Integrated multimodal network management: An agent based approach

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Abstract

Future developments of mobility go strongly through a complementarity and blending of modes. From this point of view, the potential benefits (i.e. societal, monetary) of mobility management beyond modes is very interesting to study. Integrated multimodal traffic management refers to the coordination of individual network operations, to create an interconnected mobility management system. In many networks across the world there has been a considerable investment in communication and sensing technologies along major corridors of the network. An integrated multimodal traffic management system aims at exploiting the full potential of deployed intelligent transport technologies to improve not only the operation and performance of the network but also the demand traveling in the network, influence the mode choice, travel time, delay, fuel consumption and emissions. Moreover, it should increase the reliability and predictability of travel in the network. Commuters consider and plan their mobility comprehensively, they have access to multimodal information and routing (i.e. apps), and the same should hold in the infrastructure supply side (i.e. traffic network operators).

Most trips use multiple modes of transport, including mobility services; future mobility management systems should consider inter-layer communication, and their complementarity and collaboration. Currently we are limited to lack of communication and/or collaboration between inter-modal infrastructures. Each operator makes decisions independently, and thus, may negatively affect users' mobility. For instance railway and road traffic optimize their performance separately, but an integrated framework could be beneficial. The complementarity of most transport modes (speed, accessibility capacity) is in fact ignored in most traffic control approaches. Essentially, modes are complementary, in terms of speed, accessibility, and capacity: while trains can achieve a high capacity for a restricted set of nodes (stations), cars can connect almost any two points; furthermore, in urban areas, active modes such as walking or cycling enable accessing (almost) all places. The Success of a multimodal traffic management system depends on careful planning on one hand, and on the other hand on an integrated system level perspective among the network operators, which calls for advanced transportation analysis tools to estimate and predict network performance under different strategies and analyze the network for different tactical purposes.

Future traffic control beyond modes aims to study the benefits of a nation wide integrated multimodal traffic management system.

Keywords

Integrated Multimodal Network Management; Disruption Management.

1 Introduction and problem statement

Future developments of mobility go strongly through a complementarity and integration of modes. From this point of view, the potential benefits (i.e. societal, monetary) of mobility management beyond modes is very interesting to study. Integrated multimodal traffic management refers to the coordination of individual network operations, to create an interconnected mobility management system. In many networks across the world there has been a considerable investment in communication and sensing technologies along major corridors of the network. An integrated multimodal traffic management system aims at exploiting the full potential of deployed intelligent transport technologies to improve not only the operation and performance of the network, but also the demand traveling in the network, influence the mode choice, travel time, delay, fuel consumption, and emissions. Moreover, it should increase the reliability and predictability of travel in the network. Commuters consider and plan their mobility comprehensively, have access to multimodal information and routing (i.e. mobile apps), and the same should hold in the infrastructure supply side (i.e. traffic network operators).

Most trips use multiple modes of transport, including mobility services; future mobility management systems should consider inter-layer communication, as well as their complementarity and collaboration. Currently we are limited to lack of communication and/or collaboration between inter-modal infrastructures. Each operator makes decisions independently, and thus, may negatively affect users' mobility. For instance railway and road traffic optimize their performance separately, but a mutually integrated framework could be beneficial. The integration of most transport modes (e.g. speed, accessibility capacity) is in fact ignored in most traffic control approaches. Essentially, modes are complementary, in terms of speed, accessibility, and capacity: while trains can achieve a high capacity for a restricted set of nodes (stations), cars can connect almost any two points; furthermore, in urban areas, active modes such as walking or cycling enable accessing (almost) all places. The performance of a multimodal traffic management system depends on careful planning on one hand, and on the other hand, on an integrated system level perspective among the network operators, which calls for advanced transportation analysis tools to estimate and predict network performance under different strategies and analyze the network for different tactical purposes.

