EVALUATING DISRUPTION MANAGEMENT STRATEGIES IN RAIL TRANSIT USING SIMMOBILITY MID-TERM SIMULATOR : A study of Singapore MRT North-East line

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ABSTRACT

Service disruptions are among the greatest enemies of attractiveness and trust in public transport. In many cities in the world, plenty of effort has been put for policies, technologies, information services and travel options, in order to raise attractiveness of rail, metro and bus services for travelers preferring private vehicles, but it often takes only a few really bad experiences to fall back to less sustainable options.

While preventing all disruptions may be out of reach due to their nature (e.g. power failures, inclement weather, medical emergencies, intrusions), one can focus on their consequences. Yet, such assessment needs to cover the entire transportation system as it may significantly affect the performance of other modes as well, especially in urban areas. With a comprehensive and well-calibrated simulation model, one could assess impacts of potential disruption and test mitigation strategies. This is, however, a type of scenario where careful representation of just-in-time agent-interaction dynamics and limited access to information needs to be taken into consideration. In other words, simulation of travel disruptions requires a representation of within-day behavior with incomplete information and en-route routing, which are known to be a challenge in travel models.

This paper demonstrates the use of a multi-modal simulation tool, the SimMobility Mid-term model (SimMobilityMT), in the study of a disruption scenario occurred previously in Singapore's mass-rapid transit (MRT) system. In order to simulate within-day behavior and agent interactions, SimMobilityMT uses a publish/subscribe mechanism that is able to asynchronously propagate information across agents and trigger en-route rerouting decision making processes, as agents become aware of the disruption (e.g. when they arrive to the MRT station).

For empirical analysis purposes, we test a bus-bridging disruption management strategy, using shuttles between pairs of MRT stations. We compared the results with a baseline, where no disruption is occurring, according to several metrics, namely travel times, dwelling time, waiting times, denied boarding and mode share. Unsurprisingly, the bus bridging strategy substantially outperforms a scenario where there is no pro-active support from the operators.

Keywords: Disruption Management; Agent-based Simulation; SimMobility Mid-term; Singapore Mass Rapid Transit;

INTRODUCTION

Rail transit networks and mass rapid transit systems are developed in cities with the main aim to move high number of commuters from their origins to desired destinations. In peak times these origins and destinations are primarily at residential areas, workplaces, and schools. These systems have been developed to reduce burden on the road network and ease traffic congestion. Cities like Hong Kong, Singapore, Tokyo, London and New York are examples where more than 50% individuals rely on public transport for their daily commute [1]. With a vast number of different technologies and infrastructural components involved in train operations, there are always chances for unexpected events to occur, causing disruptions. These events can lead to the rapid degradation of service provided and the results of such impediments can be significant [2]. Longer duration of disruptions causes increased delays, but even worse, users lose confidence on the transit system. If disruptions are not managed properly, in the long run, rail transit systems will fail in their purpose [3].

In order to prepare for disruptive events, the first big challenge is the specification of the disruptions themselves: where and when could a disruption happen? how could it unfold? what causes it? The range of possibilities is obviously enormous, and so is the range of potential impacts.

Due to the complexity of this phenomenon, a natural technique to study disruptions is through simulations [4]: if we are able to represent all important variables and their interactions, then our simulation could be a trustworthy oracle into the range of impacts of possible disruptions. This obviously puts great responsibility in the simulation tool. It should be detailed enough to represent important interactions, it should be computationally efficient and it should be flexible enough to accommodate a range of different disruptions.

The SimMobility integrated simulation platform [5] allows for demand and supply representations at different levels of resolution, through a multi-scale suite of 3 simulators that fundamentally differ by the decision making time scale being represented (Long-term, Mid-term and Short-term). The long-term simulator relates to decisions over months or years (such as house and job location choice); the mid-term simulator relates to minute-by-minute or hourly decisions (such as destination, mode, path or activity schedule choices); the short-term relates to fraction of second to minutes, such as lane-changing, accelerating and braking, or path choice. In this study, SimMobility mid-term (SimMobilityMT) simulator [6] is used, in which econometric Activity-based demand model is integrated with a mesoscopic dynamic traffic simulator to study the impact of disruptions and management strategies.

A particular benefit of SimMobilityMT design for transport disruption analysis is its *publish/subscribe* event mechanism: after making a choice (e.g. starting a trip), each agent subscribes to receive events that may trigger a revision of such choices (e.g. a travel delay above certain threshold; availability of new information). Upon detecting such events, SimMobility supply then *wakes up* agents as requested, and they will (potentially) revise their choices in face of new information. In this way, we simulate agent's reactions to new events while en-route. Notice that such reactions will often be associated with imperfect information about the network. While, on a day-by-day, equilibrium basis, an agent would be able to maximize utility of all her options for the entire network through time, under a disruption scenario, she has to react to available information of the moment, potentially making sub-optimal choices. Replicating this mechanism is essential for analyzing disruption scenarios.

