Data-driven disruption response planning for a Mass Rapid Transit system

Chunling Luo[1], Xinrong Li[1], Yuan Zhou[2], Aakil M. Caunhye[3], Umberto Alibrandi[4], Nazli Y. Aydin[5], Carlo Ratti[6], David Eckhoff[2], and Iva Bojic[1]

[1]Singapore-MIT Alliance for Research and Technology, Singapore
[2]TUMCREATE, Singapore
[3]The University of Edinburgh, UK
[4]Aarhus University, Denmark
[5]Singapore-ETH Centre, Singapore
[6]Massachusetts Institute of Technology, USA

Abstract

This paper studies the disruption management of a Mass Rapid Transit (MRT) network with data obtained from transportation smart cards. We introduce an optimization model for the development of efficient bus bridging services to minimize the negative effects of MRT disruption. Compared with existing approaches, our model considers the available capacity of existing buses when designing the routes and headways/frequencies of bus bridging services. The proposed model is demonstrated through one case study that assumes MRT disruption in the central business district area of Singapore. The case study shows that our approach can effectively reduce the travel delay of commuters and increase the number of commuters that can be served.

1. Introduction

For many of its early years, the Singapore Mass Rapid Transit (MRT) network system experienced disruptions only rarely, leading to it being recognized internationally for its efficiency and efficacy. According to a rail service reliability performance report from 2017, the number of these MRT disruptions, which resulted in service delays of more than 30 minutes, has increased from 9 in 2011 to 16 in 2016 [8]. As the Singapore MRT network continues to be expanded with new trains and rails and the ridership continues to increase, the need for resilience improvement strategies becomes even more important.

Namely, the average daily ridership has grown from 2.3 in 2011 to almost 3 million passenger-trips in 2016. Making the MRT network resilient to these disruptions is a challenging task that presents a vast array of research opportunities. By resilience we mean *the capacity of a system to absorb disturbance and to reorganize so as to retain essentially its structures, functions and feedback loops* [10]. Improving the resilience of the Singapore MRT network requires thus both proactive and reactive planning. Proactive planning concerns the addition of robustness, or the ability to absorb and mitigate shocks to the network. Reactive planning is themed around emergency response and is concerned with how the network responds to disruptions. Until now, resilience in the MRT has been studied at a more granular operational level, but recently it has been recommended that a more holistic perspective on system resilience should be taken [8].

A series of studies on network disruption management, including proactive and reactive planning, have been proposed in the literature to improve network resilience. For example, the disruption management process and the roles of different actors were discussed in [3]. This paper described three main challenges in disruption management: timetable adjustment, rolling stock and crew rescheduling. A summary of the algorithms developed for these three challenges for the Netherlands Railway company was provided by [7]. An integrated model for timetable and rolling stock rescheduling was developed by [1, 2], which minimizes the recovery time, the commuters inconvenience and system costs. Besides these studies on reactive planning, studies on proactive planning are also seen in the literature, such as an approach to enhance the resilience for MRT networks with localized integration with public bus services proposed in [4].

One of the most critical areas in network disruption management is the design of bridging services that can provide temporary transportation services in the disrupted parts to reduce the negative effects of disruption. Different bridging approaches have been adopted in practice, such as diverting disrupted commuters to other operating lines or other parallel public transport services, hiring taxi or bus bridging. A survey of disruption response management practices can be found in [9]. Among these response strategies, bus bridging services, which provide temporary bus transportation services to commuters, is the most common practice undertaken by transport operators in case of MRT disruption. Several approaches have been proposed specifically for bridging services in case of disruption. For example, an approach proposed in [11] suggests to examine whether and how to hire taxis to provide bridging services for short-term disruptions in public tram systems. Another paper proposed a comprehensive modeling framework and decision support system for planning and designing an efficient bus bridging network [6]. A different bus bridging service design was proposed by [5], where bridging bus routes were generated by a column generation procedure and the most effective combination of bus routes was identified via a path-based multi-commodity flow model.

However, these studies do not consider the integration between the bridging services and the existing bus routes. Namely, when MRT disruption occurs, the existing bus routes could provide complementary bus services to MRT network and divert some disrupted commuters to their destinations or other operating lines. Hence, whether and how to introduce bridging services should depend on the available complementary capacity of existing bus routes.

