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SIMULATING INCIDENT MANAGEMENT TEAM RESPONSE AND PERFORMANCE

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RESEARCH
UDOT
Keeping Utah Moving
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DISCLAIMER

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Gregory S. Macfarlane, Daniel Jarvis, Brynn Woolley, Grant G. Schultz

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Department of Civil and Environmental Engineering
430 Engineering Building
Provo, UT 84602

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16. Abstract

The effectiveness of Incident Management Teams (IMT) in reducing the duration and impact of traffic incidents is well documented. The capacity of large-scale simulation models to illustrate the negative effects of these incidents on vehicle delays and excess user costs (EUC) is also widely recognized. However, there is a gap in research integrating large-scale simulation modeling with IMT performance analysis. This study uses the Multi-Agent Transport Simulation (MATSim) framework to simulate the impact of incidents and evaluate the performance of IMT across the regional network of Utah's Wasatch Front, analyzing their operation in various hypothetical situations.

Our findings validate the role of IMT in decreasing delays and EUC. The simulation also investigates the potential effects of increased incident frequency and IMT expansion, revealing that more incidents increased delays, whereas additional IMT units can mitigate these effects and improve response times. The MATSim model we developed demonstrates the potential of dynamic large-scale modeling to evaluate incident management strategies in ways that previous studies did not. This model could serve as a valuable tool for further evaluating the performance of Utah's IMT program, with the potential to offer new perspectives on optimizing team deployment and scheduling efficiency.

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UNIT CONVERSION FACTORS

SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
°C	Celsius	1.8C+32	Fahrenheit	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for the International System of Units. (Adapted from FHWA report template, Revised March 2003)

LIST OF ACRONYMS

DTA	Dynamic Traffic Assignment
EUC	Excess User Costs
IMT	Incident Management Team
FHWA	Federal Highway Administration
MATSim	Multi-Agent Transport Simulation
NCE	Network Change Event
RCT	Roadway Clearance Time
RT	Response Time
UDOT	Utah Department of Transportation
UHP	Utah Highway Patrol
VHD	Vehicle Hours of Delay
VISTA	Visual Interactive System for Transportation Algorithms

EXECUTIVE SUMMARY

The effectiveness of Incident Management Teams (IMTs) in reducing the duration and impact of traffic incidents is well documented. The capacity of large-scale simulation models to illustrate the negative effects of these incidents on vehicle delays and excess user costs (EUC) is also widely recognized. However, there is a gap in research integrating large-scale simulation modeling with IMT performance analysis. This study uses the Multi-Agent Transport Simulation (MATSim) framework to simulate the impact of incidents and evaluate the performance of IMTs across the regional network of Utah's Wasatch Front, analyzing their operation in various hypothetical situations.

Our findings validate the role of IMTs in decreasing delays and EUC. The simulation also investigates the potential effects of increased incident frequency and IMT expansion, revealing that more incidents increased delays, whereas additional IMT units can mitigate these effects and improve response times.

The MATSim model we developed demonstrates the potential of dynamic large-scale modeling to evaluate incident management strategies in ways that previous studies did not. This model could serve as a valuable tool for further evaluating the performance of Utah's IMT program, with the potential to offer new perspectives on optimizing team deployment and scheduling efficiency.

1.0 INTRODUCTION

Incident Management Teams (IMTs) are service vehicles that collaborate with highway patrol units to manage traffic after an incident and provide timely roadside assistance. They are strategically important for improving highway operations, particularly during peak traffic times, helping to effectively alleviate congestion and associated user costs. Capable of quickly addressing a range of incidents from minor vehicle breakdowns to severe multi-car collisions, IMTs are crucial in controlling traffic and restoring normal flow on the roadways.

States like Utah have long benefited from IMT programs, experiencing notable reductions in congestion and traffic-related costs (Bennett et al., 2022). The effectiveness of IMTs, influenced by factors such as response times (Bennett et al., 2021), fleet size (Kim et al., 2012), and deployment locations (Ozbay et al., 2013), is well documented. However, the current understanding primarily stems from ad-hoc models and independent initiatives, leaving a gap in regional-scale traffic delay modeling associated with incident management.

A study by Kaddoura & Nagel (2018) highlights the efficacy of large-scale traffic models in evaluating regional incident impacts, showing increases in congestion and travel times in a simulated network. However, it doesn’t assess the effects of IMT strategies. Our research aims to fill this gap by integrating IMT data into a large-scale regional traffic model, focusing on the impacts of traffic incidents and IMT interventions within such a simulated network.

In this research, we present a model of IMT responses to incidents on freeways in the Wasatch Front region of Utah. The model uses the Multi-Agent Transportation Simulation (MATSim) framework and a custom module we developed to simulate incidents, IMT response, and evaluate IMT effectiveness. We then apply this module to several scenarios including different combinations of incidents as well as differing availabilities of IMT vehicles. These scenarios suggest that IMTs can contribute to substantially reduce incident-related vehicle delay, and illustrate that analytical approaches to forecasting their impacts are possible.

The report is organized into several chapters. Chapter 2 contains a discussion of previous research into IMT effectiveness and optimization. Chapter 3 describes the simulation and scenario construction, while Chapter 4 presents the findings of the analysis alongside a discussion of their implications. Chapter 5 concludes the report with an outline of future research motivated by this study’s limitations, and Chapter 6 contains specific recommendations to UDOT for the implementation of this report’s findings.

2.0 LITERATURE REVIEW

Traffic incident management in general—and IMTs in particular — are not strictly new innovations. The Federal Highway Administration (FHWA) publishes the *Traffic Incident Management Handbook* (Owens et al., 2010), 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 (Owens et al., 2010, pp. 1–1).

The handbook details the process of how to implement a traffic incident management program as well as improve it. It 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 on other types of first responders.

FHWA has established performance measures to develop a framework to quantify improvements to IMT operations (Owens et al., 2010). A specific measure related to this research is roadway clearance time (RCT): the time between the first recordable awareness of the incident and the time all lanes open for traffic flow. Numerous studies have assessed the impact of traffic incident management programs on traffic conditions, utilizing the performance measures provided by FHWA. A particularly noteworthy study conducted by Hadfield et al. (2021) explores the relationship between IMT response time (RT) and RCT. This research leveraged interconnected data from the Utah Department of Transportation (UDOT) and the Utah Highway Patrol (UHP), aiming to quantify the traffic improvements resulting from swift IMT interventions at incident sites. Analyzing 63 incidents, the study found that just a one-minute delay in IMT RT correlated with a 0.8-minute increase in RCT. This delay also impacted an additional 93 vehicles, added roughly 34.6 minutes to the network’s total estimated travel time, and resulted in an extra $925 in excess user costs (EUC). Hadfield et al. (2021) established a clear connection between timely IMT responses and improved traffic conditions, highlighting the importance of rapid intervention.

Skabardonis (1998) confirmed the effectiveness of IMTs in their study, concluding that IMTs in California effectively reduced incident RT and EUC. Skabardonis found that, on average, total incident RT was 15 minutes longer when California Highway Patrol responded without the support of IMTs. Using a value of time from the Texas Transportation Institute's 1998 Urban Mobility Report (Schrank and Lomax, 1998) to assign a cost to vehicles in the observed area, the authors determined that IMT units had a cost-to-benefit ratio of 5:1. They also concluded that patrol officers spent less time on incidents (including vehicle breakdowns) when assisted by IMT services.

2.1 IMT Optimization

Given the evidence that IMT programs improve traffic conditions and reduce costs for government entities and individuals, it makes sense to further research avenues to maximize these benefits. One possible strategy is the strategic placement of IMT units: optimizing their spatial effectiveness to enhance their impact. Enhancing IMT programs often focuses on the precise deployment of individual units and the strategic positioning of IMT locations where inactive teams await dispatch. For scenarios where IMT vehicles are actively on patrol, research often focuses on designing an efficient service area. 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, others opt for digital modeling as a solution.

For instance, Ozbay et al. (2013) designed a mixed-integer programming model with probabilistic constraints to optimize the allocation of IMTs across "depots" or staging areas in New Jersey. This innovative approach, grounded in known probabilities of various incident types, strategically positions IMT units to respond to incidents in the shortest time considering future incident probabilities on the network. The primary goals were to minimize incident management costs and maximize the likelihood that every incident receives assistance. The model was applied to a simplified New Jersey highway network, utilizing traffic incident data from the region to inform demand distribution. Through this application, an optimal number of depots and IMT assignments were determined. However, the lack of a comparative analysis with pre-existing depot and unit distributions meant that the exact improvements yielded by the model remained unquantified.

Where Ozbay et al. (2013) focused on optimizing the IMT allocation in specific zones, others have researched their effectiveness as roaming entities. Lou et al. (2011) developed a mixed-integer nonlinear optimization model and proposed different algorithms to minimize the RT of IMTs. They modeled IMTs within specific freeway sections. Incident frequencies were generated randomly on the network, given the 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 RT in specific areas. They implemented a template 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 RT by 16.5-20.8%.

Each of the studies mentioned attempts to understand optimal IMT deployment based on ad-hoc models, specially constructed utility functions, or similar stand-alone efforts. While their results provide valuable insights, they might be limited in their scope, as they do not explicitly attempt to model the traffic delay associated with incident management at a large scale. Research modeling the effects of incidents on region-scale traffic networks is a recent innovation, providing a more holistic view of their impact. This approach is potentially beneficial for comprehensively assessing the effectiveness of IMTs and paves the way for our subsequent discussion in Section 2.2 where we will discuss the advancements and applications of this innovative research domain.

2.2 Incident Modeling

The majority of traffic models used to study the impacts of incidents and incident management are Dynamic Traffic Assignment (DTA) models, which dynamically load individual vehicles with pre-determined paths onto networks (Chiu et al., 2011). This is in contrast to static network models that distribute loads within periods and do not consider temporal or dynamic effects. These models demonstrate how congestion and travel times fluctuate over time, varying for different network users. The capability to represent travel time variance makes DTA models particularly advantageous for depicting the unpredictability of incidents. A study conducted by Sisiopiku et al. (2007) illustrated how DTA was particularly suited to evaluate traffic and user delay associated with incidents:

> The overall approach in this study is to use the DTA capabilities to support decision-making for incident management. DTA is particularly appropriate for studying short-term planning applications such as evaluating various incident management options (Sisiopiku et al., 2007, p. 111).

In their study, the authors employed a DTA model to understand the impacts of diverse incident scenarios and to assess the effectiveness of potential incident management strategies and traffic control methods. The research commenced with a baseline scenario under standard conditions without incidents, establishing a reference point for evaluating incident impacts. Subsequent scenarios simulated capacity-reducing incidents without providing alternate or diverted routes to the simulated driver agents, and included variations in the duration and severity of the incidents. The final scenario replicated the same incidents, but provided the simulated drivers flexibility to dynamically divert to pre-set diversion routes if it was possible. This enabled the simulated drivers to optimize their routes and access preplanned diversion paths, with guidance from variable message signs or other information sources. Conducted simultaneously in Birmingham, Alabama and Chicago, Illinois, the study illustrated that providing drivers with incident information could result in travel-time savings and reduced traffic delays, and it also highlighted the DTA model's subtlety in simulating the effects of incidents and evaluating traffic management control strategies. Specifically, DTA allowed the drivers to adapt to vehicle incidents with new, shorter routes; a static model that does not allow for temporal variation in path costs or path diversion could substantially overestimate the EUC related to capacity-reducing incidents.