In this paper, we apply SimMobilityMT to study a disruption event in the Singapore Mass Rapid Transit (MRT) that occurred in the North-East (purple) line in 2013. Besides buses, taxis, walking and private vehicles, SimMobilityMT was extended to represent detailed MRT movement and operation in the mesoscopic supply simulator. Different strategies that are commonly being used to manage the situation are then evaluated.

The contributions of this paper lie in the following: (1) demonstration of publish/subscribe mechanism for en-route decision making in a transport mode; (2) replication of system performance using SimMobility under regular and realistic disruption conditions in Singapore; (3) comparison of different strategies considered by local practitioners. The paper is structured as follows: Section 3 presents a literature review on disruption simulation and analysis, strategies and performance metrics. Section 4 presents an overview of SimMobilityMT, including the details of publish/subscribe mechanism. Section 5 provides the details of experimental design and data analysis; Section 6 presents results and discussions; finally, Section 7 presents the main conclusions and lines of future research.

LITERATURE REVIEW

Disruption situations imply changes in pre-planned operational settings which are so significant that require attention and necessitate re-planning [2, 7]. Given climate change and complexity of our cities and societies (e.g. increase of terrorism threats), the likelihood of such events seems to increase in frequency [8]. For example, Dawson et al [9] investigate how sea-level rise scenarios impact railway line disruptions in coastal England, showing that, until 2020, disruptions are expected on 16 to 19 days per year. This trend seems to increase (with the sea-level rise and associated consequences) to 84 - 120 days by 2100. Despite such evidence, after analyzing four case studies of past extreme weather events leading to rail disruptions in Europe, Ludvigsen and Klaeboe [8] conclude that affected parties are badly prepared for such scenarios.

Schmocker et al.[10] categorized three incident types in rail-based passenger transport system: slow-moving delays, minor incidents, and major incidents. According to [2, 10], major incidents are the ones commonly considered as disruptions, and these result mainly in rolling stock or fixed infrastructure problems, and are likely to close track sections. Pender et al [2] presented a comprehensive international survey of 71 transit agencies. There are variety of reasons reported for disruption and the most common are as follows: intrusion and medical emergencies, weather and natural disasters, track failure and rolling stock failure. It has been found out that in dense urban areas, transit agencies take existing parallel public transport as a first alternative for recovery of disrupted situation based on the assumption that majority of the trips can be performed by using existing bus routes. Majority of agencies (85%) preferred bus bridging (a replica service to disrupted stations to restore connectivity) as the most appropriate solution for unplanned disruption, however, in many situation it cannot be only viable solution due to capacity constraints, road traffic congestion and provision of shuttle buses. In addition to bus bridging and use of parallel transport, provision of crossovers is also considered as an aspect which can minimize the impact of disruption.

There is a reasonable amount of literature that uses (or suggests) simulation modeling for emergency preparedness in transport systems. This is not surprising since simulation allows to artificially create extreme conditions and try out extreme measures. It is a non-trivial task, since such scenarios are often complex, difficult to specify, and may go beyond the transportation realm (e.g. flooding).

We can find references to simulation based emergency management for transportation as far back as 1985 [11, 12]. Like today, in these possibly seminal works, the proposal was to simulate the performance of a network under stress conditions, and to try out mitigation measures (in these particular cases, focused on evacuation). These were focused on simpler, small scale or low detail, networks, and with the increase in computing power, data availability and model complexity, more ambitious projects were developed. In 2004, a large scale model, that combines freeway and urban networks (CORSIM) was applied to test responses to several hypothetical transportation emergencies in the Birmingham, Alabama region [13]. Performance metrics considered were decrease in average speed (no disruption) scenario, travel time (delay), queuing time and queue lengths in comparison with baseline. Such statistics were considered for the affected areas as well as entire network. This work, and many others since, was focused on private traffic (e.g. [14, 15, 16]).

On the public transport side, some research exists in train line evacuation using buses in emergency situations. The general approach is that the bus service replaces the train service. For example, Teng et al [17] combine two simulators, RailSys and Vissim, to model emergency evacuation from disrupted train stations. Others combine simulation with operations research (OR) tools, to optimize bus-based disruption recovery strategies for metro trains (e.g. [3, 18, 19]). In fact, plenty of research in this area aims to optimize disruption management strategies using OR. The downside is that, given the priority to the optimization algorithm itself, the simulation models are often over-simplified. For example, many of the above approaches only consider deterministic choice for passengers (always evacuate to the bus, and take it to the destination) while in practice travelers may have access to other modes (e.g. taxi, one way car-sharing services). It is also common to work at the aggregated flow level (e.g. considering fixed ODs), but individual agents may even revise their destination choice, or cancel the trip. A comprehensive simulation framework that is multimodal and disaggregated needs to be available in order for such notable efforts to have more reliable results.

On a different perspective, a wide body of research has also dedicated to large-scale disruption scenarios, such as natural hazards, through integration of different simulators. For example, Pyatkova et al [20] integrate a traffic microsimulation tool (SUMO) with a flood model (MIKE Flood), showing the impact of flooding scenarios in terms of connectivity reliability and economical loss. Kaviani et al [21] combine traffic simulation with bushfire and flooding models in order to optimize the best location for traffic management points, locations where road blocks are established by police during emergencies to stop traffic entering areas that are considered dangerous. The integration of transport with different systems is also a necessary trend that deserves further exploration, particularly when our cities are becoming more strongly connected (e.g. energy and transport systems are becoming increasingly more connected due to electrical vehicles).

