car travel time by 313 sec (+18%) per trip. Short-term traffic incidents increase the average travel time per car trip by another 136 sec (+8%). Additionally, they found that for 44% of all car trips, the agent's transport route contained at least one road segment for which the capacity or speed limit was reduced because of an incident. Their study concluded that networks in which transport users had high levels of knowledge about the incidents and resulting traffic congestion still experienced an increase in travel time caused by long and short-term incidents. Finally, Kaddoura and Nagel asserted that "accounting for traffic incidents makes the model more realistic, allowing for an improved policy investigation" (Kaddoura and Nagel, 2018-01-01, 2018-01, p.885). The modeling performed by Kaddoura and Nagel is just one example of research on MATSim's capacity for incident-based simulations.

A MATSim model developed by Li and Ferguson (2020-01-01, 2020-01) included various rescheduling options, such as departure time, mode choice, and trip cancellation. Their simulation found that if travelers received notice of an incident, they would either depart early from their place of origin or switch to public transport (Li and Ferguson, 2020-01-01, 2020-01). The process proposed by Li and Ferguson is beneficial because it allows agents to reassess their mode choice or route assignment based on the notice of a reported incident. Li and Ferguson show that users care about total travel time and travel time variability (risk tolerance to a certain degree). The receiving of notifications about incidents by agents impacted both factors. They concluded that "the provision of real-time traffic information is a useful approach to mitigating the side-effects of incidents through helping transport users efficiently adapt their day plans" (Li and Ferguson, 2020-01-01, 2020-01, p.96).

Additionally, they found that "most of the travelers notified of being affected by incidents are simulated to depart early or switch to public transport, which effectively reduces the average travel time delay caused by disruptions" (Li and Ferguson, 2020-01-01, 2020-01, p.96). Their findings validate the conclusions of

Sisiopiku et al. (2007-01-01, 2007-01) that making incident information available to agents leads to decreases in travel time and congestion. Like the studies already mentioned, there have been various modifications to and research on MATSim and its capacity.

In Thailand's capital, Bangkok, a study conducted by Peungnumsai et al. (2019) demonstrated the potency of the MATSim framework in portraying the impact of rush hour congestion on select traffic links. Peungnumsai ran various simulation iterations, loading the selected links with a different number of agents: 10, 100, and 500. The data collected and the subsequent analysis substantiated MATSim's capability to demonstrate the congestion-induced variations in travel time. Furthermore, it was observed that as the number of agents in the simulation increased, there was a proportional surge in computing time, physical memory usage, and the size of the output file. Despite the scale of these simulations being relatively small, MATSim has the capacity to simulate up to 10-100 million agents, encompassing various modes of transportation like bicycles, motorbikes, cars, buses, and taxis (Peungnumsai et al., 2019).

In a contrasting study conducted in Copenhagen, Denmark, Paulsen et al. (2018) utilized MATSim to contrast the reliability of automobile and railway travel times. His methodology involved using an extension of MATSim centered around an event-based public transport router, which facilitates optimal route selection for public transport users by comparing the effectiveness of routes over several iterations. Paulsen's simulation of travel times for both cars and trains yielded an interesting finding: passenger delays were significantly influenced by the adaptiveness of their chosen routes. However, he noted that passenger travel times tended to be more unpredictable than trains, which escalated with the degree of route adaptiveness. He concluded that the adaptiveness of route selection contributed to significant travel time fluctuations, a conclusion that aligns with the findings of Li and Ferguson (2020-01-01, 2020-01).

In essence, the studies encapsulated in Section 2.3 validate the effectiveness of the open-source software MATSim, in simulating traffic incidents, congestion, and travel times. This evidence accentuates how the proper application of MATSim or similar Dynamic Traffic Assignment (DTA) models can account for traffic incidents, thereby enhancing the realism of the models. This type of model, in turn, can facilitate more effective policy investigation, as noted by Kaddoura and Nagel (2018-01-01, 2018-01).

2.3. Summary

As explained in this section, there has been extensive research into IMT's effectiveness and ability to restore traffic flow following long- and short-term disturbances. Additionally, several studies have examined how to effectively model traffic incidents and show their impact on travel time, congestion, and mode choice. However, in these vast arrays of findings, there is a gap in research on modeling IMT effectiveness and incident impact on a loaded with realistic agents. As a result, it is difficult for researchers to understand how changes to incident generation or IMT availability may impact traffic conditions, for good or bad. In this research, we seek to combine these two strands, attempting to model incident response in a microsimulation framework to bring realism and detail to the IMT deployment question.

3. Methodology

3.1. Incident Response in MATSim

This section of the methodology outlines the model development for the Utah IMT Optimization project. As stated in sections 2.2 and 2.3 of the literature review, the model is designed to effectively demonstrate the effects of traffic incidents on the overall traffic flow and the subsequent influence of Incident Management Teams (IMTs) when integrated into the model.

We explain how incidents and IMT vehicles are represented within the MATSim model and discuss several adjustments made to the behavior of MATSim agents within the model configuration. Our approach to incident modeling primarily draws from and expands on the research of Kaddoura and Nagel (2018-01-01, 2018-01). For a more detailed understanding, refer to The Multi-Agent Transport Simulation (MATSim) textbook.

3.1.1. Network Change Events

Each link in a MATSim network possesses specific attributes, such as link type, length, number of lanes, free-flow speed, and capacity. It is essential to adjust one or more of these parameters to simulate unexpected events at a specific time during the simulation. The capacity to modify a network, as referred to in the MATSim textbook, is known as a Time-Dependent Network, and unforeseen incidents or any factors that alter the network's characteristics are termed Network Change Events (NCEs).

Section 6.1 of the MATSim textbook outlines how to adapt the parameters of a MATSim configuration file to allow for time-variant network attributes and how to implement network change events. These events can modify a link's free-flow speed, number of lanes, or capacity. To activate a network change event, the system needs to know the time of the event (startTime), the affected link(s) (link refID), the nature of the change (free-flow speed, lanes, or capacity), and the specific value of the change.