Sisiopiku et al. (2007) used the Visual Interactive System for Transport Algorithms (VISTA) as their specific modeling tool. Despite its efficacy, VISTA was critiqued by Wirtz et al. (2005) for its inherent assumption that all drivers have perfect travel-time information for routing to the optimal path. For example, Sisiopiku et al. assumed a 100% compliance rate with the provided diversion routes in their model. However, the research by Wirtz et al. (2005) revealed that "less-informed drivers spend more time traveling than necessary, representing a departure from the user-optimal traffic conditions simulated by VISTA" (Wirtz et al., 2005). This critique does not invalidate the findings of Sisiopiku et al. (2007) but highlights the limitations of VISTA in reflecting real-world travel behavior.

VISTA is categorized as a large-scale, or mesoscopic, model suitable for modeling extensive networks. Conversely, small-scale, or microscopic, models capable of tracking precise vehicle locations, driver behavior, and vehicle characteristics, offer a highly realistic representation but are impractical for large regions (Chiu et al., 2011). In Australia, Dia & Cottman (2006) used a commercial simulation model, VISSIM, to assess the impacts of incident management on two arterial routes connecting the western suburbs of Brisbane to the Central Business District. Although VISSIM is a primary traffic modeling tool for UDOT, its detailed precision renders it impractical for modeling the regional impacts of traffic incidents and IMT along the Wasatch Front as a whole. Given this research's scope, a large-scale dynamic model would likely be the most suitable choice.

Interestingly, Pal & Sinha (2002) developed a model to replicate the impacts of incidents and the benefits of IMTs on traffic conditions in Indiana, utilizing overall traffic conditions as the performance indicator for IMT effectiveness. Various configurations of response vehicles were simulated, incorporating probability distributions of crash data, vehicle speed, and roadway carrying capacity. The study's results informed recommendations on fleet size, operation hours, patrol area design, and dispatch policy improvements. However, since the mesoscopic traffic simulations used in the study could not simulate incident response units, Pal & Sinha (2002) had to create their model from scratch. Unfortunately, their model and methodology seem tailored specifically for their study and may not be applicable to this project's context.

Similar to VISTA, MATSim stands as another large-scale modeling system that has proven effective in conducting large-scale incident simulations. While VISTA and MATSim both have the capability to simulate the regional impact of traffic incidents, MATSim presents attributes that could potentially offer a more accurate representation of real-world scenarios and driver behaviors. Also, contrary to the model crafted by Pal & Sinha (2002), MATSim operates as an open-source framework, making it ideal for adapting to different scenarios. Notably, MATSim facilitates the integration of real-world data, enhancing the authenticity and precision of network simulations. This capability is particularly pertinent to this project, as prior research conducted by Schultz et al. (2023) has made recent UDOT incident and IMT data available, which could be integrated into the simulation model for more robust and realistic results. Although MATSim has been employed to assess network impacts of incidents, its application in incident management studies remains largely unexplored, presenting an opportunity for further investigation and potential breakthroughs in the field.

Kaddoura & Nagel (2018) conducted a comprehensive study on incident modeling using MATSim, representing transport users as individual agents within an iterative framework that allows for adjustments to travel plans both within and between iterations. They accessed incident data from the regional emergency services channel coupled with data derived from the HERE connected vehicle network. This rich dataset enabled the classification of incidents as either long-term, such as multiple-day lane closures, or short-term, affecting transport supply for less than a day. Applying their model to an inner-city network in Berlin. Figure 2.1 illustrates the modeled incident severities by capacity reduction.

Figure 2.1: Traffic incidents mapped on the Berlin network (Kaddoura & Nagel, 2018)

Kaddoura & Nagel found that long-term traffic incidents increase traffic congestion and the average car travel time by 313 seconds (+18%) per trip, with higher values in peak demand periods. Short-term traffic incidents increase the average travel time per car trip by another 136 seconds (+8%). Additionally, they found that, for 44% of all car trips, the routes used by the agents contained at least one road segment for which the capacity or speed was reduced because of an incident. Their study concluded that even for networks in which transport users were aware of the incidents and resulting traffic congestion, users still experienced an increase in travel time caused by both long- and short-term incidents. Finally, the authors asserted that "accounting for traffic incidents makes the model more realistic, allowing for an improved policy investigation" (Kaddoura & Nagel, 2018, p. 885). The modeling performed by Kaddoura & Nagel (2018) is just one example of research on MATSim's capacity for incident-based simulations.

A MATSim incidents model developed by Li & Ferguson (2020) 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 if the level of service was sufficient (Li & Ferguson, 2020). 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). Receiving notifications about incidents by agents impacted both travel time and mode choice. 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 & Ferguson, 2020, 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 & Ferguson, 2020, p. 96). Their findings validate the conclusions of Sisiopiku et al. (2007) that making incident information available to agents leads to decreases in travel time and congestion. The specific reduction realized in incident-related congestion associated with mode shift is a function of the transit level of service as well as specific user familiarity; if a user does not consider transit a viable alternative, switching to it is unlikely.

This subsection highlights the capabilities of DTA models to simulate the complexities of traffic incidents, congestion, and travel times. It highlights how incorporating incident management responses into the models would enhance their ability to simulate realistic traffic conditions and support policy analysis. Given its capacity to model large-scale networks, integrate real-world data, and replicate realistic driver behavior, MATSim is deemed particularly suitable for this project.

2.3 Summary

This literature review summarizes research on IMTs’ role in reducing RCT and EUC during incidents and optimizing IMT size and distribution. However, these performance studies do not explore the broader impact of incidents and IMT responses on large-scale networks. Similarly, while DTA modeling studies assess incident impacts on network dynamics and driver behavior, they seldom consider the ability of IMTs to influence these conditions. This limits our ability to estimate IMTs’ effectiveness in congested networks. Our research aims to model incident response within the Wasatch Front, Utah, roadway network to evaluate IMT deployment strategies and effectiveness more comprehensively.

3.0 METHODOLOGY

As highlighted in the literature review, there is substantial evidence indicating that IMTs can effectively reduce RCT and EUC following traffic incidents. Additionally, the effectiveness of DTA models in analyzing the impact of such incidents has been well documented. However, there is a lack of comprehensive research evaluating IMTs' impact on entire traffic networks. To address this gap in the research, it is necessary that we develop a model capable of simulating both traffic incidents and the ensuing IMT interventions, with the objective of gauging the efficiency of IMT deployments. Due to its proficiency in regional-scale incident simulation and its authentic portrayal of driver agent behavior, MATSim has been identified as the most suitable model for this research. This section describes the methodology, expounding on the model's capabilities, the requisite data inputs, and the benchmarks established for determining IMT effectiveness.

Our methodology is structured around three main components: the functionality of the MATSim model, the setup of IMT vehicles and incidents, and the scenarios for comparative analysis. In Section 3.1, we describe the structure of the model and the functions it uses to represent incidents and IMT responses. In Section 3.2, we describe the specific implementation of this framework in a scenario with sampled incidents for the Wasatch Front.

3.1 Model Design

MATSim is an open-source framework used for conducting extensive, multi-agent transportation simulations on a large scale, meaning the model may include a regional network of all roadways and a set of traveling agents representing an entire population. Operating as a dynamic traffic simulation, MATSim is often used in demand modeling and mobility analysis (Dobler et al., 2012). Thanks to its open-source architecture, MATSim enables the seamless integration of a diverse array of modules and packages into its models. Users across the platform can create, import, and modify these components, fostering a collaborative and innovative environment.

For the purposes of our research, we developed the ImtModule, a specialized MATSim extension designed to process incidents and IMT responses within the simulation. This module leverages existing research on incident simulation, building upon these foundations to enhance the functionality of our model. The module includes software to handle stochastically arising traffic incident events, IMT vehicle dispatch algorithms, and network capacity adjustments. In this section, we describe some of the specific tools within MATSim that we used and adapted to construct a comprehensive and functional model. These tools include scoring and replanning, network change events, and IMT assignment. Together, they contribute to the authenticity and precision of our traffic simulations, particularly in the context of responding to roadway incidents, ensuring that our model provides accurate and reliable results.

3.1.1 Scoring and Replanning

In MATSim, each individual within the simulation is called an agent. These agents follow daily schedules, traveling to activities using specified modes of travel and routes assigned by a DTA-like mobility simulation. MATSim then scores the executed plans of each agent based on the realized travel times in the DTA, as highlighted by Nagel et al. (2016). Timely arrivals at destinations are rewarded with positive points, whereas delays result in deductions. Furthermore, different transportation modes are assigned utility scores, which play a crucial role in shaping the agents' travel preferences and decisions. Agents then replan, or experiment with changes to their initial daily patterns. MATSim converges to a system equilibrium by alternating between the DTA mobility simulation, scoring, and replanning phases, and people finding routes and departure times that maximize their individual score. Each agent possesses a memory that stores plans from a certain number of iterations, as well as replanning strategies that dictate how agents can adjust their plans from iteration to iteration (Horni & Nagel, 2016).

In the case of our large-scale Utah model, we generated initial daily plans using an implementation of the ActivitySim tour-based travel model developed under previous UDOT research (Macfarlane and Atchley, 2022). We then ran 350 iterations of the MATSim mobility simulation, scoring, and replanning cycle for the Wasatch Front population and network. A more detailed description of this scenario is given in Section 3.2. We limited the agents' plan memory to five iterations, meaning that the agents would store the five highest-scoring combinations of routes, modes, and departure times. The replanning strategies used include selecting the plan with the highest score 80% of the time, opting to reroute 10% of the time, and adjusting activity departure times for the remaining 10%. Our selection for the remaining scoring

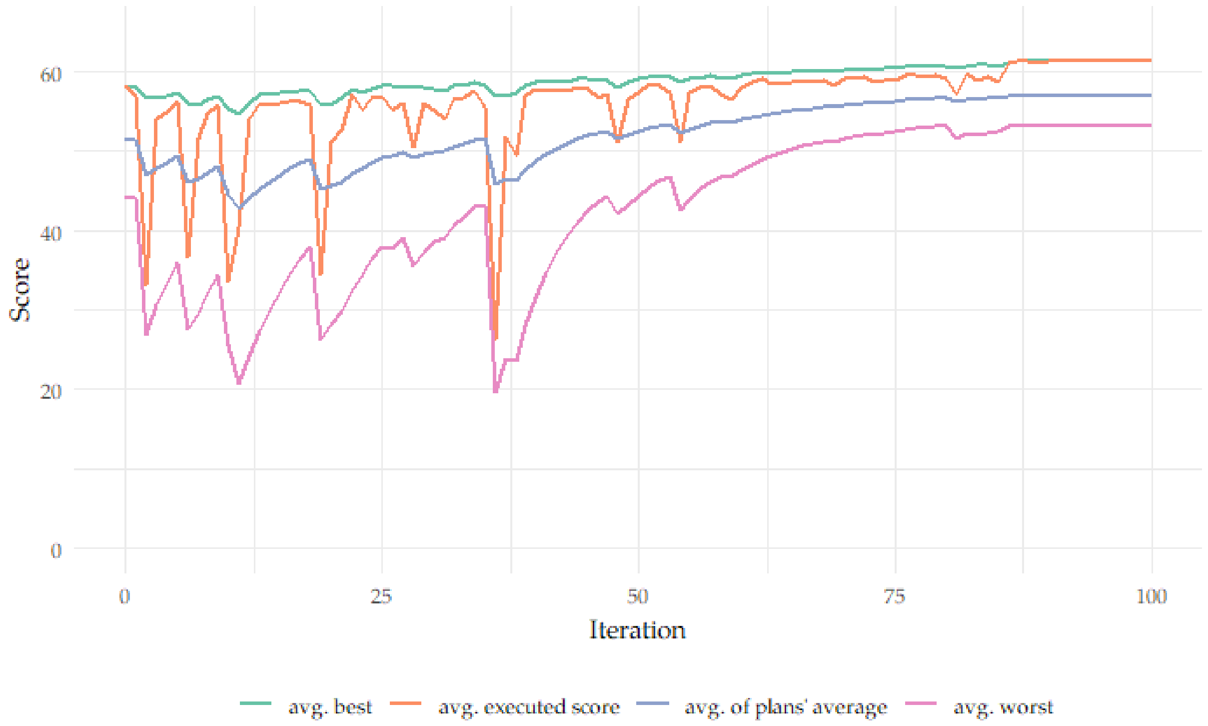

Figure 3.1: MATSim scoring statistics output example

and replanning parameters drew from the incident research conducted by Kaddoura & Nagel (2018).