In order to have a better understanding of the topic, we shortly define the multimodal trip. In this document, we define multimodal trip as a combination of two or more different forms of transport within a single trip from an origin to a destination. This trip consists of different vehicles, for instance car, bicycle, tram, bus or train, or different services such as mobility on demand services, car sharing, taxis and other express services. We use the term mode to address the form of transportation unit in a functional or vehicular sense. Therefore, a multimodal trip always consists of two or more legs with different modes, between which a transfer on foot is necessary. Typical examples of multimodal trips are chains such as walk-bus-train-walk, or bicycle-train-walk,car-train-walk or walk-tram-bus-walk. Moreover, the trip chain walk-city bus-regional bus-walk is also considered as a multimodal trip. We should notice that single mode trips such as walk-bus-walk or walk-car-walk or walk-tram-walk are defined as uni modal since the transfer process to another mode of vehicular transportation is absent. Thus, a multimodal transportation system is a system that offers different transportation modes connected by interfaces (e.g. stations) that facilitate transfers between the different mobility services defined as modes (in a functional or vehicular sense) Nes and H. L. Bovy (2004).

A review on the literature shows an increasing trend towards studying the benefits of Integrated Multimodal Network Management among different authorities and researchers. Here we briefly mention only the two most relevant research projects and interested readers are referred to review similar works such as Dawson *et al.* (2014); Nesterova *et al.* (2016); Zheng *et al.* (2016); Sierpiński and Staniek (2017); Zaiat *et al.* (2014). In the framework of Integrated Corridors Management (ICM) Kurzhanskiy and Varaiya (2015), the researchers in California are developing a multimodal traffic management system for a corridor near Los Angeles by applying different management strategies. ICM aims at deploying the strategies listed in table 1 to reduce congestion and improve mobility along the corridor. Furthermore, on top of all these technological solutions, they are building a community of stakeholders who can address corridor needs in a collaborative way in order to have a cohesive management system. The stakeholders are mainly the freeway management (Caltrans), cities traffic management, and all the agencies involved in rail lines, bus services, and parking facilities Berkeley Univesity of California (Accessed: 2019-09-17).

Another approach to discuss the benefits of a multimodal management systems is to investigate it in an extreme situation (i.e. floods, hurricanes, snow, etc.) and see how the coordination of different transport operators can contribute to a better management of transport infrastructure. Researchers in UK have applied this methodology to analyze the system criticality of Britain's multi-modal transport network Pant *et al.* (2015). They suggest a multi-dimensional metric set for assessing the relative criticality of different nodes and edges in the network based on: (i) traffic flows, (ii) traffic disruptions, (iii) rerouting capabilities, and (iv) multi-modal impacts. Initial analysis for Great Britain's multi-modal transport systems demonstrates how criticality assessment can identify key points of the multi-modal transport networks, which are the most critical to maintain a good level of national mobility. The paper concludes by considering the implications of this analysis for risk management, and the potential for developing and transferring this methodology to other spatial or economic contexts.

2 Experimental approach

In order to study the benefits of an integrated multimodal network management control strategy it is useful to focus on a special scenario in the network. In the current work we investigate how such a scheme can contribute to more efficient operation of a network in case of a disruption. The main research question that we focus on in this framework is: In case of a disruption in an urban network, how much delay will be caused if we do not apply any management, and how much of this delay can be saved with an integrated multimodal network management systems.

The network of city of Zurich with one percent of the population is simulated in the agent-

Table 1: ICM Strategies Kurzhanskiy and Varaiya (2015)

Strategy	**Benefits**
Coordination of freeway ramp meters and arterial signal systems	Leverage the capacity of both freeway and arterials to help traffic around congestion or incidents
Arterial signal synchronization	Optimize traffic flow along arterial streets (Kouvelas *et al.* (2014))
Dynamic route guidance and flow rerouting	Offer alternative routes around congested areas
Transit signal priority	Accelerate transit service by giving buses priority on arterials and on-ramps
Real-time travel demand monitoring	Enable transportation managers to see the actual extent and locations of traffic demand on the corridor
Smart parking	Locate available parking spaces at transit stations and private parking garages
Traveler communication	Provide information on traffic conditions, transit services, parking, alternate route/trip/mode options
Mode and time shift incentivization	Motivate travelers to change how (car, bus, bicycle, etc.) and when they travel

based simulator environment MATSim. In this work we consider a disruption between 7:45am to 12:00pm on the direct railway link between two main railway stations, Zurich main station (HB) and Zurich Oerlikon, depicted in Figure 1 with the orange line. The reason to choose this link is its criticality in this urban network, which is defined based on the method explained in Sarlas and Kouvelas (2019) considering the connectivity, efficiency, and betweenness indicators. We utilize MATsim software to analyse the disruption and study the implemented management strategy. MATsim is an activity-based, extendable, multi-agent simulation framework which is suitable to analyze large-scale scenarios and networks with multimodal demand. It is designed to model a single day, the common unit of analysis for activity based models Axhausen *et al.* (2016).