Within the context of the Utah IMT optimization problem, changes are triggered when an incident is reported and when an IMT arrives at the affected link. These changes will influence the link's capacity based on the incident data, which will be discussed in more detail in section 3.2.3. Unlike Kaddoura and Nagel (2018-01-01, 2018-01) 's work, this study does not consider long-term capacity reduction events such as road construction, focusing solely on short-term incidents like accidents or vehicle breakdowns. The diminished capacity of a specific link would typically affect both regular agents (those included in the baseline simulation scenario) and IMT agent vehicles. If a subnetwork is utilized, IMT trucks, similar to other emergency vehicles like ambulances and firetrucks, would be less affected by congestion caused by daily traffic or unexpected incidents.

The implementation of the MATSim within-day replanning module plays a significant role in the rerouting of other agents on the road after an incident.

3.1.2. Within-Day Replanning

« The concept of within-day replanning is applied to a certain extent in the model, as detailed in Chapter 30 of the MATSim textbook. However, I plan to delve deeper into this concept to ensure its correct application within our study. Subsequently, I will refine the wording of this section to accurately convey its implementation within our model. »

3.1.3. Vehicle Assignment

When an incident occurs within the MATSim simulation, one or more Incident Management Team (IMT) vehicles are dispatched to manage the situation. A dispatch algorithm determines the most suitable vehicle for the task. The model can select the IMT unit(s) based either on a least-cost path calculation that factors in congestion and link speed or the shortest path between the vehicle's location and the incident site. The chosen method will partially depend on how swiftly the IMT units can navigate through traffic. If a subnetwork is utilized, the IMT trucks would be less affected by congestion and free-flow speed, potentially making the shortest path calculation more suitable. Conversely, if an IMT moves through traffic like a standard vehicle, using a least-cost path calculator within the simulation would likely be the preferred option.

In the context of this project, the Utah IMT system operates in tandem with the Utah Highway Patrol system under the same dispatch service. IMTs in Utah are equipped with sirens and flashing lights similar to those on a highway patrol vehicle, and they operate within specific zones. For instance, there are multiple zones in Salt Lake and Davis Counties where IMT vehicles are distributed. Given that IMTs can navigate traffic like other emergency vehicles, the Utah Highway Patrol dispatch requests the nearest available vehicle(s) to respond to an incident when it occurs. It's worth noting that due to limited resources, an incident ideally requiring assistance from 2 or 3 IMT units may only receive one vehicle, potentially leading to longer management or cleanup times.

3.2. Incident Response

As discussed in Section 3.1.1, a critical element in simulating the effects of incidents on agents within the MATSim network is Network Change Events (NCEs). This mechanism, which illustrates how incidents can impact user behavior, will also be used to demonstrate how the reactions of IMTs influence agents' travel times and paths.

Once the vehicle assignment algorithm dispatches one or more IMT units to an incident, a decision must be made on what percentage of the incident link's capacity is restored upon the IMT's arrival. An arriving IMT can either hasten the restoration of the capacity to normal levels or enhance the capacity by a certain percentage 'X.' These adjustments hinge on the available incident data and findings from other research regarding IMT effectiveness.

Kim et al. (2012-04-01, 2012-04) discusses the cost-benefit ratio of different IMT fleet sizes, and other studies have attempted to gauge the duration of an incident's impact without an IMT and contrast that with the length of time that an incident affects traffic when an IMT is dispatched. Given the correct information or building upon certain assumptions, one can establish a capacity restoration factor to be applied upon a vehicle's arrival at an incident site.

Figure 4 below provides a potential example of how an incident, with no IMT response, might affect a network in comparison to scenarios where one IMT responds, followed by the response of a secondary unit.

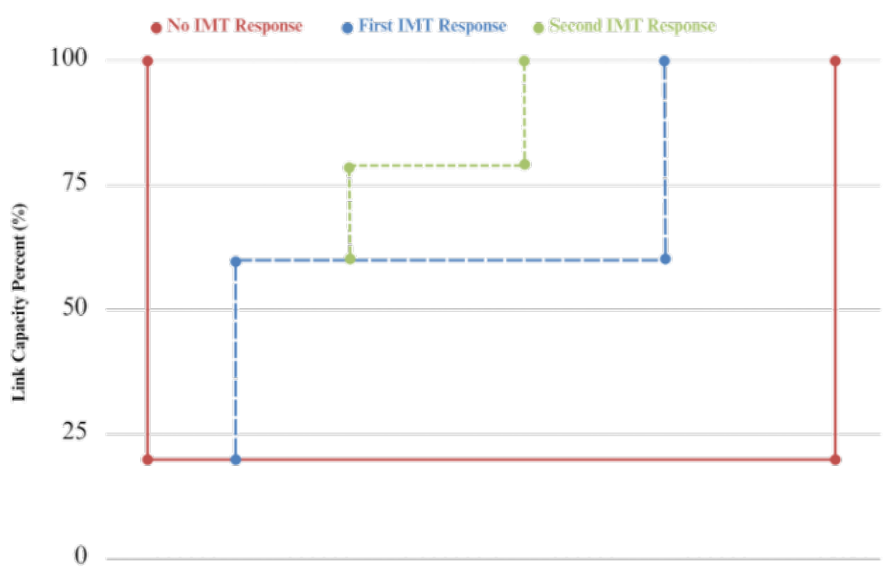


Figure 4: Figure 4: Changes upon arrival.

3.3. Simulation Scenarios

Loading incidents and IMT response vehicles into the Utah Optimization model is a significant aspect of this project's methodology. Another crucial element involves running scenarios to quantify the impact of both incidents and IMT arrivals. Various factors influence these quantitative comparisons. These include the type of network and plans files used during the simulation, the processed and selected incident data, and the locations and quantities of IMT vehicles included in the simulations. Each of these components builds on prior research related to IMTs in Utah, MATSim studies on Demand Responsive Transport (DRT), and transportation modeling research conducted by the Wasatch Front Regional Council in various traffic modeling projects throughout Utah.