After 350 iterations, we observed that the scores in this base MATSim scenario – without any incidents or IMT vehicles – were stable. That is, continued iterations of the simulation, scoring, and replanning cycle were not likely to lead to further adaptations in the agents' preferred routes or departure times. The plans of the agents at this converged, equilibrium state may then serve as a starting point for scenarios where traffic incidents add congestion to the network. Further iterations of the MATSim simulation, scoring, and replanning cycle considering incident and IMT response can then begin with a mostly converged "hot start," skipping the first few hundred iterations of the cycle. Figure 3.1 illustrates the convergence of scores in such a "hot start" scenario. The figure indicates notable plan adjustments and corresponding score changes during the first 60 iterations (iterations 351-410 considering the previously converged scenario). As the cycle progresses, the executed scores begin to restabilize. To minimize the potential for significant variance, replanning was disabled after the 85th iteration. At this point, people stop looking for new routes or modes, and MATSim simply selects from their best previously executed plans. This approach is common in MATSim practice and ensures that the final iterations, which are critical for scenario analysis, reflect a steady state. It also reflects the reality that people cannot realistically consider infinite permutations of their daily plans.

3.1.2 Network Change Events

Within a MATSim network, each link is characterized by specific attributes such as type, length, number of lanes, free-flow speed, and capacity. To effectively simulate unexpected events and their subsequent impacts on traffic flow, it is essential to dynamically adjust these attributes. This capability is vital for ensuring the realism and accuracy of our simulation. Network Change Events (NCEs) serve as the mechanism within MATSim for modifying network attributes at precise moments during a simulation. Detailed by Rieser et al. (2016), the implementation of NCEs requires specific adjustments to the MATSim configuration file to facilitate a time-variant network. These events can modify a link's free-flow speed, number of lanes, and maximum capacity. To initiate an NCE, the system requires specific information including the time of the event (startTime), the affected link(s) (link refID), the type of change (free-flow speed, lanes, or capacity), and the value of the change. NCEs are the tools used in this study to demonstrate the impact of both incidents and IMT arrivals. The code used to implement NCEs is outlined in Appendix B.

3.1.3 IMT Assignment and Response

Within MATSim, the deployment of one or more IMTs is triggered by the occurrence of an incident. The optimal IMT for the situation is determined using a least-cost path algorithm, which calculates the quickest route based on real-time traffic conditions like congestion and link speeds. This may overstate the actual travel time to the incident, however, as IMT vehicles are generally equipped with lights and are permitted to travel in the shoulder of congested highways. The available IMT that can reach the incident location the fastest, accounting for current roadway speeds and congestion, is then dispatched. If all IMTs are occupied at the time of an incident, the algorithm waits until an IMT becomes available and then dispatches it to the site of the incident. The dispatch algorithm and code are outlined in Appendix A.

When an IMT arrives at an incident within MATSim, an NCE is activated by an event handler – a MATSim tool that logs simulation events as they occur. This NCE implements the IMT's impact by restoring 25 percent of the link's capacity that was reduced due to the incident. The arrival of each additional IMT unit contributes another 25 percent to restoring the link's capacity. The value of 25 percent is a simplified value recommended by the Technical Advisory Committee for this project. Existing research we reviewed for this project did not conclusively identify how much capacity is restored by an IMT in any jurisdiction. Extant studies have focused on EUC valuation rather than the detailed operations of the IMT, which are likely to be highly variable and situationally dependent. Understanding the possible scale of this parameter and sources of its variance is a critical recommendation for continuing research but cannot be accomplished under the scope of the present project. Further research is also needed to establish the role of IMTs in reducing RCT. Schultz et al. (2023) suggested that increasing the availability of IMTs between 2018 and 2022 in Utah *increased* RCT and did not observe the RCT for incidents without an IMT response. As a consequence of these findings, we do not have the responding IMT effect on the simulated incident RCT. Therefore, the model assumes that IMT involvement leads to capacity improvement, rather than estimating RCT in the absence of IMT intervention.

Figure 3.2 illustrates the impact of traffic incidents on road capacity within the model, emphasizing the role of IMTs in mitigating this impact. The figure presents a scenario where an incident causes a reduction in a road link's capacity to 20 percent of its maximum for a duration of 60 minutes. Without any IMT intervention, this diminished capacity level would persist for the entire incident. However, the scenario changes with IMT involvement. The arrival of the first IMT 15 minutes after the incident boosts the link's capacity by 25 percent, raising it to 40 percent of its maximum value. If a second IMT team arrives 30 minutes after the incident begins, it provides an additional percentage increase of 25%, enhancing the link's operating capacity to 55% of its maximum for the duration of the incident. Full capacity is restored after the incident concludes. This visualization demonstrates the role of IMTs in restoring capacity after incidents and maintaining more efficient traffic flow during such events.

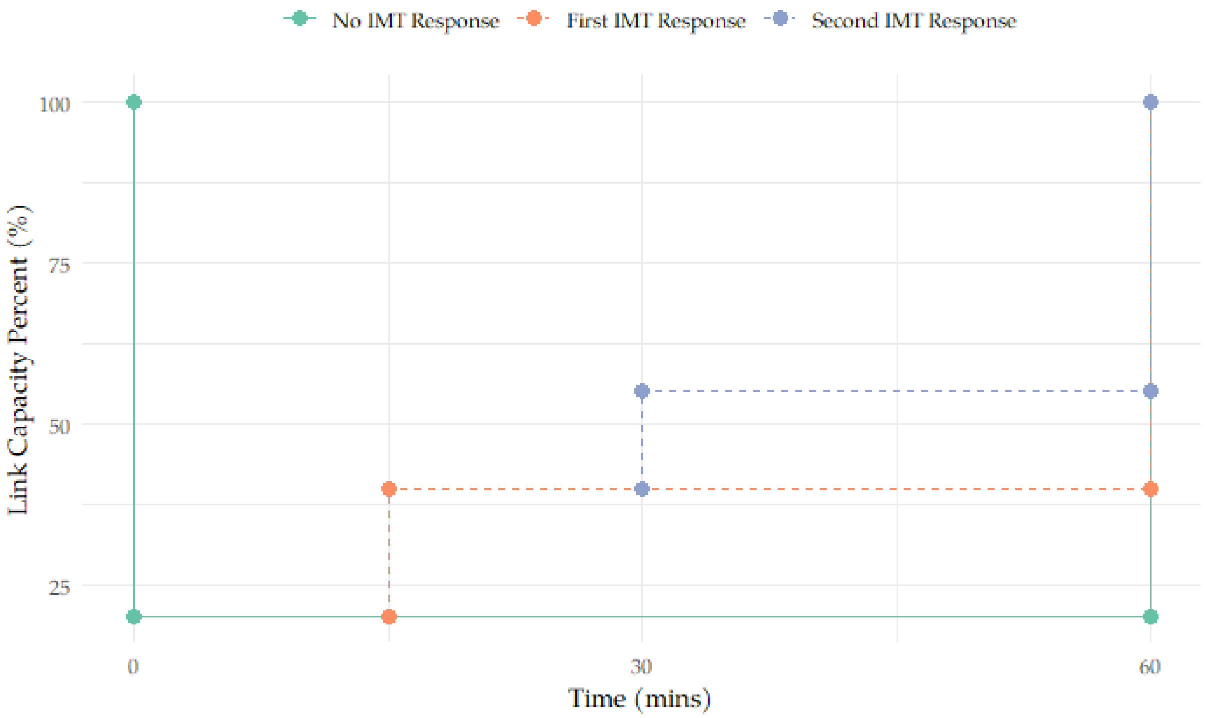

Figure 3.2: IMT capacity restoration upon arrival example

3.2 Model Implementation in Utah

To run the MATSim model with the ImtModule extension, a number of input resources are necessary. For the model to function properly, the following are needed:

- A plans file detailing the agents to be modeled, as well as their activity.
- A network file with interconnected links, enabling travel for the agents specified in the plans file.
- A configuration file outlining the scoring metrics of the simulation and establishing parameters pertaining to agent and IMT travel patterns.
- An IMT file outlining the IMTs' starting locations and hours of operation.
- An incidents file containing the necessary data to randomly effect NCEs throughout the simulation.

The network and plans files used in this research were developed and calibrated by Macfarlane & Lant (2023) and Day et al. (2023) as part of UDOT-sponsored projects studying accessibility and ride-hailing throughout the Wasatch Front. The configuration file used in the model was adapted from the Kaddoura & Nagel (2018) file, which was used for their MATSim incident analysis study. It was slightly modified to accommodate the ImtModule development, but the parameters they set were largely left unaltered. The IMT file was produced using data provided by UDOT and UHP, as outlined in Section 3.2.1. The incident data was compiled by Schultz et al. (2023) in their research of IMT performance measures and is explained in Section 3.2.2.

3.2.1 IMT Setup

The data provided by UHP details the operations of IMTs in the Wasatch Front for June 6th, 2023, representing their typical weekday activities. This schedule highlights the working hours and coverage of a fleet comprising 20 IMT units, spread across three zones: Davis, Salt Lake, and Utah counties. In this distribution, Salt Lake County is assigned 10 IMT units, while Davis and Utah counties receive 5 each. We will refer to this 20-unit configuration as the existing or current fleet in our simulations. To explore the impact of an expansion, we propose a scenario with an additional 10 IMT units, creating a 30-unit fleet termed the new or increased IMT fleet. These extra units are strategically placed within each county to ensure even coverage.

Figure 3.3 visually represents the county boundaries and the initial positions of both the existing and proposed new IMT vehicles in our simulation.