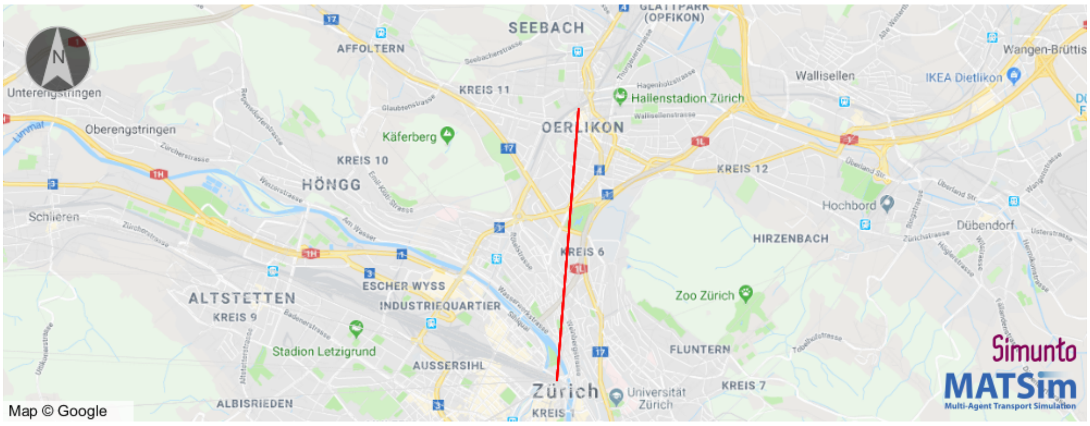
MATsim modelling is based on the co-evolutionary principle. Every user, represented by an agent, selects and executes a daily activity schedule; moreover, the users repeatedly optimize their activity schedule (i.e. adjust it aiming at a better plan) based on the score obtained by the plan they executed so far, similarly to a day-to-day equilibrium process. Activity chains for our scenario are derived from empirical data through sampling or discrete choice modelling. Each agent possesses a memory containing a certain number of day plans (usually 5), where each plan is composed of a daily activity chain and an associated score. The score can be interpreted as an econometric utility and is computed by the Charypar-Nagel utility function Axhausen *et al.* (2016):

$$S_{\text{plan}} = \sum_{q=0}^{N-1} S_{(\text{act},q)} + \sum_{q=0}^{N-1} S_{(\text{trav},\text{mode}(q))}. \tag{1}$$

In equation (1), the utility of a plan S_{plan} is computed as the summation of all activity utilities $S_{\text{act},q}$ plus the summation of all travel (dis)utilities $S_{(\text{trav},\text{mode}(q))}$, with N denoting the number of activities; trip q is the trip that follows activity q. For scoring, the last activity is merged with the first activity to produce an equal number of trips and activities.

An iteration is completed by evaluating the agents' experiences with the selected day plans (scoring). The iterative process is repeated until the average population score stabilizes. MATsim equilibrium extends the standard traffic flow equilibria, as the latter ignores activities. Eventually, an equilibrium is reached, subject to constraints, where agents cannot further improve their plans unilaterally. Note that there is a difference between the application of an evolutionary algorithm and a co-evolutionary algorithm. An

Figure 1: Disrupted railway link.



evolutionary algorithm would lead to a system optimum, as optimization is applied with a global (or population) fitness function. Instead, the co-evolutionary algorithm leads to a user equilibrium, as optimization is performed in terms of individual scoring functions and within an agent's set of plans Axhausen *et al.* (2016). In our approach, after 150 iteration the co-evolutionary equilibrium is reached (baseline) and we can implement the disruption. For the remaining of this document, we call these the baseline scenario and the disrupted scenario.