3.3.1. Wasatch Front Base Scenario

In this section, we aim to outline the origins of the network and plans file and their usage in other research conducted by the Wasatch Front Regional Council (WFRC).

« Dr. Macfarlane has provided information about the source of these plans. I will review his notes before expanding this section. »

The network and plans have been calibrated and represent a typical day's traffic in the regions where most IMT vehicles operate.

3.3.2. Incident & IMT Scenario

We will detail the various scenarios we executed in this section, specifying the types based on the number of incidents and the quantity of Incident Management Teams (IMTs) involved. We will clarify why we chose to execute the specific number of tests and scenarios.

« Brynn has prepared a table detailing these different scenario types, which we could include here if desired. »

Essentially, we have six scenarios:

1. A baseline with no IMTs.
2. A baseline with no IMTs and increased incident frequency.
3. Current IMT resources with current incident frequency.
4. Current IMT resources with increased incident frequency.
5. Improved (added) IMT resources with the current frequency of incidents.
6. Improved IMT resources with increased frequency of incidents.

Our goal is to run at least ten days of simulations for each scenario.

3.3.3. Incident Data

« TO DO: summarize the methodology used by Joel Hyer and to describe where our incident data came from »

3.3.4. Incident Sampling

To determine the appropriate modeling of incidents for a given day, reflecting the current incident frequency, we analyzed the received incident data to create a distribution of incident count frequency for sampling.

We wrote code using Pandas in Python to read data into a data frame, remove duplicate entries, and manipulate the 'Call Received Time' and 'Call Type' columns. The data frame is then grouped by date and call type to count incidents. The result is a new data frame showing incident frequency per day. These frequencies are used to create a weighted distribution for sampling. To ensure reproducibility, the code utilizes a random seed value and performs random sampling by selecting ten days from the incident number distribution based on the calculated frequencies. The sample yields ten values that will be utilized in MATSim to determine the number of incidents to be generated in the simulation for ten different simulated days.

For our increased frequency scenarios, we aimed to assess the impact of a significant surge in daily incidents on the IMT system. To achieve this, we used the higher end of the 2022 data as a reference, including one day with 21 incidents, one with 20 incidents, two with 19 incidents, and two with 18 incidents. This approach allowed us to test the effectiveness and coverage of the IMT program under more extreme demand. Because this collection is limited to 6 days, we included one additional day of each incident count, choosing to simulate two days with 21 incidents, two days with 20 incidents, three days with 19 incidents, and three days with 18 incidents.

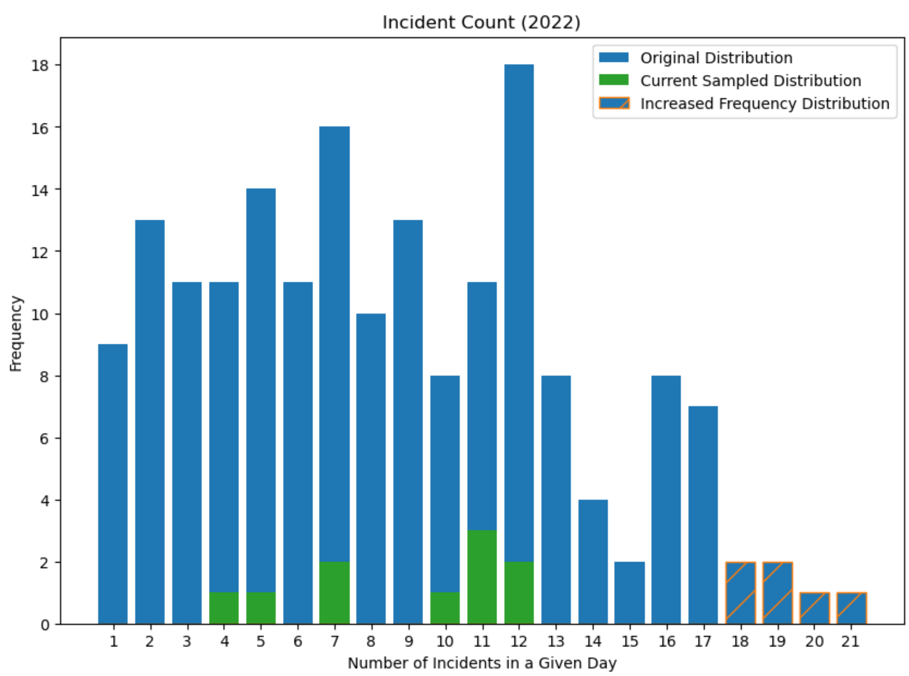


Figure 5: Figure 5: Incident Sampling.

3.3.5. Comparative Measures

« TO DO: Rewrite this section. Make it sound more academic. The goal is to provide a transition from the methodology to the results section of the paper »

As we transition from the methodology to the results, it is essential to underscore the measures employed for an exhaustive comparative analysis. Central to our examination is the metric of total vehicle hours of delay. While of considerable import, the average IMT vehicle arrival time assumes a secondary role in our analysis. Emphasis will be placed on delay durations for both incident and feeder links; the latter being defined as the connecting routes leading to incident sites.

Our inquiry extends to the variance in delay durations across diverse scenarios. We have systematically categorized the links according to their intrinsic types. A salient metric targets delay durations associated with 'motorway type' links. Concurrently, a comprehensive metric will delineate the total delay span across the entire network. It is paramount to recognize that while this overarching delay duration might be influenced by our adjustments to the MATSim model, other external variables could also play a role.

The forthcoming results section will elucidate these measures in detail, accentuating any modifications we've incorporated into the model. What follows should be regarded as a concise prologue, prepping the reader for an in-depth analytical exposition.