As mentioned by several studies, rail and public transport network are more prone to disruptions than road networks. However, very limited amount of work has been done in terms of analyzing and evaluating the impacts of unplanned disruptions [22]. Few studies have focused on vulnerability/resilience analysis by identifying important links in the public transport network and measured the impact of removing these pre-defined links on various criteria such as unsatisfied demand [23, 24, 25], increase in average travel time [24, 25], betweenness centrality measure [26], consumer surplus Cats and Jenelius [4] and demand-weighted distance [27].

Finally, regarding the performance metrics themselves, they can be further divided into two types: capacity reliability and travel time reliability. Capacity reliability is the probability that a network successfully accommodates a given level of demand [28]. Travel time reliability is defined as the probability of reaching a chosen destination within a given time [29, 30], and has been considered a key measure for transportation systems performance [31, 32]. This will too be a key measure for our analysis. We will also consider statistics that relate with capacity reliability, such as number of denied boarding and vehicle occupancy/overcrowding.

SIMMOBILITY MID-TERM MODEL

Overview

SimMobility Mid-term (MT) simulates daily travel at the household and individual level. It is categorized as a mesoscopic simulator since it combines activity-based microsimulator on the demand side with macroscopic simulation at the supply side. Figure 1 presents the modeling framework of the MT simulator implemented in SimMobility. A detailed description of each component of the MT model can be found in [6]. The demand comprises two groups of behavior models: pre-day and within-day. The pre-day models follows an enhanced version of econometric Day Activity Schedule approach (presented in [33]) to decide an initial overall daily activity schedule of the agent, particularly its activity sequence (including tours and sub-tours), with preferred modes, departure times by half-hour slots, and destinations. This is based on sequential application of hierarchical discrete choice models using a monte-carlo simulation approach.

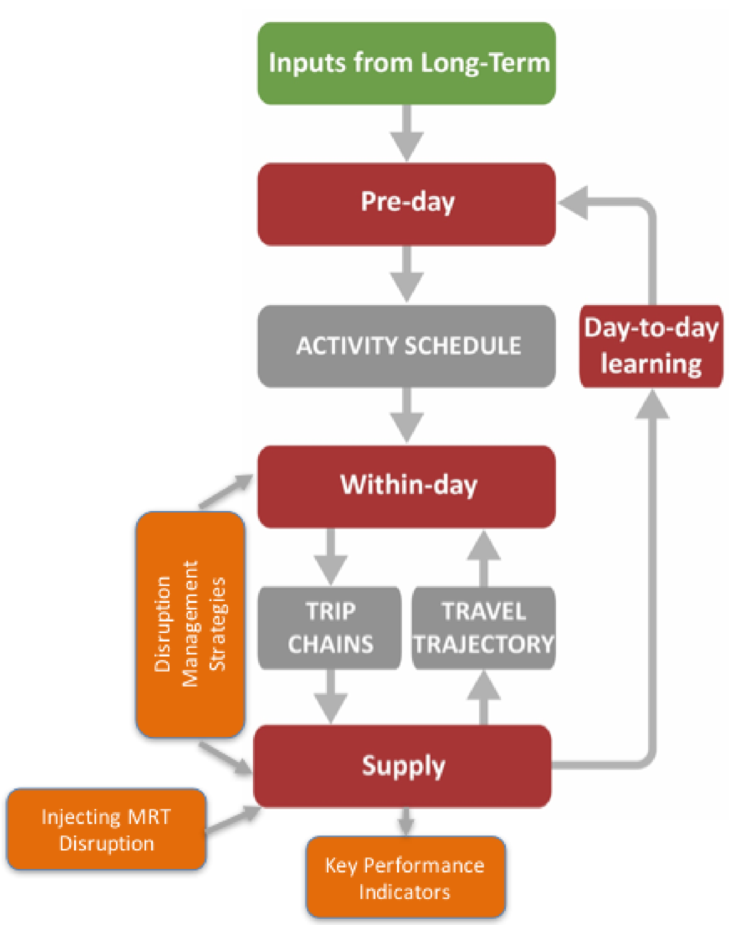

FIGURE 1 : SimMobility Mid-term overview with disruption injections

As the day unfolds, the agents apply the within-day models to find the routes for their trips and transform the activity schedule into effective decisions and execution plans. Through the publish/subscribe mechanism of event management, described below, agents may get involved in a multitude of decisions, not constrained to the traditional set of destination, mode, path and departure time depending upon their state in the event simulation cycle. For example, the agent could reschedule the remainder of the day, cancel an activity (or transfer it to another household member), re-route in the middle of a trip (including alighting a bus to change route), or run an opportunistic activity, like shopping while waiting. The supply simulator follows the dynamic traffic assignment(DTA) paradigm as used previously in DynaMIT [34], including bus and pedestrian movements. Finally, a day-to-day learning module, which feeds back network performance to the pre-day model, is introduced to update agent's knowledge (either as a calibration procedure or for a multiple day simulation).