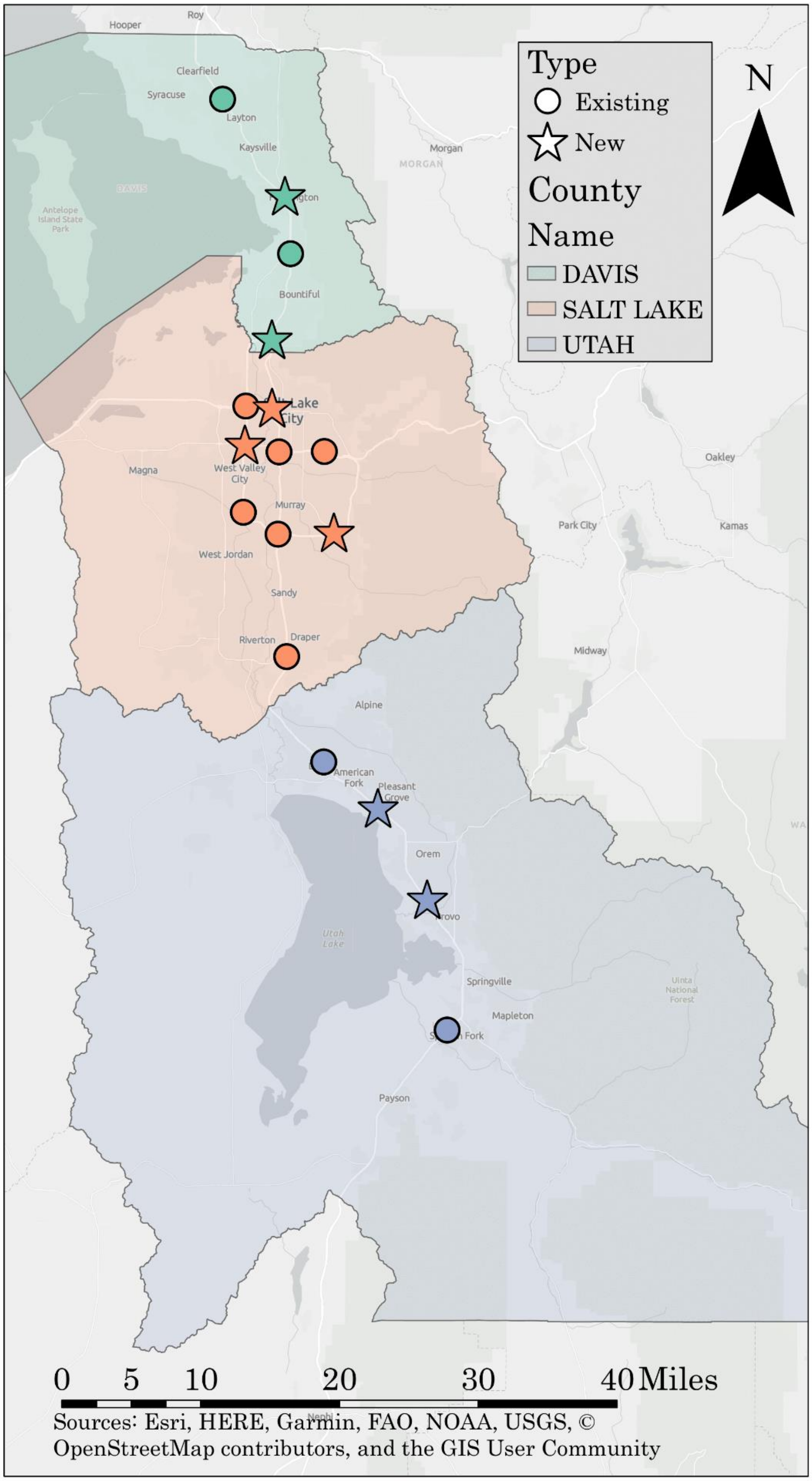

Figure 3.3: IMT starting locations example map

Figure 3.3 uses circles to mark the locations of existing IMT vehicles and stars for the proposed additions. We positioned these units strategically along major highways to achieve a balanced distribution of IMTs across each county. While this initial setup doesn't mirror the real-world scenario where drivers begin their shifts from home, it serves as a practical model for our simulations. The frequency of IMT operations on major highways like I-15, I-80, and I-215, along with the variable real-world starting points, justifies this strategic alignment along key routes. Typically, IMT vehicles do not cross county borders as dispatch services are organized by county. However, in our MATSim network, vehicles can cross into other counties depending on the incident's proximity. IMTs follow specific operational shifts, which we've programmed into MATSim to reflect their availability. In Utah, these often include a morning shift starting at 6:00 AM and an evening shift ending at 10:30 PM.

Figure 3.3 illustrates the IMT distribution during the evening shift, but it's important to note that this pattern is generally consistent during the morning shift as well.

Our research primarily concentrates on evaluating the potential impacts of expanding the IMT fleet, rather than examining the effects of their starting positions. We hypothesize that increasing the number of IMTs, assuming uniform distribution, will enhance their overall effectiveness.

3.2.2 Incident Data and Sampling

In their concurrent IMT research, Schultz et al. (2023) developed a comprehensive dataset of incidents requiring management intervention, derived from data provided by UHP. Analyzing data from 2018 to 2022, they identified 1,604 incidents over 184 days that required the assistance of either IMTs or UHP. From their established dataset of 1,604 incidents, Schultz et al. (2023) filtered the data to ensure the completeness of each incident record in the dataset, ensuring that the incident was responded to by an IMT and contained complete information on incident duration, capacity reduction and location, all of which are necessary for a comprehensive evaluation. Filtering with those requirements, they reduced the list to 411 unique incidents that received IMT assistance. This dataset is useful in understanding the frequency of daily incidents in the Wasatch Front that necessitate incident management intervention. ***Figure 3.4*** illustrates the number of incidents in a given day on the x-axis and the number of days with that incident frequency on its y-axis. We use this data to sample the frequency of incidents in our simulation in two different ways. To represent the currently observed distribution of incidents, we used a randomized sampling method to generate 10 distinct daily incident frequencies based on the original data, labeled as the "Current Frequency" group. These frequencies are represented as orange bars layered on top of the Original Distribution in ***Figure 3.4***. Additionally, to assess IMT performance in scenarios with increased incident numbers, we created an "Increased Frequency" group. This group includes the 10 highest daily incident frequencies from the original data and is similarly layered over the "Original Distribution" in the ***Figure 3.4*** bar chart.

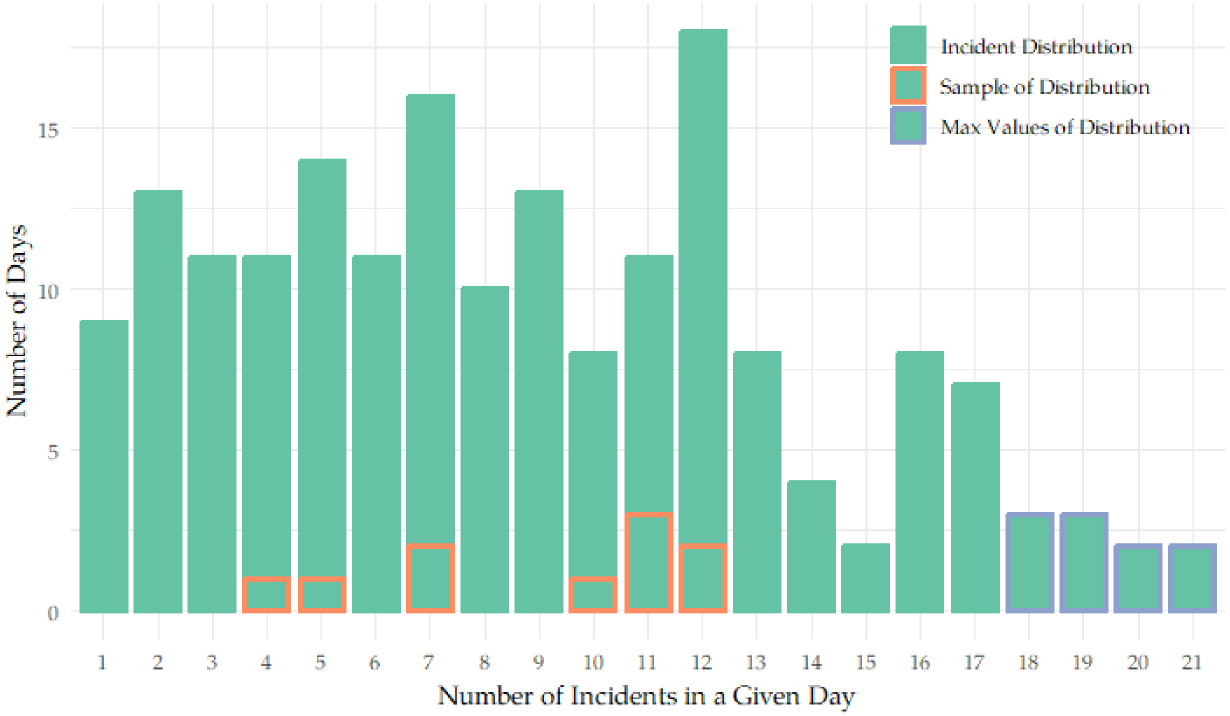

Figure 3.4: Sampling distributions for incident frequencies

We also used the dataset generated by Schultz et al. to include specific incidents in the MATSim model. From that list of incidents, we identified 411 unique incidents with varying degrees of severity, ranging from property damage to fatal incidents. Each simulated incident is modeled with a specific capacity reduction, RCT, and location, all of which are derived from the Schultz et al. incident data. It is important to acknowledge that these 411 incidents only constitute a portion of all incidents reported by UHP during this time frame. A number of additional incidents were excluded from the analysis because they lacked essential information on duration, capacity reduction, or location, all of which are necessary for inclusion in the scenario. Nevertheless, the integration of the 411 analyzed incidents with the additional incomplete records provides insights into the distribution of the incident frequency. These combined incident records informed the modeling of daily incident frequencies but were not used for incident sampling in the simulation.

In total, 20 sets of incidents were selected, evenly split with 10 allocated to the Current Incident Frequency category, and the remaining 10 to the Increased Incident Frequency category. Each value was subsequently paired with a unique three-digit seed number, used internally within MATSim to ensure a randomized selection of incidents for each simulation scenario. Following this, we employed NCEs as described above to integrate the incidents into the MATSim simulation.

3.2.3 Scenarios

In Section 3.2.2 and ***Figure 3.4***, we observe the establishment and categorization of 20 distinct combinations of incidents into Current or Increased Incident frequencies. Each seed gave rise to three separate simulation groups. The first group, No IMTs, exclusively features simulations where incidents occur without any IMT intervention. The second group includes incidents and the deployment of 20 IMTs, while the third group features incidents managed by 30 IMTs. In total, six scenario groups, each containing 10 random "days" with distinct incident sets, were established, as follows:

- No IMTs, current incident frequency
- No IMTs, increased incident frequency
- 20 IMTs, current incident frequency
- 20 IMTs, increased incident frequency
- 30 IMTs, current incident frequency
- 30 IMTs, increased incident frequency

It is important to note, as described in Section 3.2.1, that not all IMT vehicles are operational simultaneously. Due to scheduling constraints, the actual number of IMTs on the road at any given time is typically half of the total fleet size.