4. Results

4.1. Scenario Results from MATSim Simulations

The study utilized the MATSim model to conduct 20 simulations across three different scenarios: "Incidents", "Current", and "Increased". Within the "Incidents" scenario, a random subset of incidents was produced without any subsequent intervention from incident management teams (IMTs). The "Current" scenario included incidents paired with responsive measures from UDOT's existing fleet of 20 IMT vehicles. The "Increased" scenario is similar to the "Current" framework, yet it it equip with an additional grouping of 10 IMT vehicles, culminating in a fleet of 30 vehicles.

These distinct scenarios were compared internally as well as against a "Baseline" scenario devoid of any incidents or IMT presence. Cumulatively, 61 simulation scenarios were executed, each subjected to 450 MATSim iterations. This iterative approach ensured that a majority of scenarios gravitated towards a state where travel plans displayed minimal variance between successive iterations, effectively achieving an equilibrium in travel behavior by the simulation's conclusion.

Subsequent sections of this chapter are dedicated to analyzing the output results from these scenarios, emphasizing comparative metrics such as vehicle hours of delay (VHD), the ramifications of incidents, and the IMT response dynamics pertaining to these incidents.

4.2. Vehicle Hours of Delay

One of the principal metrics utilized to analyze the simulation scenarios is the Total Vehicle Hours of Delay (VHD). The analysis of vehicle hours of delay was divided into three tiers of investigation. First, the overarching network (termed "All Links"). Second, the links MATSim categorizes as motorway links — often referred to as freeway links. Lastly, the specific links where incidents occur, in addition to the two immediate upstream links. This cluster of links is labeled "Impact Links" for the purposes of this study.

Overall, it is apparent that the IMT vehicles' influence within the simulations is most apparent at the "Impact Link" level. However, their effects permeate every tier of analysis. While the outcomes of certain scenarios align with anticipated projections, others deviate from intuitive or assumed results. The subsequent analysis will commence with an exploration of the "All Links" scenarios.

4.2.1. Network Hours of Delay

Each scenario, with the exception of the baseline, encompasses ten distinct sub-scenarios. **?@tbl-network_delays_table** indicates the mean hours of delay for each scenario cluster. Additionally, it includes a comparative metric, showcasing the percentage deviation in VHD from the baseline scenario.

Within the array of scenario groupings, those equipped with an IMT fleet of 30 vehicles exhibited the most effective results, on average. Following closely were the scenarios reliant on the current fleet, and, as anticipated, the incident-only scenarios registered the maximal Total VHD values. An intriguing observation arises when evaluating the VHD in the context of incident frequency: the patterns do not align with conventional expectations. For instance, in the incident-only scenarios, the average total VHD for scenarios incorporating increased incidents escalated by approximately one percent compared to the scenarios representing the current incident frequency. Yet, when evaluating scenarios associated with both the existing and increased IMT fleet sizes, the distinction between the current and increased incident frequencies was notably marginal.

« TO DO: try to explain why it is that there is so little difference between the current and increased incident frequency groupings. Can it be attributed to the incidents that were selected? Is that something that you can discover when looking into the impacted links VHD? »

Given that the table reveals average delay values aggregated across multiple scenarios within each grouping, a graphical representation can offer enhanced clarity regarding the inherent variance within these data clusters. The ensuing figure illustrates the this data through various violin plots.

Within this visualization, each violin illustrates the density distribution of delay values. The increased width in certain sections of the violin signifies regions where a number of simulations converged around a specific delay value. Conversely, the narrow sections denote fewer simulations converging around that delay metric. To further contextualize each scenario, a dashed horizontal line

Table 1: **?(caption)**

```
# A tibble: 7 x 4
# Groups:   Scenario [4]
  Scenario  `Incident Frequency` `Total VHD` `Change In VHD (Percent)`
  <chr>     <chr>                      <dbl>                     <dbl>
1 Baseline  -                          74568.                      0  
2 Incidents Current                   103159.                     38.3
3 Incidents Increased                 104178.                     39.7
4 Current   Current                    96697.                     29.7
5 Current   Increased                  95678.                     28.3
6 Increased Current                    93769.                     25.7
7 Increased Increased                  93560.                     25.5
```

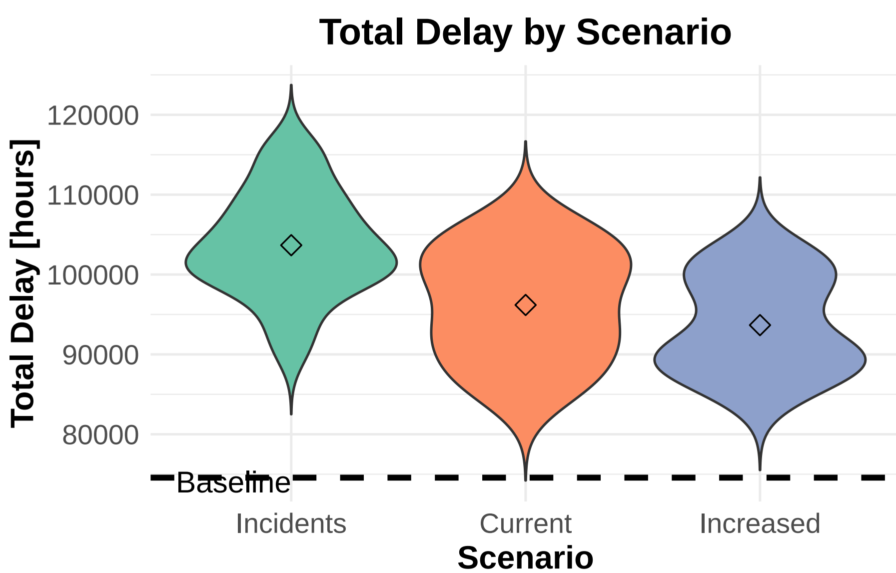


Figure 6: VHD for scenario groups in violins.