In the disrupted scenario the selected link between Zurich HB and Oerlikon is blocked (i.e. we set its speed equal to zero); this way we expect that no agent will be willing to choose this link in the next iteration due to its low utility which translates to low scoring for all plans using this link. The agents learning process in case of disruption is a day-to-day replanning approach: each iteration is considered as one day and during that, agents cannot replan their schedules. Throughout each iteration, agents have a plan to follow (commuting to work, shopping, leisure activities, etc.) and between iterations they will try to improve their scoring by choosing a new trip, changing the travel mode, or even changing part of their plan. This plan is then saved in the agent's memory, which contains a predefined number of plans. Before moving to the next iteration, agents are able to: (a) discard the plan with the lowest score; (b) eventually generate a new plan; (c) choose a plan for the next iteration according to the computed MATsim scoring function. In order to reach the co-evolutionary equilibrium, or in other words stabilization of the agents, after appying the disruption we execute the scenario for another 150 iterations.

The baseline scenario, similarly, is executed for 150 iterations to have an equivalent equilibrium scenario to compare the results. It is worth mentioning that in MATsim 11 standard version, the configuration setting that defines the possibility of random behaviour of an agent during a simulation cannot be turned off completely. Therefore, various baseline scenarios with 300 repetitions have been executed and compared to understand how much this setting can affect the results.Furthermore, in order to analyze the effect of the disruption we mainly focus on the delay of agents as key indicator; delays are calculated based on the mode that the agent has used as follows:

- Car Delay:
  Given $\mathcal{J}$ set of agents, $j \in \mathcal{J}$;
  Given T_{c} set of leg trips made with a car during one iteration;
  Given TT travel time of the trip;

$$carDelay_j = \sum_{t \in T_{\mathrm{c}}} (\mathrm{A}ctualTrip_t^{TT} - \mathrm{B}estTrip_t^{TT}) \tag{2}$$

Supposing that an agent has to go from activity A to B, the actual trip travel time $\mathrm{A}ctualTrip_t^{TT}$ at time t is calculated by computing the difference between the arrival time of the agent in B with the car minus the time he entered the vehicle on his last leg leaving activity A. The best trip travel time $\mathrm{B}estTrip_t^{TT}$ is the travel time computed by Dijkstra to go from activity A to B with the best possible traffic conditions. The car delay is therefore the summation of all delays accumulated for each leg in which an agent has used a car.

- Public transport (PT) delay:
  Given $\mathcal{J}$ set of agents, $j \in \mathcal{J}$;
  Given $T_{\mathrm{p}t}$ set of leg trips made with a PT during one iteration;

$$\mathrm{P}TDelay_j = \max_{t \in T_{\mathrm{p}t}} (\mathrm{W}aitTimeAtPTStop_t) \tag{3}$$

If an agent decides to take multiple public transport means during his journey, only the highest delay experienced will be considered as his PT delay. If an agent rides both car and PTs, he will be considered in both equations (2) and (3). The PT delay is therefore the maximum between all delays experienced for each leg in which an agent used a PT during the iteration. In this work, We have decided not to compute the bike and walk delays, which are always assumed to be arbitrarily close to zero.

3 Quantitative results

After running the simulations for both scenarios some useful insights have been achieved that will be presented in the following. In Table 2 the two scenarios are compared and we can see a significant increase, around 14% in PT delay in the disrupted scenario. Moreover a 6% decrease is reported in the total car delay in the disrupted scenario, mainly because there are less people taking a car (number of agents using a car can be observed in Table 3). Note that this simulation is repeated for 150 iterations: i.e. agents are somehow “aware”, due to the scoring of their plans, that the disruption exists at a certain point in time. If an agent decides to fulfill his plan, and wants to go through one of the disrupted links, that plan will have a very low score. This is because the scoring function penalizes an agent based on how much he waits at a PT stop. Considering this fact, we can argue that the results for the disrupted scenario are actually the result for a managed scenario, in case the management strategy is only to inform the commuters to reroute themselves.

After having 150 iterations we can argue that the state of user equilibrium has been reached. Since each agent can store only five plans as defined in the configurations, this usually lead to a situation where agents want to benefit from the alternative routes to avoid the disrupted links. Furthermore, we can see from Table 5 that the number of agents that experienced a significant amount of delay (more than 60 minutes) is more than double compared to baseline scenario (8 compared to 22, equivalent to 800 respectively 2200 travelers if we scale up to the total population). This can be explained considering that there are agents that are required to pass the disrupted links to reach their destination anyways, or there has been no other alternative plan that can provide a better utility for them.