For the particular application of MRT disruption scenario analysis, we extended SimMobilityMT in the following way: MRT disruption injection, following the publish/subscribe mechanism (explained below); disruption management strategies, which implement the strategies presented in section 5; key performance indicators, which collects the results presented in section 6.

Publish/subscribe mechanism

The publish/subscribe mechanism is popular within software engineering for asynchronous communicating between software objects. For example, a smart phone app may *subscribe* to a *location update* event such that, when the device changes location (or reaches a certain location), the app is informed and can react accordingly. In some sense, the publish/subscribe mechanism mimics the perception/reaction capability of a sentient being in a very efficient way: instead of checking constantly for an event, an app can become dormant, yet alert to new information. This, we believe, is similar to human's own information management strategy: one can decide to execute some plan (e.g. travel in some route), but will stay alert to events that may imply revision of such plan.

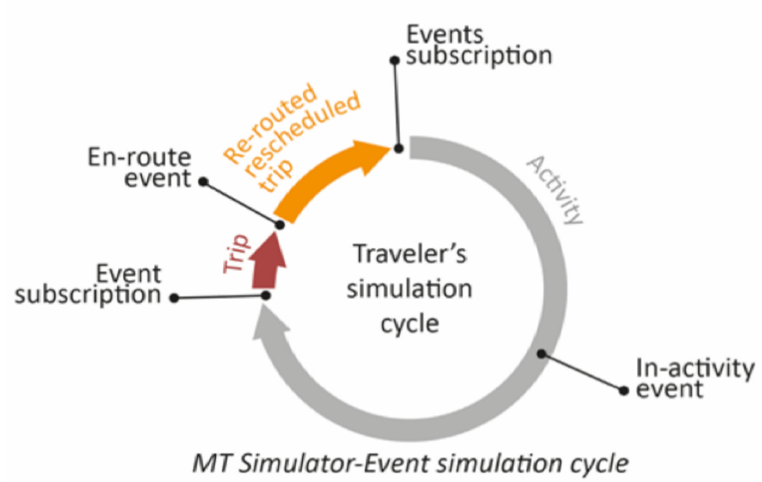

FIGURE 2 : Illustration of publish/subscribe cycle in SimMobilityMT

Figure 2 illustrates the publish/subscribe cycle in SimMobilityMT. Before starting a trip (or an Activity), an agent subscribes to events that may demand her attention. Examples include excessive delay during the trip (e.g. arriving to a specific way point more than X minutes late; an information system informs about a delay), a disruption in the system, household interactions (e.g.

spouse asking to pick-up children). After revising her choice, changes in the trip or activity are executed (and new events are subscribed to), and this cycle repeats for the whole life of the agent.

In other words, agents need only be active when they make decisions, which happens when triggered by their perception. The perception is represented as the reception of an event information that is relevant for the agent. When not processing events, agents are in an auto-pilot mode, being simply moved by the supply according to plan. This auto-pilot mode is where agents spend most of their simulation time: each decision that is made is translated into a plan that is executed by the simulator. Until this plan is complete or a subscribed event occurs, the agent is in the auto-pilot mode.

In practice, this mechanism allows for computationally very efficient interaction between supply and demand. The supply side, time-step based, simply picks the latest plan information for each agent and executes it. A global events manager module, checks at each time step, which subscribed events occur and wakes up the respective agents. If the agent changes its plan due to an event, it will be reflected for the next time step, which will be executed by the supply simulator. This publish/subscribe mechanism is fundamental for opportunistic activity scheduling, as suggested in [35]. For example, an agent could subscribe to an event to "wake him up if he is 5 minutes to a supermarket".

In SimMobility, the concept of agent" is extended to any decision maker, including at the supply side. In some cases, such representation is necessary to simulate complex decision making processes (e.g. taxi dispatching), and this will be illustrated in a simple example in our case study. Whenever a breakdown is to be injected (e.g. from a configurable input file or a historical database) in the MRT case-study, a *disruption event* is published first at the MRT supply side. It is received by the *station agent*, responsible for managing the station, and the *train controller*, in charge of the movement of the vehicles (see Figure 3). The station agent will transmit the information to the passengers waiting in the station and to the train driver agent, which will in turn transmit to the passengers. On the train controller side, it will transmit to the train scheduler, which will cancel the next departing trains.