With the development of new technologies aimed at improving the information available about public transport systems, a large amount of data has become available in the process of building a resilient MRT network. With the help of data obtained with transportation smart cards (e.g. EZ-Link card in Singapore) and public MRT/bus line information, we are able to elicit the origin-destination demands and available complimentary capacity of existing buses, which can be helpful for the design of bus bridging services. In this paper, we thus propose an approach to develop efficient bus bridging services to minimize the negative effect of MRT disruption. Our model accounts for the available complementary capacities of existing bus routes when designing the routes and frequency of bridging buses. We demonstrate our methodology on one case study of MRT disruption in Singapore's Central Business District (CBD) area.

2. Methodology

We develop a mathematical optimization model that allows bus bridging services to be integrated with the existing bus services. Namely, when MRT disruption occurs, disrupted commuters can either make use of the complementary services provided by existing buses or services provided by bridging buses. The proposed model not only designs the bus bridging service routes, but also determines the frequency of each route.

2.1. In/out passenger flows dataset

The basis for our approach is comprehensive passenger data recorded for Singapore MRT and bus services for a duration of three months. Each record in this dataset has a timestamp of tap-in/out together with an MRT/bus stop identification. With that information, for each smart card, we can reconstruct the traveled route. Additionally, we used information about latitudes and longitudes of MRT/bus stops, official records on MRT/bus service and MRT/bus line information including operational starting time and ending time, traveling time and frequency of MRTs/buses. Based on the dataset and the MRT/bus line information, we elicit the following information: 1) the number of commuters traveling between each pair of origin-destination stations; 2) the time table and routes of MRT/bus services; 3) the travel time of the commuters; 4) the available capacity of each MRT and bus line. This information will be used as an input of our model.

2.2. Bridging services response plan

The design of bridging services includes two main steps: 1) generating a candidate set of bridging routes and 2) route selection and bus allocation. One common practice for generating a candidate set of bridging routes is to replicate the MRT services by running buses parallel to the disrupted rail lines. Other approaches include using shortest path algorithm [6], a column generation procedure [5], or to generate candidate bus bridging routes considering more factors such as the pattern of commuter travel demand, travel time and transfer. In this paper, we focus on the second step (i.e. route selection and bus allocation) as the candidate set of routes is one of inputs of our model and can be generated using one of the aforementioned existing approaches.

Before presenting our optimization model, we have to define the following sets: 1) $\mathcal{R}$ denotes the set of bus routes r; $\mathcal{R}^0$ and $\mathcal{R}^+$ denote the set of existing bus routes and candidate bridging bus routes, respectively; 2) $\mathcal{K}$ denotes the union of disjoint commuter group k that includes all commuters who go from origin station o_k to destination station s_k; 3) $\mathcal{R}^k$ is used to denote the set of bus routes that connect bus station o_k and destination s_k, that is, commuters in group k can and only can take bus routes in $\mathcal{R}^k$; 4) L_r denotes the set of edges/legs l for bus route r.

Our optimization model aims at minimizing the total travel time of commuters after disruption, including the riding time on the bus and the waiting time. First, we adopt the time-space network proposed by [5] to model the time-dimension. For each group k, we discretize the whole time period into $\bar{u}$ periods associated with demand $d_{(k,u)}$ such that $\sum_u d_{(k,u)} = D_k$, where D_k is number of commuters in group k during the considered period. For each bus route r, we discretize the whole period into $\bar{v}$ service slots. The set of services slots for route r is denoted by $\mathcal{B}_r := \{(r,v), \forall v = 1, 2, ...\bar{v}\}$. Commuters in group k arrive at bus station o_k at time $\tilde{t}_{(k,u)}$, wait for bus on route $r \in \mathcal{R}^k$ to come, board and travel on bus for c_{kr} units of time. If the coming bus is full, then the commuters have to wait for the next bus. Let $w((k,u),(r,v))$ denote the waiting time of commuters in group (k,u) when bus slot (r,v) is taken. We have: $w_{((k,u),(r,v))} = \max\{0, t_{(k,(r,v))} - \tilde{t}_{(k,u)}\}$, where $t_{(k,(r,v))}$ is the time when bus service slot (r,v) arrives at the origin station o_k of group k. The commuter cannot take bus slot that arrives o_k before his arrival and it is reasonable to assume that commuter will not be willing to wait for a very long time (say, longer than a limit $\bar{w}$). Hence, we define set Ω that excludes those impossible combinations of $((k,u),(r,v))$: $\Omega = \{((k,u),(r,v)) : t_{(k,(r,v))} - \tilde{t}_{(k,u)} \geq 0, w((k,u),(r,v)) \leq \bar{w}\}$, where $\bar{w}$ is the limit of waiting time. We generate the matrix of $w_{((k,u),(r,v))}$ for all (k,u) and (r,v) based on the time-space network and use it as input coefficients for the model. Our optimization model will not only select the bridging bus routes, but also simultaneously determine the frequency/headway of the selected bus routes and the allocation of available bus resources among each route.