For the PT delay analysis, we can see from the plot in Figure 2 that the moving average of delay related to PT users in the disrupted scenario is significantly higher compared to the

Table 2: Scenario Comparison

	Baseline	Disrupted
Total car delay (min)	123624	115885
Total PT delay (min)	18098	21437
Car delay + PT delay(min)	141722	137322

Table 3: Delay Comparison for all agents

	delay(min)		number of agents		average delay(min)		percentage of agents	
	Baseline	Disrupted	Baseline	Disrupted	Baseline	Disrupted	Baseline	Disrupted
Car	123624	115885	7291	7184	16.95	16.13	48%	47%
PT	18098	21437	2501	2570	7.23	8.35	17%	17%

baseline. Also, the average delay in the disrupted scenario is slightly higher compared to the baseline, with significant peak for the highly delayed agents, 142 minutes in disrupted scenario, double the average delay compared to the baseline seen in Table 5. This is also shown in Figure 2, where the various peaks represent agents that did not manage to avoid the disrupted links.

If we look at the histograms in Figure 2(b), we can see that agents that travelled more than 80km using a PT have experienced in the disrupted scenario from 10 to 15 minutes more delay on average compared to the baseline scenario. This is explained by the fact that the disruption is affecting also long-distance trains in the network. The travel distance histogram in Figure 2 illustrates that more agents experienced delay for short distances.

Interestingly, as can be seen in Table 6 in contrast with what we expected, the number of agents that used the car and the PTs are very similar in both scenarios, with only 1% difference. From the results of Table 6 it can be observed that the modal split based on travel time percentage for PTs in the disrupted scenario increased compared to the baseline (by 3%), with a correspondent 1% increase in the travel distance covered. This is due to the higher delays caused by the disruption. We can conclude that the impact of

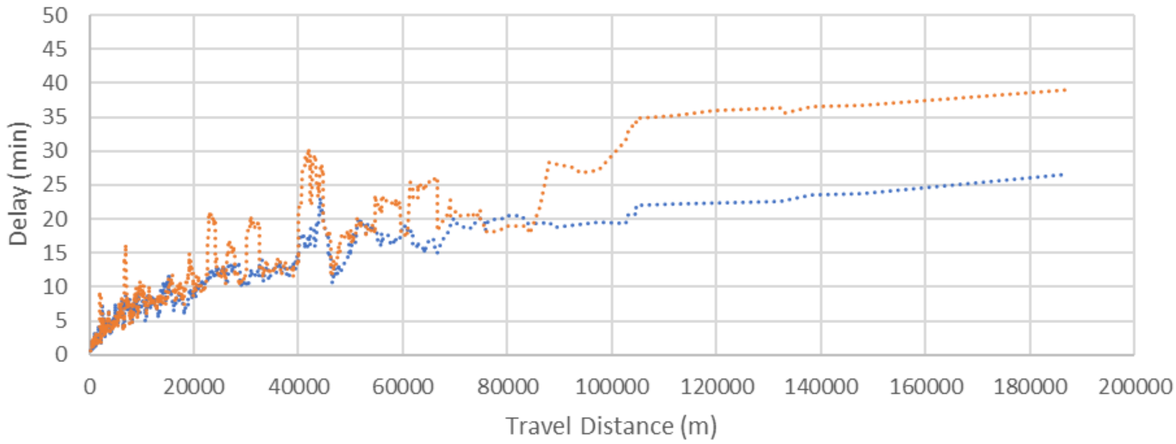
Table 4: Delay Comparison for agents delayed more than 5 minutes

	delay(min)		number of agents		average delay(min)		percentage of agents	
	Baseline	Disrupted	Baseline	Disrupted	Baseline	Disrupted	Baseline	Disrupted
Car	119128	111428	5392	5288	22	21	36%	35%
PT	15393	18732	1096	1157	14	16	8%	8%