Scenarios are evaluated by comparing each group with a baseline scenario that assumes no incidents or IMT interventions. In this study, the primary metrics for analyzing the traffic impact of incidents and IMTs are the vehicle hours of delay (VHD) and RT. The MATSim outputs for each scenario include the average delay – measured as the difference in travel time from the free-flow speed – per link over 15-minute periods. Additionally, we compiled a file for each scenario documenting the traffic volumes for each link during these time intervals. Multiplying the traffic volumes by the average delays yields a detailed delay file, which represents the aggregate delay on each network link for the simulated day, including all travel from all agents in the MATSim scenario. The formula for calculating the link-specific delay in a scenario is provided as:

$$\text{VHD} = \sum_{i=1}^{N} \sum_{t=1}^{96} a_{ti} * v_{it} \qquad (3.1)$$

Where a_{it} denotes the average delay for a link i in time bin t, while v_{it} corresponds to the volume of vehicles traversing that link during the same interval. By summing this value for all time periods and all links in the network N, we calculate the VHD for the entire scenario. This total can be disaggregated by motorway (or freeway) links and links directly affected by incidents.

For comparative analysis among multiple scenarios with different incidents, the average VHD is computed across all scenarios within each group. The analysis divides the average VHD into three distinct categories: Network Links, Motorway Links, and Impacted Links. Network Links provides a macroscopic view of network-wide delays, Motorway Links focuses on key routes such as freeways, and Impacted Links offers a detailed analysis of the delays at incident sites and their immediate surroundings. This multi-tiered approach to analysis facilitates a comprehensive evaluation of the widespread and specific traffic impacts of incidents.

In addition to VHD, the study investigates the performance and operational efficiency of IMTs. Metrics such as the average travel times, travel distances, and incident RT are compared across the 20 IMT and 30 IMT groups. This, in turn, informs strategic decisions regarding resource allocation and deployment, ensuring that IMT vehicles are optimally used to mitigate traffic delays and enhance roadway safety.

4.0 RESULTS

This section details the outcomes of the Utah IMT optimization project, employing the MATSim model to execute a series of simulations across a range of scenario groups. Specifically, the groups—No IMTs, 20 IMTs, and 30 IMTs—were compared with a Baseline scenario with no incidents, facilitating an evaluation of the repercussions of traffic incidents and the effectiveness of IMTs in alleviating traffic disruptions.

The following sections analyze the results derived from the simulated scenarios. This analysis uses VHD as a comparative metric examining delay at the network, motorway, and incident links levels in Sections 4.1.1, 4.1.2, and 4.1.3. The results also compare IMT performance based on the IMTs' average response times, total travel time, and total travel distance in section 4.2.

This analysis uses comparative metrics such as VHD, the consequences of traffic incidents, and the dynamics of the IMT responses in relation to the incidents they manage.

4.1 Vehicle Hours of Delay

The studies referenced in Section 2.1 demonstrate the value of IMTs in reducing RT and EUC on roadway segments affected by incidents. Similarly, the results from this transportation model highlight the impact of IMTs at reducing delay, particularly when focusing on the segments of roadways where incidents occurred; see Section 4.1.3. In contrast to the cited studies, our model also explored the broader implications of incidents and their corresponding IMT responses on the simulated network. In a majority of scenarios, these results also suggested a strong positive correlation between IMTs and the reduction of RT and VHD, which are key determinants in the computation of EUC.

4.1.1 Network Hours of Delay

In the comparison of network VHD across simulations, the scenarios were grouped by IMT response and incident frequency. Each group encompassed 10 simulated scenarios, which each involved different selections and numbers of incidents, except for the Baseline scenario, which stands alone. ***Table 4.1*** presents the average VHD for each group, based on the delays recorded in the final iteration of each simulation. These average VHD values are subsequently compared against the Baseline scenario to calculate the percentage change in VHD.

Upon comparing the results across different groups, it was observed that scenarios with 30 IMTs experienced the lowest average VHD. They were closely followed by the 20 IMT group, and, as expected, the scenarios that did not have any IMT responding to incidents registered the highest average VHD values. It is also noted that introducing incidents to the Baseline scenario without any IMT response resulted in an average VHD increase of 39.0%. However, this increase dropped to an average of 29.0% when 20 IMTs were available, and further reduced to 25.6% with the availability of 30 IMTs. Additional analysis of the data revealed that, compared to the No IMTs group, the 20 IMTs group decreased the average VHD by 7.2%, while the 30 IMTs group reduced the average delay by 9.6%.

While the relationship between the IMT group and VHD appeared straightforward, the correlation between Incident Frequency and VHD was not as clear-cut. In the No IMTs group, scenarios with increased incident frequency showed only a 1.0% increase in VHD compared to those with the current frequency. Intriguingly, for both the 20 IMT and 30 IMT groups, an increase in incident frequency actually led to slight decreases in average VHD. The cause of this decrease is unclear, but potential explanations will be discussed in Chapter 5.

Table 4.1: Average VHD on Network per Typical Day

Group	Incident Frequency	Average VHD	Change from Baseline (%)
Baseline	No incidents	74,568	0.0
No IMTs	Current	103,159	38.3
No IMTs	Increased	104,178	39.7
20 IMTs	Current	96,697	29.7
20 IMTs	Increased	95,678	28.3
30 IMTs	Current	93,769	25.7
30 IMTs	Increased	93,560	25.5

Figure 4.1 shows the VHD across all links in the network for each of the 60 simulations – six scenario groups of ten simulations each. In this figure, the “Mean” values in red are the same values in Table 4.1, but shown in context with all of the individual scenario results. These

disaggregated results reveal more about the variance in the delay measurements. For example, the “No IMTs Increased” scenario only has a mean VHD value across all links approximately 1,000 hours higher than the “No IMTs Current” scenario group. But the individual scenario results reveal that while the mean is relatively similar, the scenarios are more closely clustered; this implies that without IMTs, an increase in high incident days may lead to more days with high average delay values. Following similar logic, the addition of IMT response lowers the mean VHD for the scenario groups modestly, it also strongly limits the number of days with high VHD values. This suggests that considering the network as a whole, the benefits of IMT might be most strongly observed on extraordinary days rather than on days with an average number of incidents.

While IMTs are aimed to benefit the entirety of the traveling public, it is important to note that all simulated incidents were located on motorway links, predominantly along the major interstates of Utah’s Wasatch Front. This encompasses key routes such as I-15, I-80, and I-215, as well as other significant freeways and highways. The next section will provide a detailed analysis of the simulation outcomes specifically related to these links.

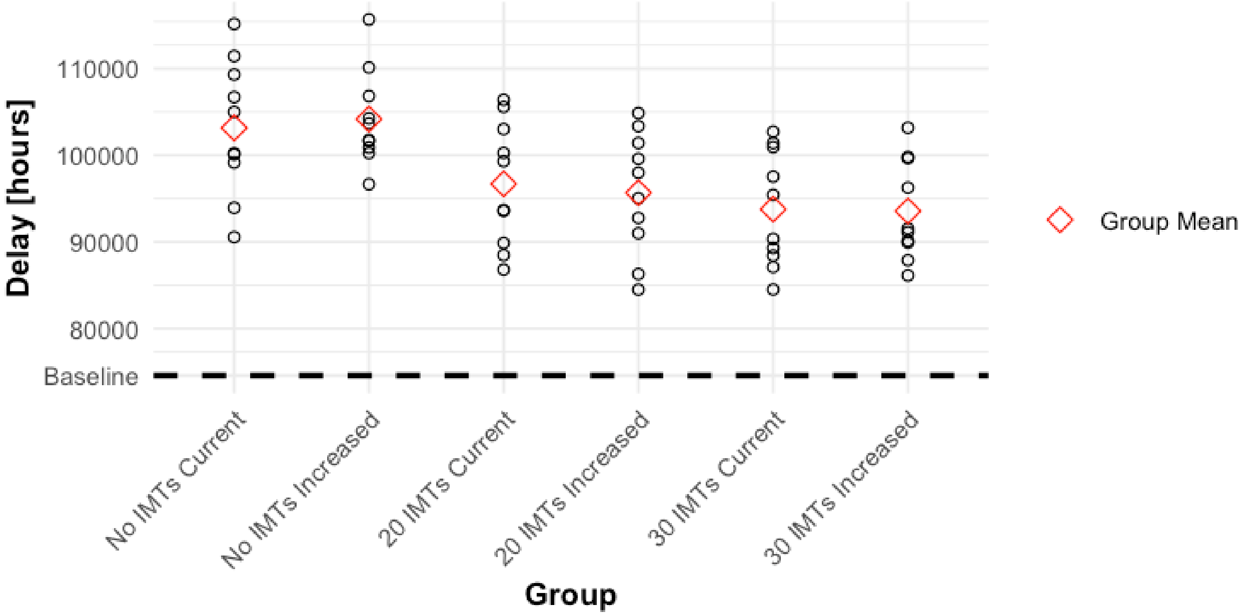

Figure 4.1: Average network VHD distribution

Table 4.2: Average VHD of Motorway Links

Group	Incident Frequency	Average VHD	Change from Baseline (%)
Baseline	No Incidents	15,335	0.0
No IMTs	Current	24,242	58.1
No IMTs	Increased	22,321	45.6
20 IMTs	Current	18,924	23.4
20 IMTs	Increased	19,176	25.0
30 IMTs	Current	17,569	14.6
30 IMTs	Increased	18,327	19.5

4.1.2 Motorway Link Hours of Delay

The network used in our model is derived from the Wasatch Front Regional Council travel demand model network. Within this network, the term ‘motorway’ denotes a specific type of link, also known as a freeway or expressway in different contexts. To ensure consistency throughout this document, we primarily refer to these road segments as ‘motorway’ or ‘motorway links.’ It is important to note, however, that in the simulation, incidents can occur on both interstates and major highways along the Wasatch Front.

To compare average simulation performances, ***Table 4.2*** breaks down the average motorway VHD for each scenario group, categorized by IMT response and incident frequency. The mean results of these groups show that in comparison to the Baseline scenario with no incidents, incident-related delay adds approximately 9,000 hours of vehicle delay on motorways in the region, an increase of approximately 58 percent. In comparison with the overall network means in Table 4.1, these results suggest that IMTs play a strong role in alleviating incident-related VHD on motorways, with the 20 and 30 IMT scenarios showing progressively steep reductions in VHD. ***Table 4.2*** reveals that, in comparison to the Baseline scenario, the average VHD on motorway links increased by approximately 7,000-9,000 hours, or 45.6-58.1%, when incidents were introduced. But incorporating IMT response at either the current level of 20 teams or an increased level of 30 teams reduces the average amount of motorway VHD relative to the no-IMT scenario.

As with the network-wide analysis in Section 4.1.1, we can benefit from examining the distribution of individual scenario results. Figure 4.2 shows the total motorway VHD for each of the 60 scenarios; as previously, the red markers indicate the group mean and are equivalent to the numbers shown in Table 4.2. Again, a striking finding illustrated in this figure is that increasing the number of IMT vehicles may play a larger role in limiting the VHD on the worst days rather than lowering the delay on an average day. This is observed by noting the strikingly lower values of VHD for both 30-IMT scenario groups. It should be noted that the individual scenarios show some instances where the total VHD on motorways is lower than the Baseline without any incidents. Depending on which incidents are included in the simulation, the MATSim optimization algorithm may be able to continue finding better paths, particularly as IMTs are available to clear up the incidents that do occur. Regardless, some variation in stochastic outcomes is expected from large and complex simulations.