We define a discrete set of bus deployment plans: $\mathcal{P}_r := \{(r,h) : h \in I, \forall h_r^{min} \leq h \leq h_r^{max}\}$, where each plan (r,h) is characterized by route index r and the bus headway h; h_r^{min}, h_r^{max} denote the minimum and maximum allowed headways for the route r, respectively. Let $\mathcal{P}^+$ be the union of $\mathcal{P}_r, \forall r \in \mathcal{R}^+$. The bus deployment plans for existing route $r \in \mathcal{R}$ are already determined and their headway is $h_r^0, \forall r \in \mathcal{R}^0$. Let $\beta((r,h),(r,v))$ be a binary variable that equals 1 if the bus deployment plan $(r,h) \in P_r$ covers bus services plot (r,v), and 0 otherwise. The decision variables for our model are:

- $y(r,h) \in \{0,1\} : \forall r \in R^+, (r,h) \in \mathcal{P}_r$. $y(r,h)$ takes 1 if bus deployment plan (r,h) is employed and 0 otherwise.
- $\chi_{((k,u),(r,v))} \geq 0$: the number of commuters in group (k,u) who take bus service slot $(r,v) \in \mathcal{B}_r$.
- $\eta(k,u)$: the number of commuters in group (k,u) who are unable to get on any bus by the waiting time limit $\bar{w}$.

Let c_k^0 denote the travel time of a single commuter in group $k \in \mathcal{K}$ when no disruption occurs. The bus bridging route selection and deployment problem can be formulated as:

$$\min \sum_{((k,u),(r,v))\in\Omega} (c_{kr} + w_{((k,u),(r,v))} - c_k^0)\chi_{((k,u),(r,v))} + \sum_{(k,u)} \theta_{(k,u)}\eta_{(k,u)} \tag{1}$$

$$s.t. \sum_{(r,v)\in\mathcal{B}} \chi_{((k,u),(r,v))} + \eta_{(k,u)} = d_{(k,u)},\ \forall (k,u) \tag{2}$$

$$\sum_{(k,u)} \gamma_{(k,(r,l))}\chi_{((k,u),(r,v))} \leq \beta_{((r,h_r^0),(r,v))}Q^0_{(r,v)},\ \forall (r,v) \in \mathcal{B}_r, \forall l \in L_r, \forall r \in \mathcal{R}^0 \tag{3}$$

$$\sum_{(k,u)} \gamma_{(k,(r,l))}\chi_{((k,u),(r,v))} \leq \sum_{h|(r,h)\in\mathcal{P}_r} \beta_{((r,h),(r,v))}Qy_{(r,h)},\ \forall (r,v) \in \mathcal{B}_r, \forall l \in L_r, \forall r \in \mathcal{R}^+ \tag{4}$$

$$\sum_{h|(r,h)\in\mathcal{P}_r} y_{(r,h)} \leq 1,\ \forall r \in \mathcal{R}^+ \tag{5}$$

$$\sum_{(r,h)\in\mathcal{P}^+} n_{(r,h)}y_{(r,h)} \leq A^{max} \tag{6}$$

$$\chi_{((k,u),(r,v))} = 0, \forall r \notin \mathcal{R}^k \tag{7}$$

$$y_{(r,h)} \in \{0,1\}, \forall (r,h) \in \mathcal{P}^+; \tag{8}$$

$$\chi_{((k,u),(r,v))} \geq 0, \forall ((k,u),(r,v)); \quad \eta_{(k,u)} \geq 0, \forall (k,u) \tag{9}$$

The objective function (1) minimizes: 1) the total increase in travel time for commuters taking buses and 2) the number of commuters who cannot board, weighted by a penalty parameter $\theta_{(k,u)}$. Constraint (2) guarantees that the total number of commuters who boarded plus the number of commuters who did not board equals the travel demand.