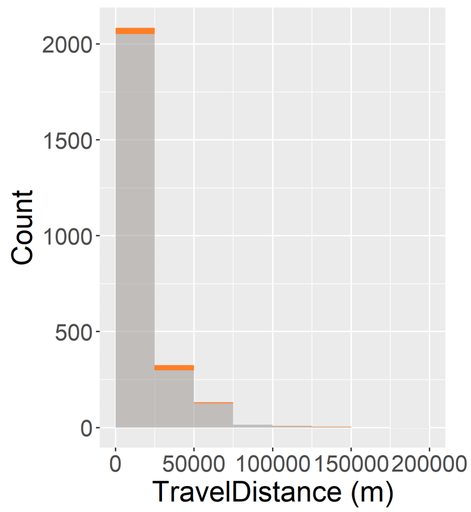
Table 5: Delay Comparison for agents delayed more than 60 minutes

	delay(min)		number of agents		average delay(min)		percentage of agents	
	Baseline	Disrupted	Baseline	Disrupted	Baseline	Disrupted	Baseline	Disrupted
Car	14974	10207	197	136	76	75	2%	1%
PT	612	3138	8	22	76	142	1%	1%

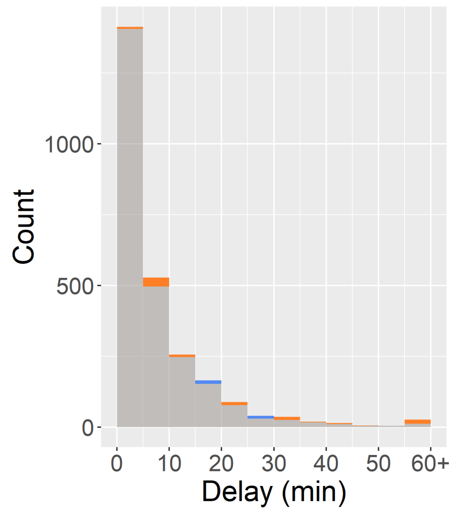
Figure 2: (a) PT delay comparison (b) Distribution of travel distance (c) Distribution of delay



(a)



(b)



(c)

● Baseline ● Disrupted

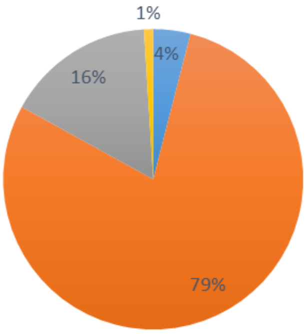
this small disruption did not change much the behaviour of the whole population, but instead provoked a higher amount of delay in the PT users, with an average increase in the delay experienced by PT users of 1 minute.

For the Car Delay analysis, we can see in Figure 4 that we have on average the same delay (16 min for both baseline and disrupted scenarios); moreover, 1% less agents used a car in the disrupted scenario, deciding instead to use a PT or bike, as observed in modal split in

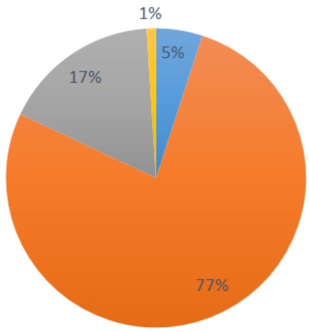
Table 6: Modal Split (MS) based on Travel Distance (TD) and Travel Time (TT)

	Baseline		Disrupted		Baseline		Disrupted	
mode	TD(m)	MS	TD(m)	MS	TT(min)	MS	TT(min)	MS
Bike	10840076	4%	11659573	5%	2990366	8%	3216434	9%
Car	220432577	79%	217000000	77%	20034848	54%	18589544	50%
PT	46107745	16%	48361126	17%	11746400	32%	12849082	35%
Walk	3231551	1%	3218906	1%	2429738	6%	2420230	6%

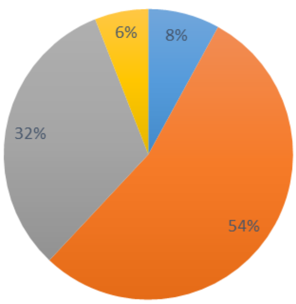
Figure 3: Modal Split based on Travel Time and Travel Distance for Baseline and Disrupted scenarios