Table 2: **?(caption)**

```
# A tibble: 7 x 4
# Groups:   Scenario [4]
  Scenario  `Incident Frequency` `Total VHD` `Change In VHD (Percent)`
  <chr>     <chr>                      <dbl>                      <dbl>
1 Baseline  ""                        15335.                        0
2 Incidents "Current"                 24242.                       58.1
3 Incidents "Increased"               22321.                       45.6
4 Current   "Current"                 18924.                       23.4
5 Current   "Increased"               19176.                       25.1
6 Increased "Current"                 17569.                       14.6
7 Increased "Increased"               18327.                       19.5
```

has been superimposed, signifying the Baseline scenario, serving as a reference point for comparison. Additionally, the diamond markers situated within each plot symbolize the mean delay for all simulations in the respective scenario.

Upon inspection of these violins, several observations can be made. For instance, in the "Incidents" scenario, the delay distribution is characterized by a relatively constricted spread at the lower end, fanning out around the 100,000 mark, with the mean delay skewing closer to 104,000, influenced by the values approaching 120,000 total hours of delay. The distribution within the "Current" scenario exhibits significant variability, reflected in its consistent width. The scenario with the "Increased" IMT fleet manifests marginally reduced variability in comparison to the "Current" scenario, and contains pronounced sections around 90,000 VHD and 100,000 VHD.

While the preceding section discussed delays for the entire network, it's relevant to highlight that all simulated incidents occurred on motorway links, chiefly along the major interstates of Utah's Wasatch front. This includes key routes such as I-15, I-80, I-215, among other prominent freeways and highways. The following section delves into the simulation outcomes specifically pertaining to these motorway links.

4.2.2. Motorway Link Hours of Delay

Recognizing the utility of comparing average simulation performances, the table labeled `motorway_delays_table` below details the mean Total VHD for each grouping, categorized by scenario and incident frequency values.

Contrasted with the network_delays table, focusing solely on motorway links reveals that the average VHD surge for incidents-only scenarios relative to the baseline of the same links exceeds 45%. Interestingly, in comparison with the full network delay scenarios, both the "Current" and "Increased" IMT vehicle fleet scenarios demonstrated improved average performances on motorways, converging towards, and occasionally even dropping below, the baseline delay measures on these links.

Intriguingly, the trend discerned among the full network links (which presented a challenge in correlating additional incidents with increased delays) inverts in the context of motorway links. Here, the IMT scenarios seem to fare better (indicating reduced delays) in contexts with fewer incidents, and slightly worse in scenarios with incident incident counts. However, it's curious to observe that in the "Incidents" scenario, the mean delay across scenarios was notably poorer in contexts with twelve or fewer incidents than in those with a heightened incident tally.

For a more granular understanding of the variances within to the scenario groupings, the motorway_violin plot provides additional insights.

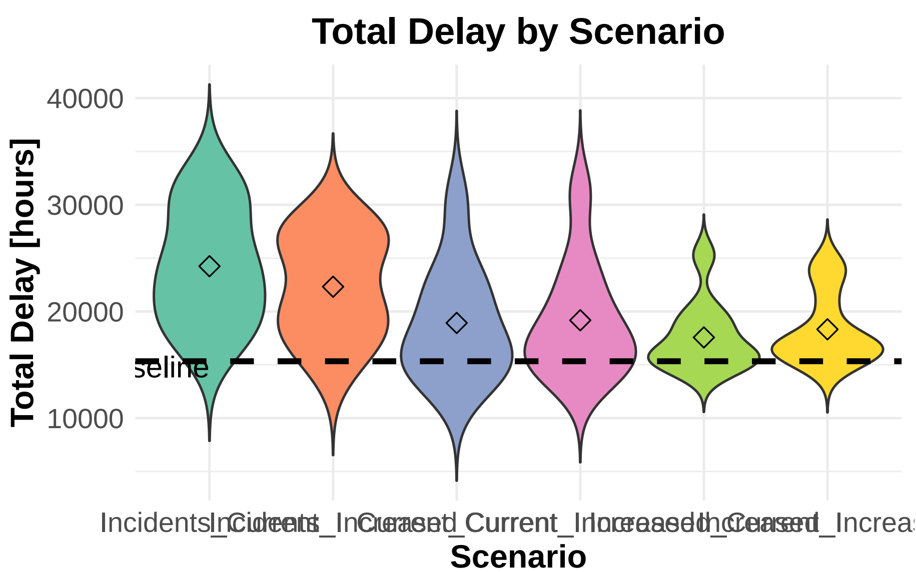


Figure 7: VHD for scenario groups in violins.

As depicted in the violin plot, both the "incidents-only" scenario groupings exhibit wide spans throughout their plots, signifying a pronounced variance in delays across the simulations. Notably, the plots for both the "Current" and "Increased" IMT fleet scenarios are wide near the baseline mean value, which hovers around 15,000 VHD. This expansion, however, diminishes as the scenarios transition to higher total delay hours. Particularly in outlier scenarios, the "Increased" fleet, equip with additional vehicles, seems to mitigate delay increases along the motorway links more effectively than is occasionally evident in the "Current" vehicle scenarios.

Continuing the discussion, the final tier for comparing VHD is the 'Impacted Links' on the network. These refer to the links where the simulated incidents take place, as well as the two links immediately preceding each incident link.