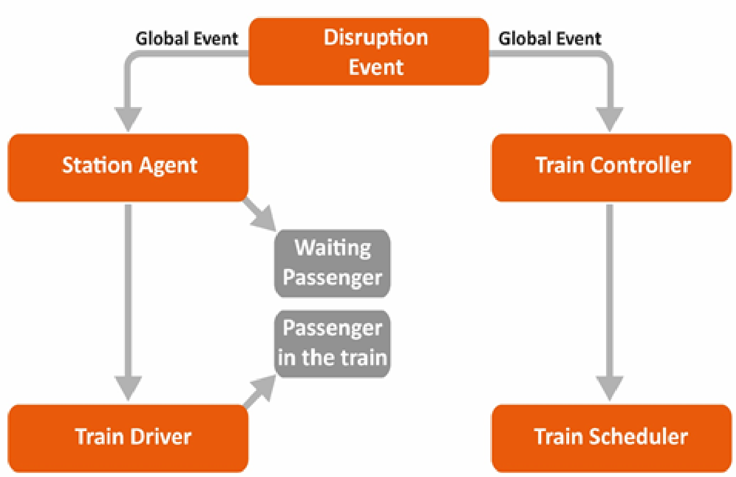

FIGURE 3 : Interactions triggered by a disruption event

The passengers will then re-run their destination, mode and route choice models, and revise their plans accordingly. This is done with imperfect information, i.e. they will reuse their latest available information, considering the announced disruption, but ignoring related changes in the network (e.g. revised travel times).

EXPERIMENTAL DESIGN

Our case study is related to a specific disruption that affected the North East (NE) Line of the Singapore Mass-Rapid Transit (MRT). This line links the north-eastern part of Singapore (Punggol) with the center-south (Harbourfront). To expand its reach in the north-east area, 4 LRT lines, working in a loop, connect to Punggol and Sengkang (NE16).

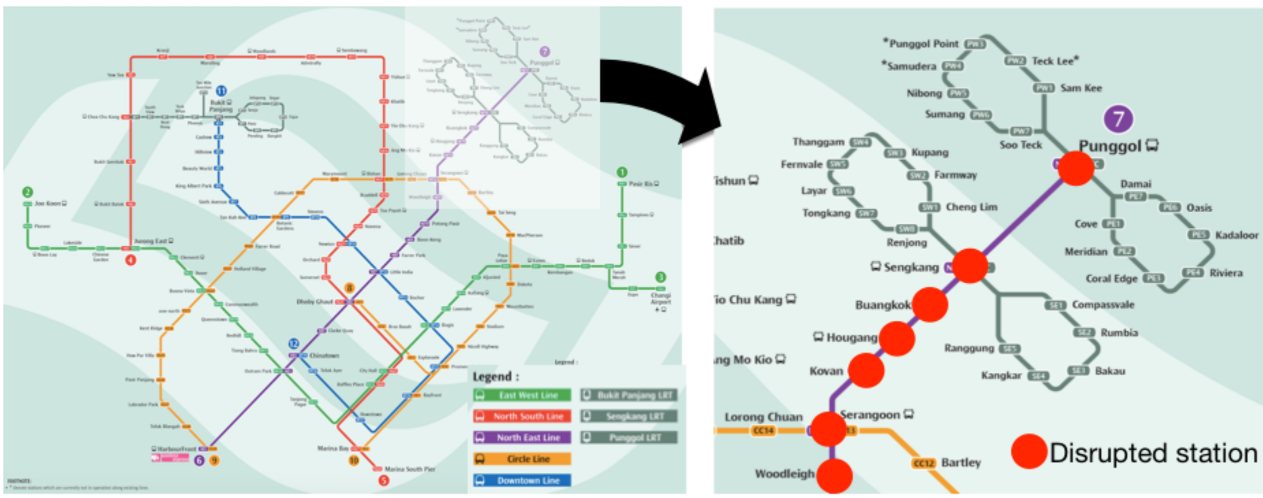

FIGURE 4 : Singapore MRT network and disruption details

On June 19, 2013, from 6:15 to 8:35pm, service on the NE line was disrupted between the stations of Punggol (NE17) and Woodleigh (NE11), but kept operating between Harbourfront (NE1) to Woodleigh (NE11). This scenario is illustrated in Figure 4. At 6:15pm, a train heading towards Harbourfront (NE1) stalled as it was approaching Hougang Station (NE14), and a push-out rescue attempt, it was determined to detrain the vehicle, implying a longer than usual operation [1].

Fortunately, such a disruption had limited impact because of the time of day, only marginally overlapping with work-home commute peak hour travels. However, the concern was raised about potential disruptions of comparable magnitude at peak-hour times. More importantly, what are the measures that mitigate the most of negative impacts.

Our study replicates the above event except for the time of day, we will focus on 8 to 10am of a weekday. We will simulate 3 different scenarios:

- No disruption. This scenario serves mostly to create a baseline for comparison, showing the best possible values for our evaluation metrics, and illustrating what an average commuter would expect. This will be called *base case*
- No extra service. In this case, we simulate the disruption and it is left to the commuters to seek for other options from the commonly available set, namely buses, taxis, or walking. This will be called *strategy 1*.

[1]For more details, go to https://www.sbstransit.com.sg/press/2013-06-19-01.aspx

- Shuttle service. We add an extra service, of bus bridging between every two MRT connected stops between NE11 and NE17. In this way, commuters have shuttle buses as an added alternative to regular buses, taxi and walking. This will be called *strategy 2*.