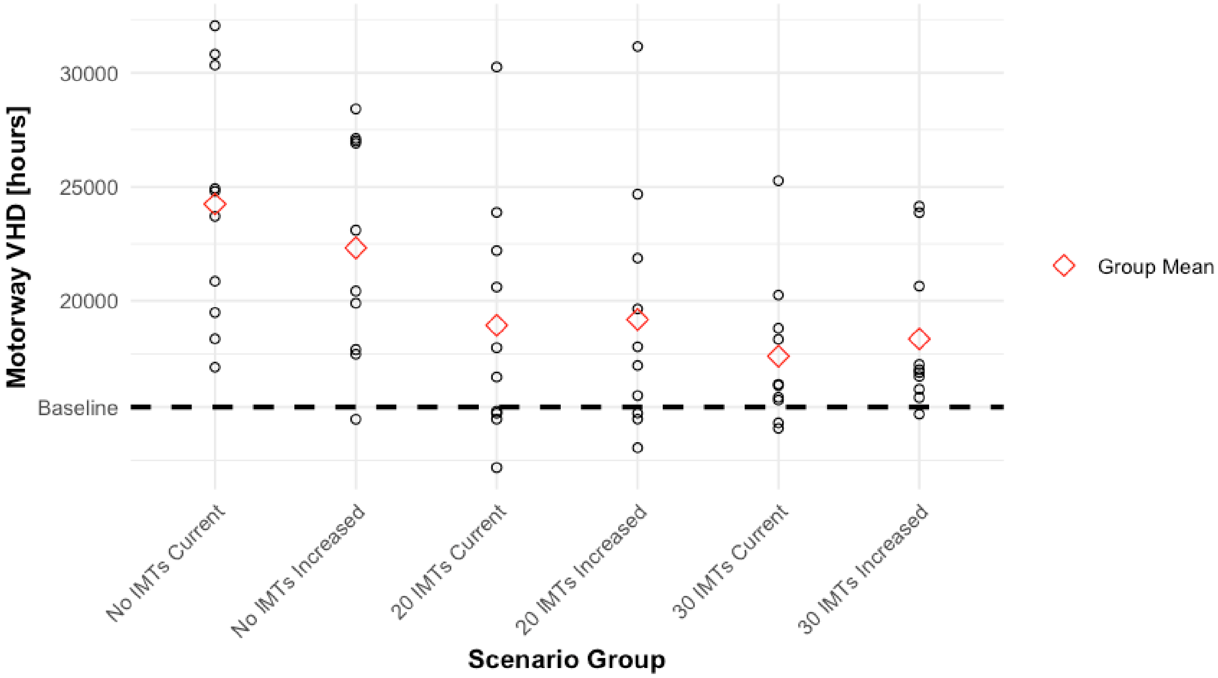

Figure 4.2: Average motorway VHD distribution

4.1.3 Impacted Links

The final section of our VHD analysis delves into the delays experienced on incident links and their immediate upstream counterparts. This level of analysis aligns with the methodologies employed in the studies by Bennett et al. (2021) and Skabardonis (1998), as it focuses on the most directly observable repercussions of incidents and IMTs. Unlike these authors' focus on the impacts of IMTs on roadway clearance time, our investigation centers on VHD as an indicator of EUC. As detailed in Section 3.1.3, the IMTs in our simulation did not curtail the duration of individual incidents (RCT); instead, they enhanced roadway capacity while the incident was ongoing. Nonetheless, given that EUC is intrinsically related to delay, this section offers an evaluation of IMT performance most directly comparable to the analyses conducted by Bennett et al. (2021) and Skabardonis (1998).

Given the variation in link lengths across the motorway, in some cases, analyzing just two additional links may not fully capture the delays caused by a specific incident. Nevertheless, ***Table 4.3*** provides insights into how delays on impacted links vary based on incidents and IMT deployment. For additional context about ***Table 4.3***, 'Total VHD' represents the delay on impacted links both during the incidents and for one hour after clearance, aiming to capture any residual delay shock waves that an incident might cause. The Baseline scenario appears twice, as the collection of links in the Current and Increased incident scenarios are different; in this case the delay is unrelated to incidents *per se*, but rather is the delay present on those links in a typical daily scenario. Adding incidents increases the delay on those links substantially, and increasing the availability of IMTs reduces the delay. Under Current incident frequencies, increasing the fleet to 30 IMT units almost restores the baseline levels of delay on the immediately affected links. As in the preceding analyses, stochastic variation in the incident draws and MATSim scenarios may lead to different impacts – the Increased incidents sampled appear to have a lower per-incident delay due to their locations – but the overall trend of IMTs successfully reducing incident delay holds.

Table 4.3: Impacted Links Delay

Group	Incident Frequency	Total VHD	Avg. Delay Per Incident [hrs.]
Baseline	Current	326	3.6
No IMTs	Current	3,808	42.3
20 IMTs	Current	723	8.0
30 IMTs	Current	366	4.1
Baseline	Increased	540	2.8
No IMTs	Increased	3,154	16.3
20 IMTs	Increased	1,645	8.5
30 IMTs	Increased	1,115	5.8

Note: Current Frequency contains 90 incidents; Increased Frequency contains 193

4.2 IMT Performance Analysis

Equally critical to understanding IMT performance is assessing the efficiency of each IMT in reaching their intended destinations. This results segment delves into IMT travel behavior, capturing metrics such as average travel times and distances, along with their average incident response times. The analysis encompasses both 20 IMT and 30 IMT scenarios, but only using the Current incident frequency scenario group. Travel times for IMTs 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. Utilizing this IMT travel data, plots were generated to illustrate the average travel times and distances for each dispatched IMT within a given scenario.

Figure 4.3 illustrates the average travel time for each dispatched IMT, while Figure 4.5 shows the average travel distance. Though the two measures are highly correlated, they represent different performance measures. The average time to respond to an incident has been shown to significantly affect the total EUC (Schultz et al., 2023), while the total distance traveled is a good measure of the efficiency of operating the service. To compute the average travel time per IMT we took the cumulative travel time for all dispatched IMTs in every scenario and divided that by the number of teams deployed. This analysis clearly shows that for the same simulated incidents, the 30 IMT scenario both reduces response time (and thereby EUC) as well as reduces the amount of distance and resources the IMTs need to use.

In this research, each IMT began its shift at a consistent location. Altering the starting locations of the IMTs or having them operate in a roaming manner can significantly influence the time and distance traveled and thereby the effectiveness of the IMT system (Lou et al., 2011). Determining the optimal starting points for IMTs was not the primary focus of UDOT in this research – the shift starting locations in the UDOT IMT system are usually the homes of the IMT operators and were therefore not considered – but the methodology and software tools we developed in Chapter 3 provide an opportunity for future research along these lines.