Let $\gamma((k,(r,l))$ be a binary variable that takes 1 if leg l is used by commuter group k when they take bus route r and otherwise 0. Constraints (3) and (4) ensure that on each leg $l \in L_r$ of each bus service slot (r,v), the number of commuters on the slot (r,v) does not exceed the available bus capacity $Q^0_{(r,v)}$ of existing bus routes and total capacity Q of introduced bridging bus routes, respectively. Constraint (5) restricts that at most one bus deployment plan can be employed on each route. Constraint (6) guarantees that the total number of buses additionally deployed should not exceed the bus resource capacity A^{max}, where $n_{(r,h)}$ is the number of buses required for route r with headway set as h. Constraint (7) ensures that commuters in group k only take bus route r that connects o_k and s_k (i.e. $r \in \mathcal{R}^k$). Constraints (8) and (9) define the domain of decision variables.

3. Case Study

In this section we demonstrate our methodology by studying one hypothetical disruption case in the Central Business District (CBD) area of Singapore during morning peak-hours (i.e. 7:00 AM - 9:00 AM). This region was chosen as it covers the central part of the Singapore MRT network, with a mixture of residential areas, business areas as well as commercial ones. The case study concerns a single-direction disruption of the purple MRT line, where the MRT links from station A to station D are disrupted (see Figure 1). We assume that the disruption lasts for the whole peak-hour period and that we need to assign bridging buses to cope with the morning peak-hour demand. Historical data shows that about 7,400 commuters would be affected if this disruption would actually

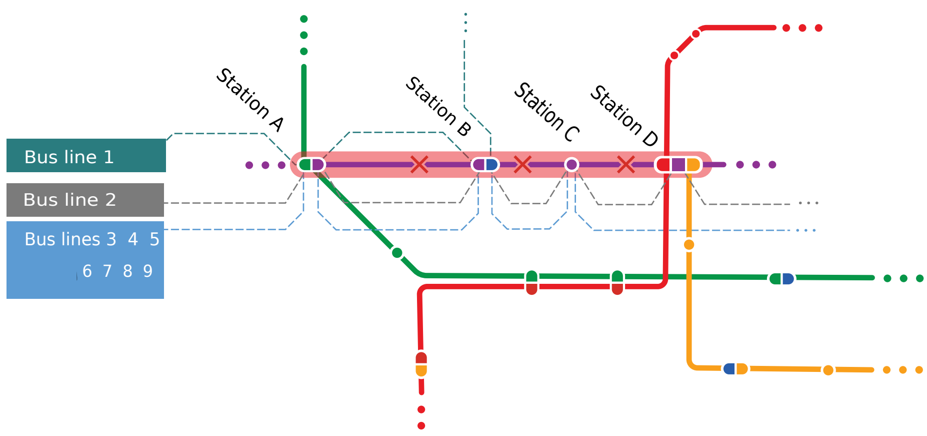

Figure 1: Region we focus on. The affected MRT stations are: station A, B, C, D.

take place as described. Figure 1 shows the MRT network (represented by solid lines) and the existing bus lines (represented by dashed lines) in the disrupted area.

As mentioned before, the existing buses can provide complementary bus services to the affected commuters. In total, about 100 buses on these lines normally would pass the disrupted area during the affected hours, with an average free capacity per bus per link approximately equal to 74. In order to deal with the consequences of the assumed disruption, we first generate the candidate bus bridging routes via replicating the MRT services, considering all possible bus routes parallel to the purple MRT line and then use the proposed optimization model to find the optimal route selection and bus allocation. Namely, the commuters can either be diverted to their destination if they alight in the disrupted area, or to station D to take other operating lines. Travel demand and available capacity of existing buses are derived from historical smart card data.

The parameters of the optimization model are set as follows: the maximum number of bridging bus A^{max} to be deployed is arbitrarily set to be 10 (later on we perform a sensitivity analysis to explore the impact of different bridging bus fleet sizes); minimum and maximum headways of bridging bus services are set to 1 min and 31 min respectively, with minimal incremental value set to be 30 seconds; the capacity of bridging bus Q is set to be 87 (the capacity of one type of bus in Singapore); the limit of waiting time $\bar{w}$ is set to equal 30 min and penalty parameter $\theta(k, u)$ is set to be 90 mins. The minimum and maximum headways are set considering factors such as headway ranges of existing buses, the high morning peak-demand and the capacity of stations, while the penalty parameter is set to 90 min in order for it to be larger than the maximum waiting time (30 minutes) plus on-board time of disrupted commuters (shorter than 31 minutes).