Table 3: **?(caption)**

```
# A tibble: 8 x 4
  Scenario  `Incident Frequency` `Total VHD` Average Delay Per Incident [hours~1
  <chr>     <chr>                      <dbl>                              <dbl>
1 Baseline  Current                     326.                               3.62
2 Incidents Current                    3808.                              42.3 
3 Current   Current                     723.                               8.03
4 Increased Current                     366.                               4.06
5 Baseline  Increased                   540.                               2.80
6 Incidents Increased                  3154.                              16.3 
7 Current   Increased                  1645.                               8.52
8 Increased Increased                  1115.                               5.78
# i abbreviated name: 1: `Average Delay Per Incident [hours]`
```

4.2.3. Impacted Links

Impacted links are described as the links where an incident occurs, along with its first two “Feeder” links. These are the two links through which traffic most commonly flows before reaching the incident motorway link. Given the variation in link lengths within the motorway, in certain instances, taking into account just two additional links may not adequately capture the delay prompted by a specific incident. Nevertheless, the `impacted_summary_table` offers significant insights about how delay on impacted links fluctuates based on the simulation scenario. For context regarding the table, Total VHD is computed by considering the duration of the incidents (from start to finish) and adding one hour post resolution of the incident. In the simulations conducted, IMT vehicles only enhance the capacity of the incident link, without shortening its duration. Therefore, for the ‘Incident Impact Time’, which encompasses the incident duration and an added hour, the delay values of the incident link and its two Feeder Links are aggregated to compute a ‘Delay from Incident [hours]’ variable, showcased in the subsequent scatter plot. To curate the summary_table, the values from all ‘Delay from Incident [hours]’ entries within a scenario and incident frequency group were summed. This sum equates to the Total VHD of delay value for each respective scenario. The results are presented below:

As observed in the table, the Baseline scenario is divide into two segments, ensuring a more precise comparison against the remaining three scenarios. Even though the Baseline scenario lacks incidents, its values stem from the cumulative delay times for the same links evaluated in other scenarios.

From the cumulative delay data, it’s clear that, in line with other VHD comparisons, the VHD in the Increased IMT scenario most closely mirrors the baseline. This is followed by the Current fleet scenarios and then the Incidents-only groupings. As expected, a rise in incident frequency leads to an increase in Total VHD. However, the consideration of additional links makes a direct comparison of these values less straightforward.

In another perspective, the 'Average Delay Per Incident [hours]' column divides the total VHD by the number of incidents within a given category (90 incidents in the current scenario and 193 in the increased frequency scenario). This calculation reveals a notable observation: when comparing the average delay per incident between the current and increased incident frequencies under the incidents scenario, there's a significant 160% increase in the Average Delay Per Incident. This suggests that the incidents selected in the current scenario might have been, on average, more impactful than those in the increased scenario.

For a more granular view, the scatter plot below organizes data by seed type. Incident numbers and seed values serve as y-axis labels (e.g., "12_141" indicates a scenario with 12 incidents associated with the seed value 141). The scatter plot is presented as follows:

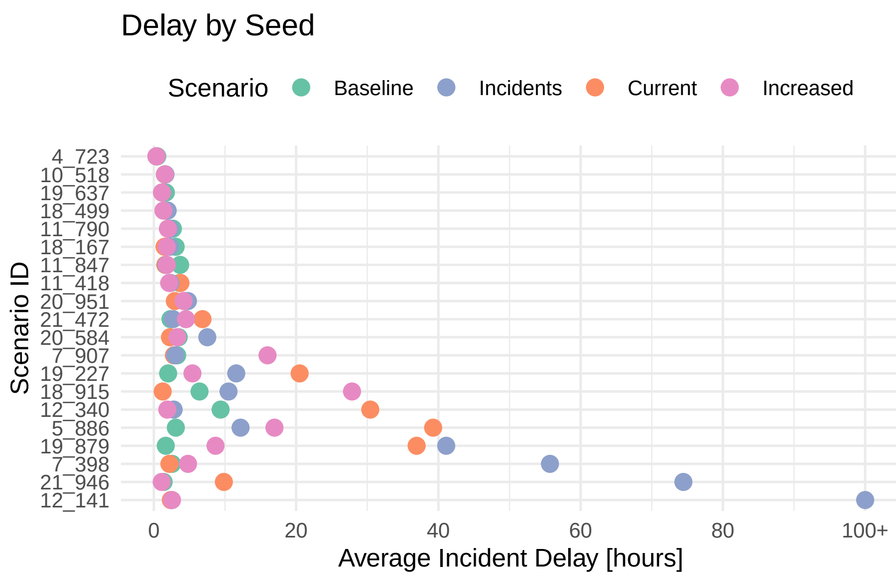


Figure 8: Average VHD per incident sorted by Seed.

The scatter plot provides deeper insight into the nuances of the average incident impact calculations. In a manner similar to the Impacted Links Table, the scatter plot presents delay in terms of average delay per incident, which averages the delays from the incident links and their corresponding feeder links. At first glance, the data points representing the Baseline and Increased-IMT scenarios (in pink and green) seem to situate to the left of the blue dots depicting the Incidents-only scenarios. However, upon closer examination, one might discern that in certain scenarios, the Current-Fleet, Improved-Fleet, and occasionally both, perform sub-optimally compared to the Incidents-Only scenarios. This might initially appear counter intuitive, hinting at the possibility that factors beyond link capacity can influence delay. There exists an inherent randomness in

MATSim's iterative process. The manner in which agents re-plan their journeys might, at times, influence delay as significantly, if not more, than variations in link capacity stemming from incidents and IMT arrivals. Notably, for the four Scenario IDs with the highest Average Incident Delays, the IMT units appear to substantially reduce the average delay on the affected links.

Moving ahead, another crucial variable emerges: the performance metrics associated with the IMT trucks. Such metrics encompass total travel time, the average distance traversed by each truck, and their average response time. Similar to VHD, these truck-related metrics might hold significance for UDOT and other transportation agencies. They will be elaborated upon in the subsequent section.

4.3. IMT Vehicle Analysis

Equally critical to understanding how IMT implementation affects agent delay and travel time is assessing the efficacy of IMTs in reaching their intended destinations. This results segment delves into truck travel behavior, capturing metrics such as average travel times and distances, along with their typical incident response times. The analysis encompasses both the Current-IMT-Fleet scenarios and the Increased-IMT-Fleet scenarios—the latter introduces 10 more vehicles to the pre-existing fleet of 20. Before delving deeper, some context regarding the positioning of these vehicles within the network and their operational hours.