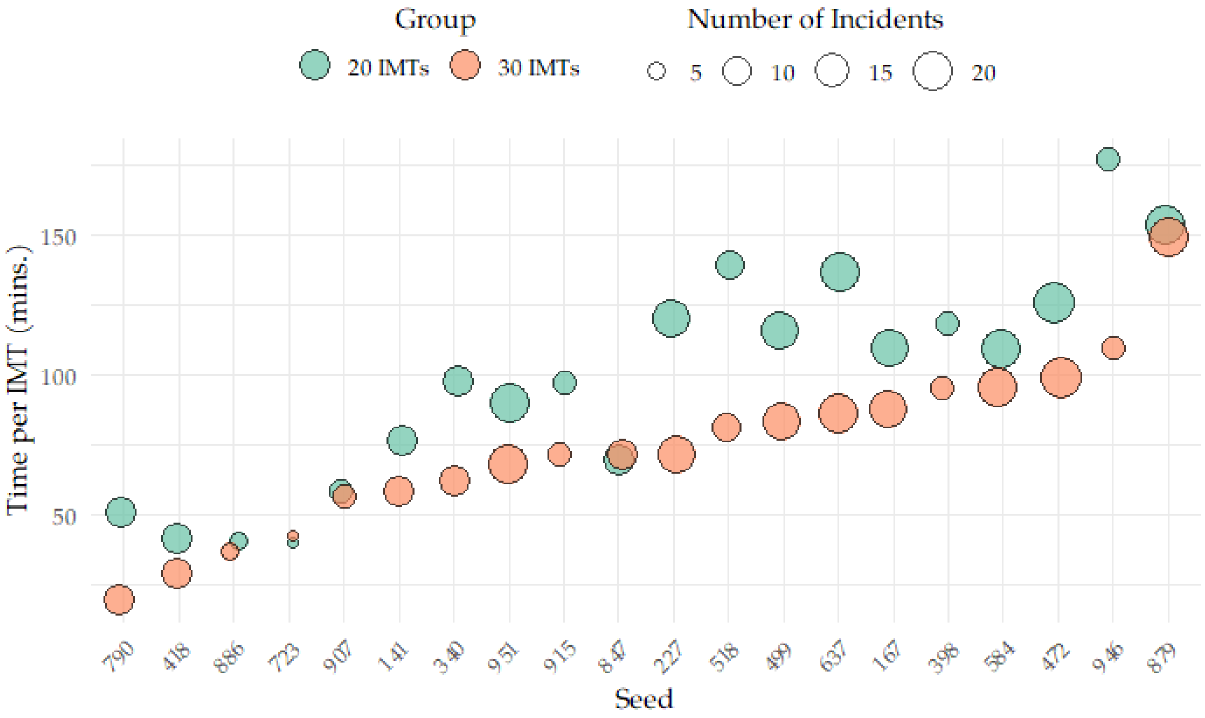

Figure 4.3: Average daily IMT travel time per dispatched team

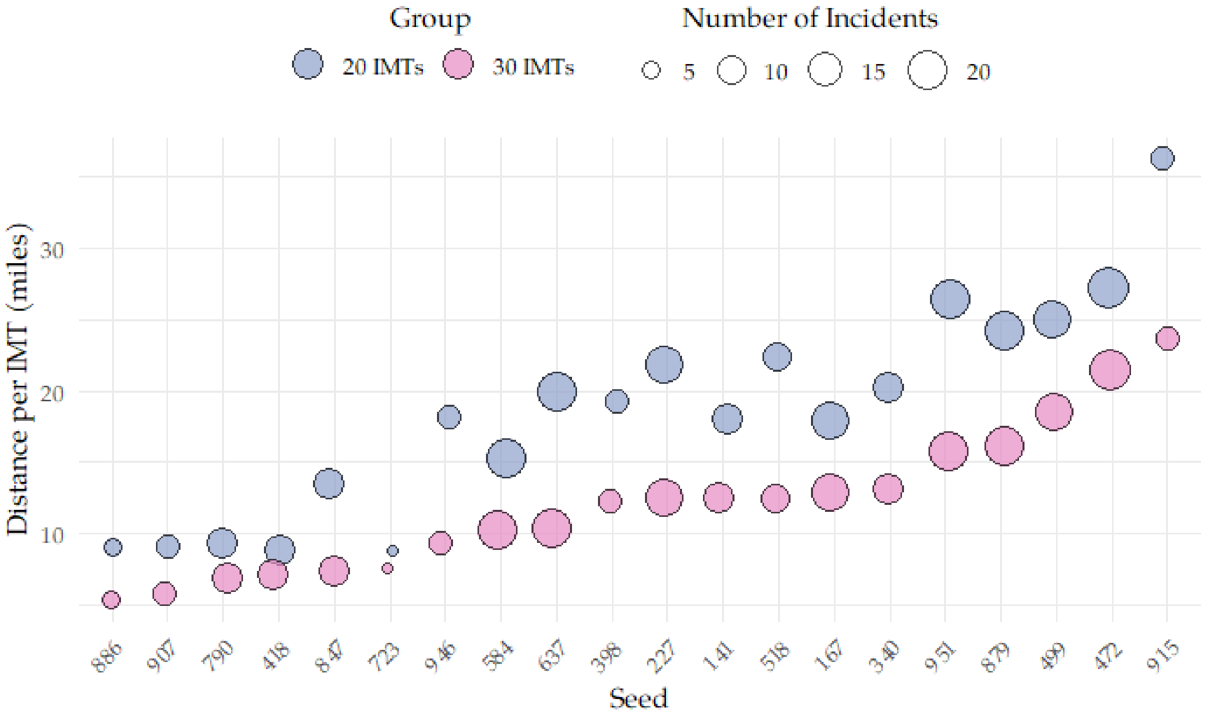

Figure 4.4: Average daily IMT travel distance per dispatched team

The study conducted by Bennett et al. (2021) highlights that in Utah, a one-minute increase in IMT RT results in an approximate 0.8-minute increase in RCT. This finding emphasizes the critical role of IMTs' RT in reducing RCT and subsequent delays. While not examining RCT, this study also investigated the RT of IMTs when dispatching both 20 and 30 units. As indicated in ***Table 4.4***, across all simulated scenarios, a fleet of 20 IMTs produced an average incident RT of 15.0 minutes. Notably, the 15.0-minute average arrival time for the 20 IMT scenarios aligns closely with the actual median arrival times recorded in the 2023 study of Utah's IMT performance (Schultz et al., 2023). Additionally, increasing the IMT fleet to 30 units resulted in an average response time of 11.0 minutes, 4 minutes less than the 20 IMT group arrival times. ***Table 4.4*** illustrates the average arrival times of the 1st, 2nd, and 3rd IMT, as well as the average for all units' arrival times.

Table 4.4 provides insights into the IMT response patterns, capturing their arrival at 280 out of 283 incidents across both scenarios. Note, three unattended incidents fell outside of the IMT operational hours. Among the incidents that were managed, support from a second IMT was requested 116 times, from a third IMT 23 times, and a fourth IMT was called upon 3 times. However, due to the extremely small number of incidents requiring a fourth IMT, this category was deemed too limited for significant analysis and was subsequently excluded from ***Table 4.4***. When comparing arrival times, scenarios with 30 IMTs consistently outperformed those with 20 IMTs, demonstrating lower RT across all incident categories. As noted earlier, the average RT with 30 IMTs was 4 minutes less than with 20 IMTs. Hadfield et al. (2021) estimated that a one-minute delay in RT added 34.6 minutes to the estimated travel time, and an increase of $925 in EUC. Based on these findings, reducing the RT of IMTs by an average of 4 minutes could result in EUC savings of approximately $3,700 per incident.

A closer analysis of the IMT travel data reveals significant insights into operational efficiency. The data indicate that the group with 30 IMTs was markedly more efficient than the group with 20 IMTs. Specifically, the 20 IMT group accumulated a total of 105 hours of travel time, while the 30 IMT group managed to reduce this to 77 hours—a significant decrease of 27% in total IMT travel time. Additionally, the data show that with 20 IMTs, units were often dispatched to multiple incidents in quick succession, negatively impacting their arrival times. In contrast, the scenarios with 30 IMTs, supported by a larger fleet, saw fewer instances of

Table 4.4: Average IMT Arrival Times

Group	All IMT [mins]	1st [mins]	2nd [mins]	3rd [mins]
20 IMTs	15.0	11.0	21.1	28.9
30 IMTs	11.0	8.9	13.2	21.2
Number of Incidents	280	280	116	23

consecutive deployments, leading to more timely arrivals. This increased efficiency with the 30 IMT group becomes particularly evident in high-frequency incident situations, especially when comparing the arrival times of the 2nd and 3rd IMT between the two scenario groups.

4.3 Results Summary

We evaluated the impact of deploying fleets of 20 and 30 IMTs using our MATSim model, enhanced with a custom IMT analysis extension, comparing these scenarios to ones without IMT support. Our findings suggest that IMTs are effective in reducing VHD on roadways and in decreasing incident response time. Further, the results suggest that increasing the availability of IMTs would reduce the VHD impact of unusually severe incident days, primarily by limiting response time and ensuring that a responding vehicle is available. However, a number of simulation results yielded some unexpected outcomes. We will delve into these discrepancies in the limitations section of our conclusions,

5.0 CONCLUSIONS

This paper contributes to the existing body of knowledge on IMT effectiveness and traffic incident modeling. It highlights the importance of strategic IMT deployment and the necessity for ongoing evaluation and adaptation of these strategies to meet changing demands in highway operational systems. Our study focuses on the Utah Wasatch Front Region, employing simulation modeling to evaluate IMT effectiveness. Previous studies have established IMTs' significance in mitigating traffic disruptions, such as incidents and vehicle breakdowns (Bennett et al., 2022; Hadfield et al., 2021; Schultz et al., 2023; Skabardonis, 1998). Furthermore, mesoscopic DTA modeling has proven beneficial for in-depth analyses of incident impacts and management strategies [Kaddoura & Nagel (2018); Li & Ferguson (2020); Sisiopiku (2007)].

However, there is a noticeable lack of large-scale simulation models applied to evaluating IMT performance. These models offer unique insights and enable scenario testing that may be challenging with traditional methods. To address this gap, we developed a specific simulation model for assessing IMT operations across Utah, seeking to improve our understanding and the effectiveness of these teams.

We used our model to analyze VHD and various IMT performance measures across different incident types and IMT configurations. Our analysis primarily focused on comparing the outcomes based on the number of IMTs deployed in each scenario. The results indicated that the existing fleet of 20 IMTs deployed by UDOT effectively respond to incidents and reduce delay. In comparison to scenarios with incidents alone, a 20 IMT configuration reduced highway delays by 18.2%, resulting in an average VHD reduction of 4,232 hours per simulated day. Increasing the fleet size to 30 IMTs improved incident mitigation and led to a reduction in delay of 22.9% and an average VHD savings of 5,334 hours.

Additionally, in our simulation, a fleet of 30 IMTs showed lower RT compared to a fleet of 20 IMTs, with average RT decreasing from 15.0 minutes to 11.0 minutes. Notably, the 15.0-minute average arrival time for the 20 IMT scenarios aligns closely with the actual median arrival time recorded in Hyer's 2023 study on Utah IMT performance (Schultz et al., 2023). Additionally, increasing the IMT fleet to 30 resulted in a cumulative reduction of 28 hours in travel time across 20 scenarios. This translates to an average decrease of 1.4 hours in IMT travel time per simulated day.

5.1 Implications

In their study on Utah’s IMT performance, Hadfield et al. (2021) found that a one-minute delay in IMT RT led to a 0.8-minute increase in RCT, an additional 34.6 minutes in total estimated travel time, and an increase of $925 in EUC. Building on these findings, we estimate that reducing the IMT RT by an average of 4 minutes — a potential outcome of adding 10 more IMTs to the fleet — could result in EUC savings of approximately $3,700 per incident. As UDOT evaluates the effectiveness of its IMT program and contemplates potential expansion, this study’s insights will help facilitate informed decision-making. Our results suggest that increasing the IMT fleet has the potential to decrease VHD and improve response time.

The model we developed for this project addresses two significant ‘what-if’ scenarios, applicable to UDOT or any other transportation agency aiming to optimize its IMT program:

1. What if the number of incidents in our region surges? How might this impact our incident management program’s effectiveness?
2. How much can we realistically reduce delay by increasing the size of the IMT fleet? Or, is there a point where additional IMT vehicles see diminishing returns?

While our primary objective was to address these scenarios, the model’s versatility enables future exploration of additional questions, such as identifying the optimal deployment locations for IMTs in a system, or assessing whether the current operational hours of the IMT program are optimal. In short, if the IMT system expands, where would the additional teams have the most impact? For instance, additional vehicles might be deployed in the peak hours when the costs of traffic demand are highest, or they might be deployed at times where no coverage is available; understanding the simulated response times from this model could provide insight prior to analyzing post-hoc statistics, which are often noisy or unclear.

5.2 Limitations

The limitations of this study are mainly attributed to the model we developed and the aspects that can be enhanced. As outlined in Section 3.1, we opted for MATSim to simulate IMT performance due to its ability to handle large-scale networks, incorporate real-world data, and mimic authentic driver behavior. While MATSim can realistically portray driver behavior, employing additional methods could have further enhanced its performance in our simulations. We described how agents in MATSim alter their routes through an iterative scoring process influenced by various factors including late arrival, mode choice, and activity type. Although this method is generally effective, it may present challenges when simulating unforeseen events like traffic incidents. As Dobler et al. (2012) highlight in their chapter of the MATSim manual, employing a within-day replanning tool is helpful within the MATSim framework, especially for handling unexpected situations. They note that while the iterative modeling approach of MATSim is adept at reaching user equilibrium under typical conditions, it tends to falter during sudden events. This can result in seemingly irrational behaviors, such as agents changing routes before an incident takes place.

The scenario depicted in ***Figure 5.1*** serves as an illustrative example of the potential routing issues that can arise in MATSim when within-day replanning is not applied. In this instance, an agent is navigating from a start point marked by the red dot to a destination marked by the green dot. At 14:02, a traffic incident disrupts the agent's original route. Nevertheless, due to the anticipatory nature of MATSim's iterative approach, the agent already reroutes at 14:00—2 minutes before the incident occurs. This early route change showcases the challenges of solely relying on an iterative modeling strategy for responding to sudden events. It also emphasizes the benefit of incorporating a within-day replanning feature, which relies on a single iteration to provide more accurate and realistic navigational adjustments.

Unfortunately, the problem showcased in ***Figure 5.1*** surfaced at times throughout our MATSim simulations. In certain scenarios, agents would preemptively avoid specific road links anticipated to have incidents, rather than adhering to more realistic behavior patterns observed on real roads. Typically, drivers maintain their intended course until directly confronted with congestion or delays, at which point they may choose to reroute. This variance between the simulated and actual driver responses to unforeseen road incidents underscores a key area for enhancement in our simulation model, ensuring it more accurately reflects realistic driving behavior.

It is also not clear that in general, traffic follows a clean user equilibrium behavior. Previous UDOT research suggests that motorists will continue using roads with higher functional classes even when alternative routes could be modestly faster, given the incomplete information that drivers face (e.g., Schultz et al, 2023b). It is likely that some motorists are highly adaptive, changing quickly in the face of new information. Others may not be as well informed on alternate routes or may be less sensitive to minor delays. Research on the applicability of general equilibrium in modern highway networks is needed.