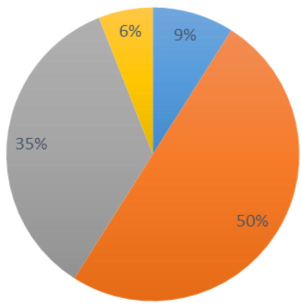
(a) Baseline:Travel Distance



(b) Disrupted:Travel Distance



(c) Baseline:Travel Time

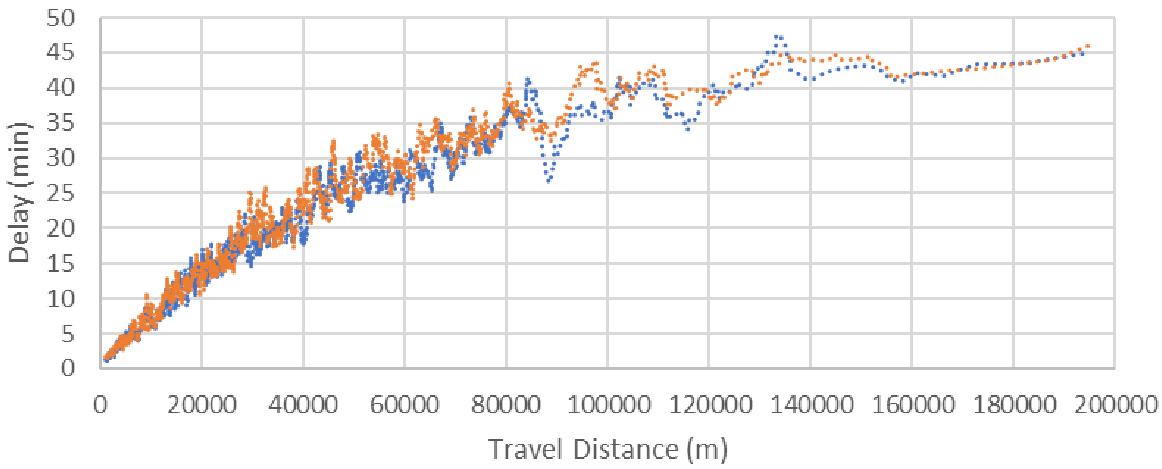


(d) Disrupted:Travel Time

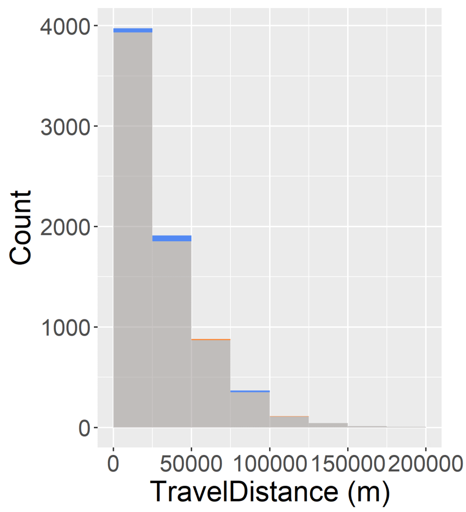
● Bike ● Car ● PT ● Walk

Table 6 and Figure 3. The delay histogram in Figure 4 demonstrates that the disruption affected mostly the agents that are commuting for short trips in the city. Those latter cases show an increase in number of agents that experienced 5 to 20 minutes delay for the disrupted scenario. The histogram regarding the travel distance covered in Figure 4 also provides evidence that less people took a car in the disrupted scenario, shifting to another transport mode, especially for short distance trips.

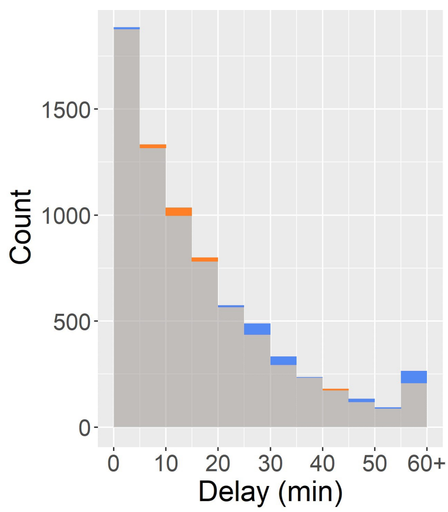
Figure 4: (a) Car delay comparison (b) Distribution of travel distance (c) Distribution of delay



(a)



(b)



(c)

● Baseline ● Disrupted

4 Conclusions

In the current work we presented our approach to study the benefits of multimodal integrated network management systems. We focused on a disruption scenario and investigated what is the potential of delay savings by applying a minimum management strategy. The preliminary results in the current work are the beginning of our future works towards implementing multimodal integrated strategies and studying how integration of different operative stakeholders in transport networks can improve the mobility services.

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