This simulation will be run in the SimMobilityMT software, which was calibrated using the Weighted Simultaneous Perturbation Stochastic Approximation (W-SPSA) algorithm [36]. The parameters being calibrated include day-pattern, time-of-day, mode, destination choice, private and public route choice, supply speed-density parameters, capacities of mid-block sections, and capacities of segments near intersections. The synthetic population was generated based on local data (e.g. national census called as SingStats) [For more details please see [37]. The data for the calibration process came from GPS floating car data from taxis and 29 screenlines that contain 403 counting locations. The processed classified counts and zone-to-zone travel times are aggregated by 30 minutes. For aggregate counts on the basis of screenlines we obtain a root mean squared error normalized (RMSN) of 0.19. Using a hybrid objective function, for counting locations and zone-to-zone travel times we obtain an RMSN of 0.52. The large and sparse number of measurements and the nature of the demand calibration process constrained by a fixed population and its *inderect* demand generation through activity-based models limits the rapid and efficient convergence of the calibration process, although we believe there is room for improvement.

Some details of the supply are also worth mentioning, such as capacities and schedules of buses and taxi service. Singapore operators use three different bus types, each one with different maximum capacity including seating and standing (single-decker: 85 passengers, double-decker: 134 passengers, and long-bus: 149 passengers). We did not have access to exact bus capacity assignment, and it is not our intention at this moment to study optimal assignment, so we decided to use a single "average" bus capacity of 100 passengers. Regarding bus schedules, we used the Google Transit Feed Specification (GTFS) as provided by the Singapore Land Transport Authority (LTA) itself. Regarding number of taxis, there are around 28,000 vehicles registered and various operators are managing the operations. The daily ridership is estimated to be around 0.9 million passenger trips. Recently, with introduction of *Uber* and *Grabcar*, the number of potential "taxis" is difficult to represent. Upon analysis of the base case, we confirmed the realism of the results in terms of daily MRT and bus ridership and average travel times experienced by user while traveling in public transport. Our simulation results are reasonably close to the numbers mentioned in LTA statistics.

To evaluate the impact of the different strategies, we will use the following metrics:

- **Measure 1 (M1)**: Average Travel Time (min), for those trips that utilized disrupted MRT stations during considered time window;
- **Measure 2 (M2)**:Average Dwell time (seconds), for bus stops nearby disrupted MRT stations during considered time window;
- **Measure 3 (M3)**:Average Waiting time at Bus stops (min), for bus stops nearby disrupted MRT stations during considered time window;
- **Measure 4 (M4)**:Number of denied boardings, for bus stops nearby disrupted MRT stations during considered time window. A denied boarding happens when bus capacity is reached and a passenger cannot enter (if N passengers are denied boarding to a bus, we count N, the number of persons affected);

- **Measure5 (M5)**:Average Delay Time (min), for the trips that utilized disrupted MRT stations during considered time window by Destination.
- **Measure6 (M6)**:Mode share. We want to evaluate how mode share changes, with introduction of the extra option, of shuttles.

RESULTS AND DISCUSSION

For each scenario, we starts the simulation at 0:00 of the same day and ended at 12:00 noon (mid-day) to guarantee all trips initiated in the analysis period are completed (i.e. in practice total simulation goes from 0:00 to 12:00), all simulations took 91.45 min, 97.6 min and 96.2 min, for base case and strategies 1 and 2, respectively, on a 30 core High Performance Computer (HPC) machine. For the base case, the total number of origin/destination trips (including access, egress, multiple legs) registered is 2.21 millions for the whole simulation and whole island, while during the study period (8-10+extra 2 hours), we counted about 878 thousand OD trips, which can be decomposed into 1.2 mill sub-trips (or legs). For strategies 1 and 2, the numbers are comparable (eventually with slight increase in number of sub-trips), since we kept the same overall demand generated from Preday module of SimMobilityMT. The total number of travelers directly affected by the disruption is about 42 thousand. The results of these simulations, according to the metrics of section 5, are summarized on Table 1

The results are generally intuitive, and the base case (no disruption) shows the best performance, with an average travel time of 52 minutes. Notice that this corresponds to full door-to-door travel time, for all trips that are directly affected, and it includes access and egress walking, and other modes involved in the journey. The average waiting time roughly corresponds to the headway of most bus lines involved. Regarding the denied boarding, mostly such events effectively happen around two stations (Hougang and Sengkang), which are also large bus interchange terminals. It is also clear that the average travel time degrades substantially unless there is no active mitigating measure, since Strategy 1 performs much worse than Strategy 2, as we can see by all measures. Notice again the substantial number of denied boardings, which will be analyzed below.

To better understand the impact of this disruption across the whole island of Singapore, we estimated a bi-dimensional kernel density over the map of Singapore. Each observation (of a delay) is represented by its destination point and then smoothened using a kernel density function, essentially giving a spatial distribution of delays. We further discretized the result to make it more understandable, and the result is shown in Figure 5). Notice that the resulting "regions" have no necessary correspondence with actual administrative areas. We attached a number to each one to illustrate the percentage of trips (that start or cross our MRT disrupted line) that end in that area to emphasize their relative importance.