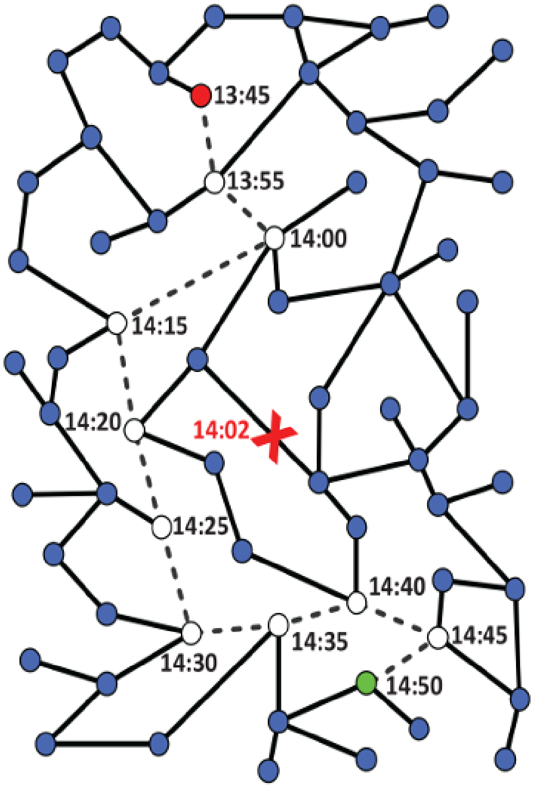

Figure 5.1: Within-day replanning approach for a MATSim routing problem (Dobler et al., 2012).

5.3 Next Steps

Moving forward, enhancing the simulation of IMT response and performance could be achieved by implementing the adjustments mentioned in the previous section, specifically concerning the replanning and configuration settings of the MATSim model. Future steps could also involve exploring additional methods for simulated analysis of IMT performance measures. Depending on the specific requirements of UDOT or other transportation agencies, the simulation could be modified to evaluate optimal IMT starting locations, hours of operation, or their overall cost-benefit ratio.

Overall, the simulation we developed largely corroborates previous findings regarding the efficacy of IMTs. While it necessitates certain adjustments to enhance its reliability, it demonstrates potential as a tool for examining IMT performance in ways that previous studies have not.

6.0 RESEARCH IMPLEMENTATION

The objective of this research was to construct a simulation engine or environment that could be used to preemptively evaluate the effectiveness of IMT deployments in the Wasatch Front region of Utah. Previous attempts by UDOT to evaluate the effectiveness of the IMT program have relied on post-hoc analyses of incident-related traffic data (e.g., Schultz et al., 2022). These studies have shown that IMT is effective at reducing incident-related VHD, but can only provide circumstantial evidence that expanding or modifying the program would result in continued improved outcomes. Prospective evaluation of decisions is as important to the success of UDOT's programs as is retrospective assessment.

This research demonstrates the potential power of prior analysis and simulation to evaluate proposed policies related to traffic incident management on a regional scale. Smaller-scale simulation (for example, of a corridor) can illustrate the importance of restoring capacity after incidents, but it cannot fully account for driver diversions or evaluate the systemic impacts of these incidents. Corridor simulation also cannot account for the availability or location of potential responding IMT units. To implement the research in this report, UDOT should develop a plan to evaluate proposed changes to the IMT program using regional mesoscopic simulation methodologies of the kind provided in this report. The software developed for this research is available under open-source licenses, as are the files necessary to run the simulations. UDOT should retain staff or engage with professional services firms capable of running the software or conducting similar prospective analyses.

This research also demonstrated specific gaps in our understanding of how IMTs affect incidents that require additional research or understanding, and which could be the subject of future IMT assessment efforts. In particular, understanding how IMTs at an incident affect the capacity of the roadway and the total incident clearance time is critical to refining this simulation as well as understanding the effects of IMT on incident delay more broadly. More generally, UDOT – and other highway agencies – should investigate motorist decision-making behaviors with relation to route choice and incident-related diversion.

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APPENDIX A: IMT DISPATCH ALGORITHM

Our MATSim model employs a Java-implemented algorithm within the `IMT.optimizer` package to determine the most appropriate IMT to dispatch to an incident when it occurs. Its primary objective is to identify the closest available teams to the incident's location based on the calculated travel time.

Code Structure:

The `ClosestImtFinder` class encapsulates the algorithm and utilizes a variety of resources to calculate travel times and determine the optimal IMT response.

Components of ClosestImtFinder:

- `Fleet`: Represents the collection of all IMT units available for dispatch.
- `LeastCostPathCalculator`: Utilized to determine the fastest path from one network location to another.
- `TravelTime`: Estimates travel times for various routes in the network.

Key Methods:

- `calculateArrivalTime` Method:
    - **Purpose**: To compute the estimated arrival time of an IMT vehicle at a specific incident location.
    - Parameters:
        - `vehicle`: The IMT vehicle under consideration.
        - `toLink`: The road network link where the incident has occurred.
        - `incidentStart`: The simulation time at which the incident was reported.
    - Process:
        - Checks the vehicle's availability based on its schedule and current task; unavailable vehicles return a value representing infinity.
        - For available vehicles, computes the fastest path and the estimated time of arrival from the vehicle's current position to the incident link.
- `getClosestVehicles` Method:

- **Purpose**: To find and list the closest IMT vehicles based on their arrival times to an incident.
- Parameters:
    - `toLink`: The incident location in the network.
    - `respondingIMTs`: The desired number of IMT vehicles to respond.
    - `incidentStart`: The time of the IMT dispatch request.
- Process:
    - Filters the fleet to include only vehicles in service at the time of request.
    - Sorts the available vehicles by their calculated arrival times to the incident.
    - Selects the top vehicles as per the specified `respondingIMTs` count.
- **Output**: Provides a prioritized list of IMT units for dispatch based on their estimated arrival times.

Dispatch Mechanism:

The dispatch mechanism kicks in following the `getClosestVehicles` method, which produces a prioritized list of IMT units based on how quickly they can arrive at the incident site. This list is instrumental in the decision-making process, allowing for the dispatch of the fastest available IMT units to manage the incident efficiently.

Java Code Implementation

The following Java code illustrates the `ClosestImtFinder` implementation which has been described in the sections above. Comments within the code provide quick references to the narrative descriptions.

```java
package IMT.optimizer;

import ...

/* Searches for the closest IMT vehicles to an incident link. */
public class ClosestImtFinder {

    private final Fleet fleet;
    private final LeastCostPathCalculator router;
```

```
    private final TravelTime travelTime;

    public ClosestImtFinder(Fleet fleet, LeastCostPathCalculator router,
                            TravelTime travelTime) {}

/* Calculates arrival time for an IMT vehicle at the incident start. */
    private double calculateArrivalTime(DvrpVehicle vehicle,
                                        Link toLink,
                                        Double incidentStart) {
        if (!isVehicleAvailable(vehicle, incidentStart)) {
            return Double.POSITIVE_INFINITY;
        }

        // Determine the path and calculate arrival time
        Link fromLink = Schedules.getLastLinkInSchedule(vehicle);
        VrpPathWithTravelData pathToIncident =
        VrpPaths.calcAndCreatePath(fromLink, toLink, incidentStart,
                                   router, travelTime);
        return pathToIncident.getArrivalTime();
    }

/* Checks vehicle availability based on its schedule and current task. */
    private boolean isVehicleAvailable(DvrpVehicle vehicle,
                                       Double incidentStart) {
        Schedule schedule = vehicle.getSchedule();
        Task currentTask = schedule.getCurrentTask();
        return schedule.getStatus() ==
          Schedule.ScheduleStatus.STARTED &&
          currentTask.getTaskType() ==
            Optimizer.ImtTaskType.WAIT;
    }

/* Retrieves a list of the closest IMTs based on arrival times. */
    public List<DvrpVehicle> getClosestVehicles(Link toLink,
                                                int respondingIMTs,
                                                double incidentStart) {
        return fleet.getVehicles().values().stream()
                .filter(vehicle -> vehicle.getServiceBeginTime()
                    <= incidentStart &&
                    vehicle.getServiceEndTime() >= incidentStart)

                .sorted(Comparator.comparingDouble(vehicle ->
                calculateArrivalTime(vehicle, toLink, incidentStart)))
                .limit(respondingIMTs)
                .collect(Collectors.toList());
    }
}
```

APPENDIX B: IMT NETWORK CHANGE EVENTS

The `ImtEventHandler` class, which is a component of the `IMT.events.eventHandlers package`, has been specifically designed to process IMT events within a MATSim scenario. It monitors the `ImtEvent` types that occur when an IMT reaches an incident link. Subsequently, the data from those events is utilized to generate a change event, which serves to restore a part of the capacity of the affected incident link.

Components of ImtEventHandler:

- `Scenario`: Represents the scenario for which the event handler is processing events, containing all relevant information such as the network and its properties.

Key Methods:

- `ImtEventHandler` Constructor:
  - **Purpose**: Initializes a new instance of the `ImtEventHandler` with the given scenario context.
  - Parameters:
    - `scenario`: The MATSim scenario object that provides the context for the event handling.
- `handleEvent` Method:
  - **Purpose**: Determines if an event should be processed and calls another method to handle it if it’s a specific `ImtEvent` representing an IMT arrival at an incident link.
  - Parameters:
    - `event`: The generic `Event` object that the simulation framework produces during the simulation run.
  - Process:
    - If the event is an instance of `ImtEvent` and its arrival time is less than the incident end time, it calls the `handleImtEvent` method to process the event.

- `handleImtEvent` Method:
  - **Purpose**: Handles the `ImtEvent` by creating a `NetworkChangeEvent` and applying it to the simulation's network.
  - Parameters:
    - `imtEvent`: The `ImtEvent` that encapsulates information about an IMT's activity in the network.
  - Process:
    - Instantiates a new `NetworkChangeEvent` using the time from the `imtEvent` as the IMT's arrival time.
    - Sets a change in flow capacity for the network link affected by the IMT event, using the capacity provided by the `ImtEvent`.
    - Adds the `NetworkChangeEvent` to the network, which effectively adjusts the incident link's capacity in response to the IMT's actions.

System Integration:

The `ImtEventHandler` is integrated into the simulation to respond dynamically to incidents. When an `ImtEvent` occurs, indicating that an IMT has arrived at the incident link in the network, the event handler adjusts the network's conditions to reflect this change. This adjustment simulates the effects of IMT actions on traffic conditions by restoring capacity to a link affected by an incident, which can impact traffic flow and overall network performance within the simulation scenario.

Java Code Implementation

The following Java code illustrates the `ImtEventHandler` implementation which has been described in the sections above. Comments within the code provide quick references to the narrative descriptions.

```
package IMT.events.eventHanlders;

import ...

/* This class implements BasicEventHandler to handle IMT events. */
public class ImtEventHandler implements BasicEventHandler {

    private final Scenario scenario; // The MATSim scenario context.

/* Constructor takes a scenario context for event handling. */
    public ImtEventHandler(Scenario scenario) {
        this.scenario = scenario;
    }

/* Handles IMT events by delegating to handleImtEvent method. */
    @Override
    public void handleEvent(Event event) {
        if (event instanceof ImtEvent imtEvent &&
        imtEvent.getArrivalTime() < imtEvent.getEndTime()) {
            handleImtEvent(imtEvent);
        }
    }

/* Processes ImtEvent by creating and applying a NCE */
    private void handleImtEvent(ImtEvent imtEvent) {

        NetworkChangeEvent imtArrival =
          new NetworkChangeEvent(imtEvent.getArrivalTime());

        double currentCapacity = imtEvent.getCurrentCapacity();
        imtArrival.setFlowCapacityChange(new
          NetworkChangeEvent.ChangeValue(
          NetworkChangeEvent.ChangeType.
            ABSOLUTE_IN_SI_UNITS, currentCapacity));

        imtArrival.addLink(scenario.getNetwork().getLinks().get
          (imtEvent.getLinkId()));

        NetworkUtils.addNetworkChangeEvent
          (scenario.getNetwork(), imtArrival);
    }
}
```