« TO DO: Consider relocating the ensuing IMT setup section to the methodology chapter. Also, decide on the sequencing of the IMT Vehicle Analysis and the Vehicle Hours of Delay section for better flow. »

4.3.1. IMT Vehicle Setup

The Utah Department of Transportation's current IMT fleet is organized into three zones corresponding to the three counties they serve within the Wasatch Front: Davis, Salt Lake, and Utah counties. Figure 6, titled "IMT Starting Locations," illustrates the boundaries of each county and the starting points for both existing and new IMT vehicles.

In this figure, the existing vehicles are represented by circles, while stars indicate the new additions. These starting locations are designed to ensure a roughly even distribution throughout each respective county based on shift types—either day or afternoon. This arrangement doesn't exactly mirror the real-world starting points for IMT truck drivers, who often begin their shifts from their homes. However, as the majority of their work is concentrated along major interstates like I-15, I-80, and I-215, and given the variability in starting locations from day to day, positioning them along these primary routes made sense for the given MATSim Scenario simulations. Importantly, the "Increased-IMT" scenario includes all the vehicles from the "Existing" or "Current" fleet, with an additional 10 new vehicles distributed across the three counties.

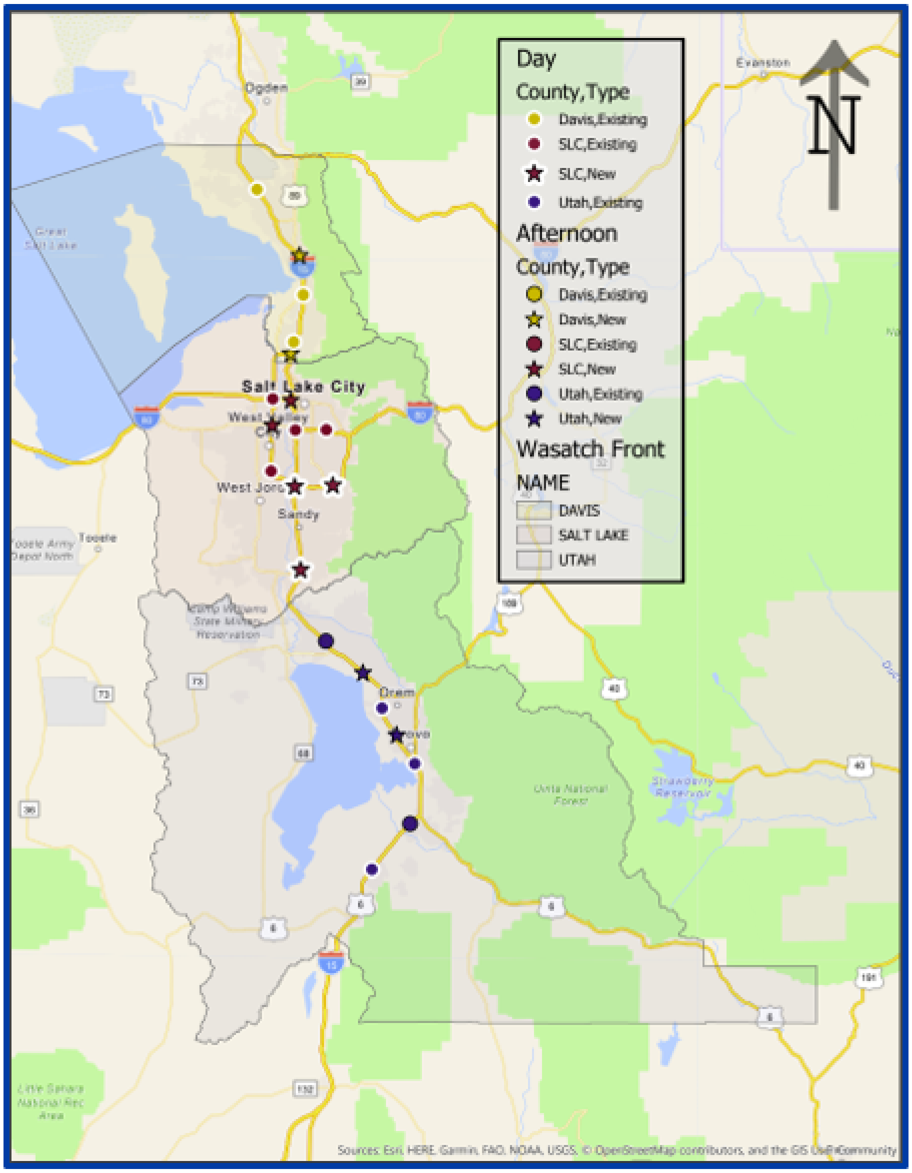


Figure 9: IMT Starting Locations.

The focus of our investigation isn't necessarily on the influence of starting locations on IMT effectiveness. Instead, the focus is an analysis of the potential impacts of increasing the number of vehicles in the Incident Management team fleet, assuming these vehicles are distributed in a roughly equidistant manner.

Additionally, it's important to mention vehicle scheduling. All three counties utilize both day and afternoon shifts. In Salt Lake and Davis counties, the day shift typically spans from 6:00 AM to 2:30 PM, with the afternoon shift running from 2:00 PM to 10:30 PM. In contrast, vehicles in Utah County operate from 6:00 AM to 4:30 PM and from 9:30 AM to 8:00 PM. These timeframes, combined with the starting links for each scenario, are adjustable parameters within the trucks file for the MATSim scenario runs.

In practice, IMT vehicles rarely cross county borders during operations since they collaborate closely with the Utah Highway Patrol (UHP) dispatch service. This service typically refrains from directing vehicles across counties. While MATSim allows for setting such virtual boundaries, we didn't apply this constraint to our established network. This means that, based on proximity to an incident, an IMT vehicle might move from Davis to Salt Lake County or from Salt Lake to Utah County and vice versa. With the vehicle configurations clarified, our focus shifts to evaluating the performance of these vehicles across the 20 operational scenarios.