TABLE 1 : Results summary

Measures	Base case	Strategy 1	Strategy 2
M1. Average travel time (min)	52.8	111.6	74.8
M2. Average dwell time (seconds)	45	58	52
M3. Average waiting time at stops (min)	4.69	8.4	5.8
M4. Nr. denied boardings	867	13960	5539

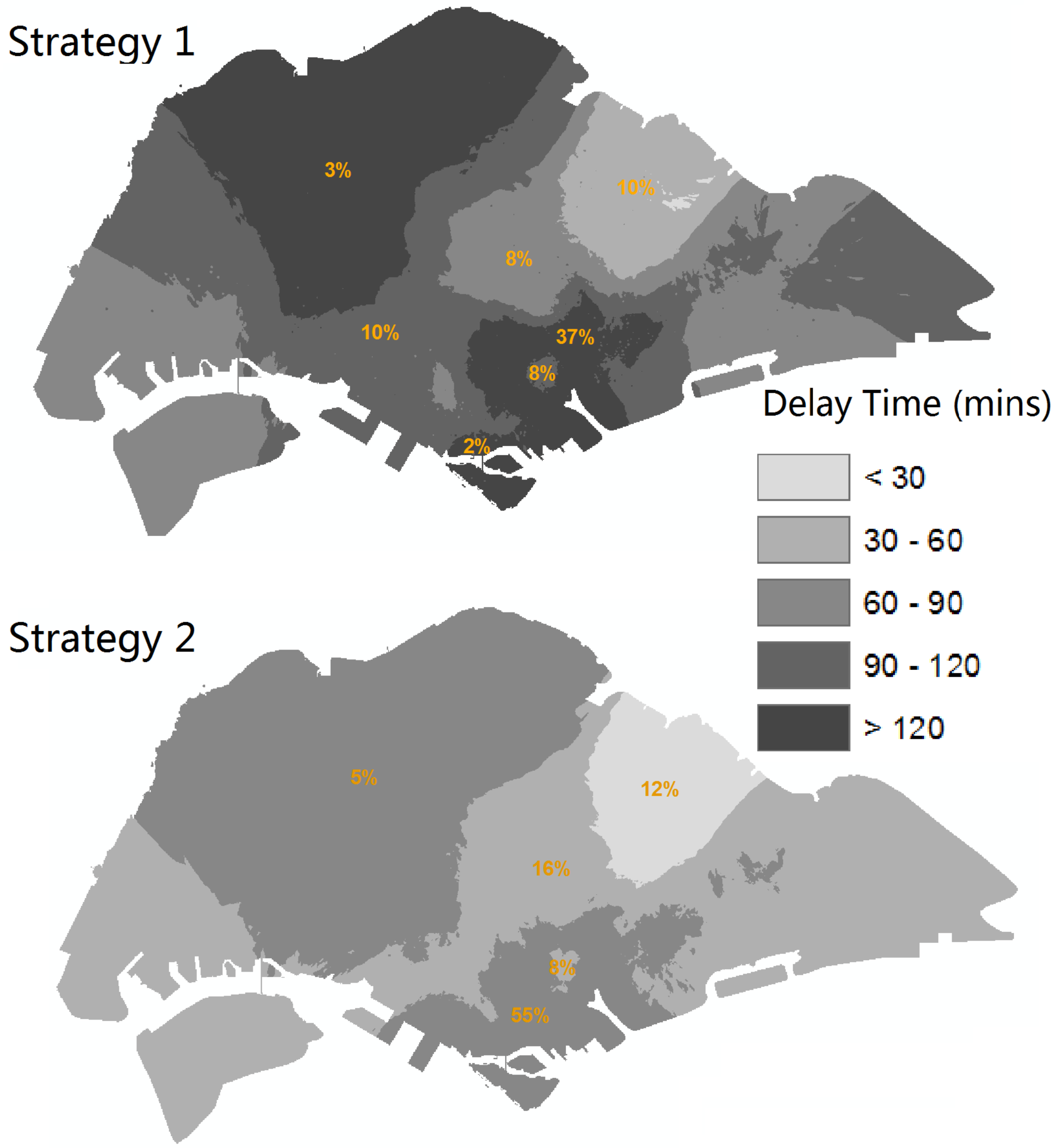

FIGURE 5 : Spatial distribution of M5: Delays across Singapore, for Strategy 1 (top) and Strategy 2 (bottom). Numbers in percentage relate to the respective area, and correspond to the share of analyzed trips that end in that area.

We can take a few interesting notes from the figure. First, the areas that are more affected by the disruption seem to be the central business district (CBD) and the north-west area. The former is extremely relevant, particularly if we take into consideration that the majority of the trips effectively have CBD as destination (about 50%). The latter is probably a consequence of the fact that north-west and north-east having poor direct connectivity. It is also very clear that in practically no location in strategy 1 is better than strategy 2, delay-wise. Finally, the only area that has small delay impact due to the disruption is effectively the north-east itself, which is understandable.