4.3.2. IMT Travel Time

Travel times for IMT trucks can be extracted from the event files, which are produced as a standard MATSim output. These files provide insights into the distance and time traveled by each IMT vehicle. Utilizing this truck travel data, plots were generated to illustrate the average travel times and distances for each dispatched truck within a given scenario. Figure **?** illustrates the average travel time for each dispatched vehicle:

Figure **?** indicates the average travel time per scenario for each dispatched truck. In every scenario, the cumulative travel time for all dispatched vehicles was computed, followed by division by the count of trucks deployed. Furthermore, an analysis of the **?** data reveals that scenarios with an "Increased" fleet of 30 vehicles generally dispatched more trucks than scenarios with a fleet of only 20 vehicles. A nearly analogous methodology was employed to generate the **?** discussed in the subsequent section.

4.3.3. IMT Travel Distance

As with the variation in truck_time across different scenario alternatives, there is a clear distinction between 'Increased' and 'Current' IMT fleet scenarios in terms of the average distance traveled per dispatched vehicle. These results are visualized in the Figure **?**.

The data presented in the above figure underscores a direct correlation between an increased number of vehicles and a decrease in average distance traveled per truck. Notably, the "Increased" vehicle fleet benefited in both time and

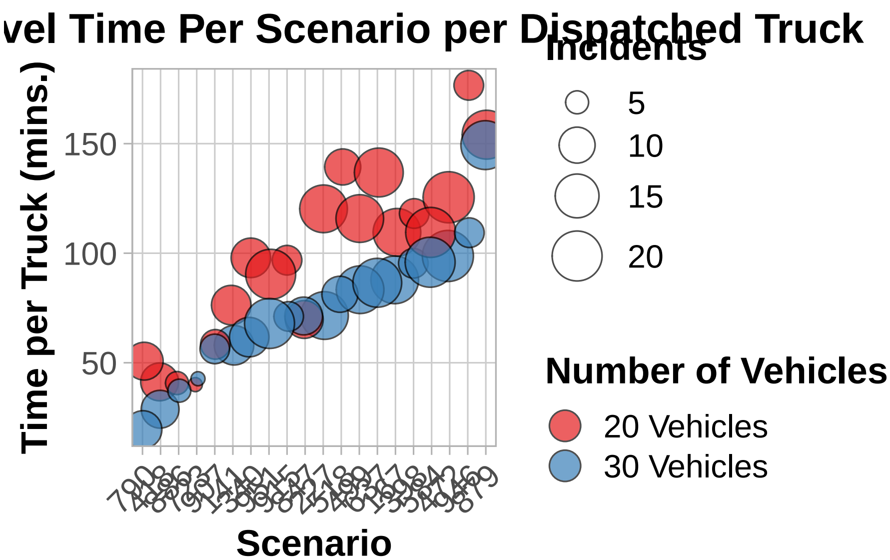


Figure 10: Average Time Traveled Per Scenario per Dispatched Truck

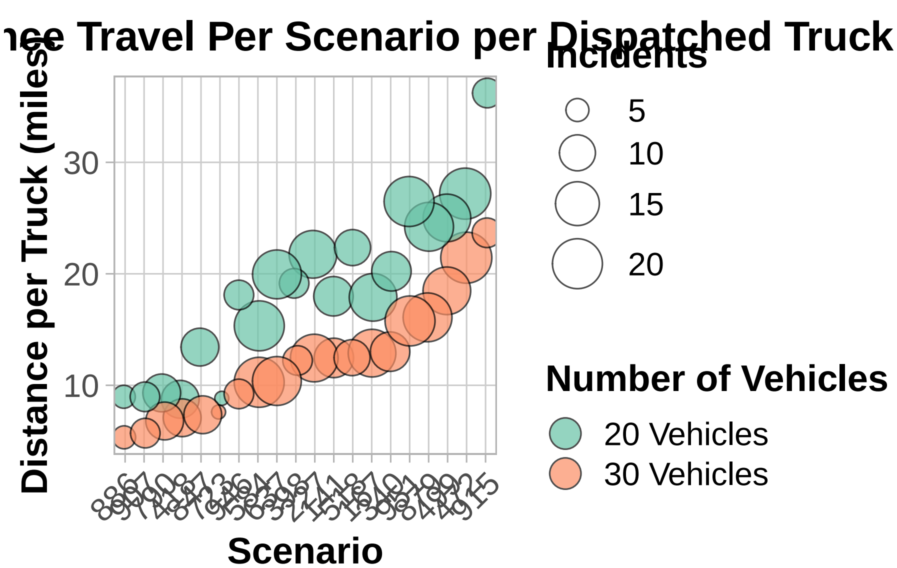


Figure 11: Average Distance Traveled Per Scenario per Dispatched Truck

distance scenarios by commencing from identical locations as the "Current Fleet" scenarios. This advantage was made more noticed by the addition of vehicles to bridge the spatial intervals between the existing vehicles.

Altering the starting locations of the vehicles or having them circulate in a route, as opposed to commencing their activities from a stationary location, could potentially influence both the time and distance traveled in either a favorable or adverse manner. However, it's pertinent to note that the Utah Department of Transportation was not principally focused on determining the "optimal" starting location for IMT vehicles in this research. While this aspect was not explored in the present study, it presents an intriguing avenue for future investigations using the IMT deployment MATSim package associated with this report.

4.3.4. IMT Response Times

« TO DO: In this section, we will present a detailed analysis of the average vehicle response time to each incident, based on the data visualized in a plot prepared by Brynn. Upon completion of her NFS work, she will further elaborate on the findings and their implications. »

« TO DO: For optimal comprehension and flow, it is important to determine the most suitable sequence for presenting the results. The chosen order will ensure better transitions from the methodology section and will set the stage effectively for the conclusion.»

5. Conclusions

This section need not be overly long. You should address any limitations of your results, such as dependence on underlying assumptions or geographic scope. You should also provide a map for future research.

Finally, you should underline the contributions of this work and any practical relevance.

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