Regarding number of denied boarding and average waiting time, we plot the differences with the base case in Figure 6

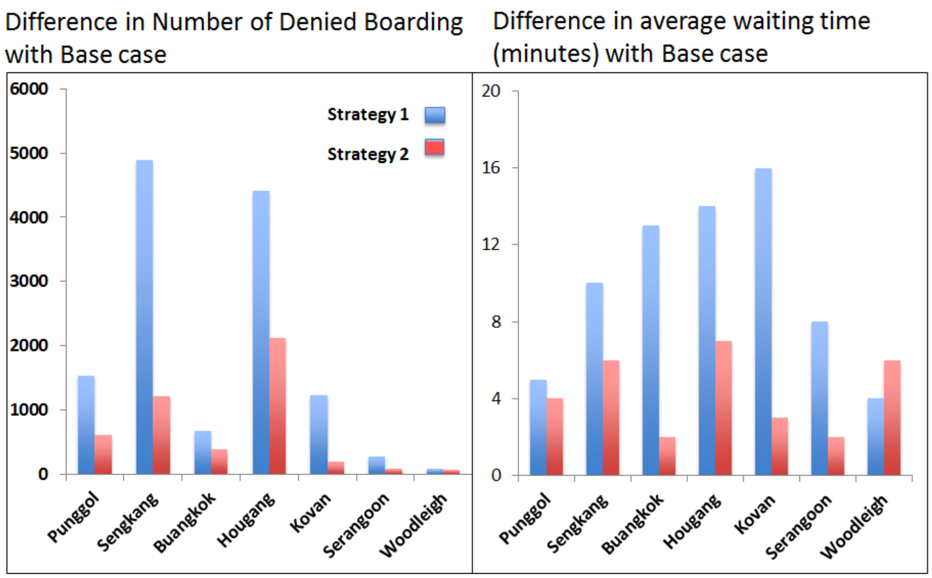

FIGURE 6 : Comparison between Strategies 1 and 2 with differences from the Base case, for the bus stops around affected MRT stations: M4: Denied boardings (left), M3: Waiting times (right)

Regarding denied boarding, notice that the big effect happens in the bus stops around two stations mentioned above, Hougang and Sengkang. In absolute terms, even with Strategy 2, there is a substantial number of denied boarding, which reveals that bus lines that had already been in capacity limit, likely serve demand that has relevant overlap to the NE line. Of course, this effect would be expected to increase denied boarding in all lines, but the impact on those two stations is striking, particularly for Strategy 1.

Finally, with respect to mode share, Figure 7 summarizes the results. Unsurprisingly, the most prevalent mode shifting is from bus to shuttle buses (which is no cost service), while taxi also lost a considerable amount.

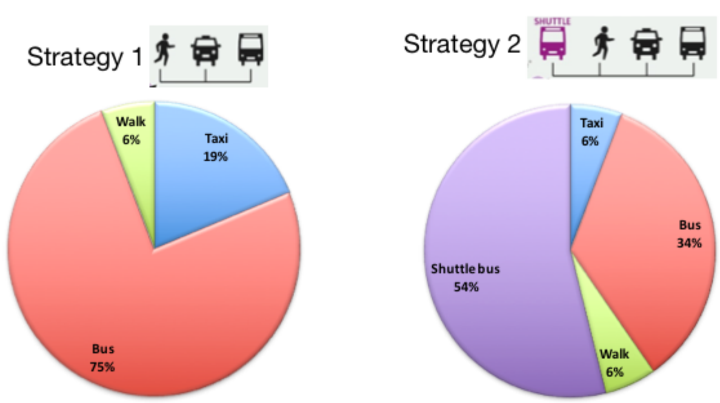

FIGURE 7 : M6: Mode shares for Strategies 1 and 2

CONCLUSIONS AND FUTURE WORK

This paper demonstrated the use of a simulation tool, the SimMobility Mid-term model (SimMobilityMT), in the study of a disruption scenario. SimMobilityMT is particularly suited for such a challenge, since it allows agents to revise their decisions on a within-day basis, for example while en-route, with limited information access. It uses a publish/subscribe mechanism to achieve such functionality.

We particularly focused on a mass-rapid transit (MRT) disruption that occurred previously in Singapore, calibrating our model accordingly and designing realistic options for mitigation of the disruption. We compared the results with a baseline, where no disruption is occurring, according to several metrics, namely travel times, dwelling time, waiting times, denied boarding and mode share. Unsurprisingly, the bus bridging strategy substantially outperforms a scenario where there is no pro-active support from the operators.

The key role of this paper was to validate empirically the SimMobilityMT on a full multi-modal scenario, with a challenging dynamics that requires systematic en-route revision of decisions, in terms of software performance and model reliability. To our knowledge, these objectives were largely accomplished.

The next steps may include several directions. Regarding the strategy, we could allow it to be itself dynamic (e.g. using pricing), or optimize the strategy parameters (as done by [3, 18, 19, 19]). SimMobilityMT is also ready to exploit other modes, such as autonomous mobility [5, 38]. One can also study other disruptive scenarios such as planned large events (e.g. Singapore F1 race), this time with the benefit of having a clearer specification of the disruption, but still implying potential en-route decision making from agents side.

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