The proposed model was coded in Python and solved in about 2 minutes by CPLEX V12.8.0 running on a personal computer with Intel Core i7 at 2.6GHz and 16 GB RAM. The bridging services plan generated by our optimization model is shown in Table 1. As it can be seen, all of the bridging buses are allocated to divert commuters to station D from different affected MRT stations. This is because of two reasons: 1) all commuters who do not alight in the disrupted area are diverted to station D, which connects three MRT lines, to take other operating lines; and 2) only one of the existing bus lines (i.e. bus line 124 shown in Figure 1) can provide complementary bus services to station D.

Furthermore, mainly due to resource constraints, other candidate routes are not selected, such as bridging routes that would directly connect stations C and D, probably as it could only provide a bridging service to one commuter group. Additionally, if the existing buses could provide enough complementary services for some commuter group, then there is no need to provide bridging bus for them. For example, B $\rightarrow$ C route is

Table 1: Optimal bus bridging services, where N stands for the number of allocated bus.

Bridging bus route path	Headway	N
A $\to$ D	3 mins	9
A $\to$ B $\to$ D	28.5 mins	1

not selected because: 1) few commuters take MRT during morning peak-hours for such a short distance; and 2) all of the existing bus lines except for bus line 1 can serve the affected commuters traveling that route.

Using the proposed bridging service plan, about 43.2% and 40.9% commuters can be served by the bridging buses and existing buses, respectively. We observe that the existing buses can serve up almost half of all affected commuters. Hence, in this case, the complementary capacities of existing buses are relatively important and should not be ignored when designing bridging bus plans.

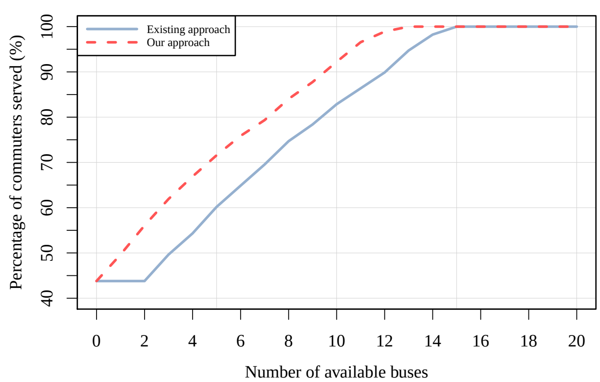

Figure 2: Percentage of commuters served (higher is better).

The red lines in Figures 2 and 3 show the results of a sensitivity analysis performed to explore the impact of the bridging bus fleet sizes when using our approach. As the size increases, the average travel delay (including possible longer on-board time and waiting time for a bus) of all commuters decreases almost linearly and the percentage of served commuters increases. However, the average travel delay and percentage of served commuters almost no longer improve when the number of available buses exceeds 15, as all affected commuters are served. Assigning more than 15 buses would thus only increase costs, but would not generate any additional benefits. Moreover, we compare our approach with the existing approaches which do not consider complementary capacities of existing buses when allocating bridging buses.

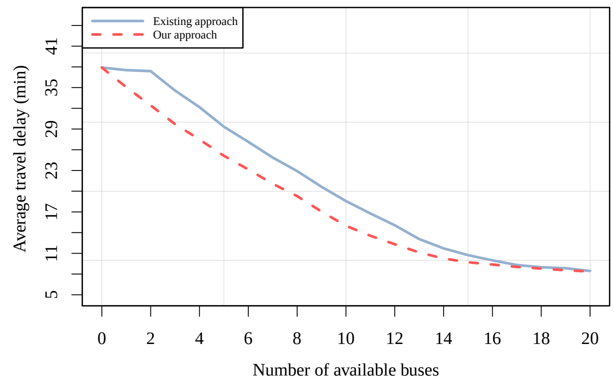

Figure 3: Average travel delay (lower is better).

The difference between the blue and red lines in Figures 2 and 3 show that our approach always performs better in terms of both the average travel delay and the number of served commuters, especially when the number of available bridging buses is limited. In particular, when the number of available buses is less than 15, then our approach can serve about 10% more disrupted commuters than the existing approaches. This is mainly because existing approaches may allocate buses to serve commuters who can already be served by existing buses and result in oversupply on some routes and under-supply on other routes.

4. Conclusion

The optimization model proposed in this paper can be used for designing bus bridging services in response to MRT disruptions. Our approach can determine the routes to select and their corresponding headways in integration with the existing bus services, which can provide complementary services to MRT services in cases of disruption. We showed the effectiveness of our model via a case study in the central business district of Singapore. The results confirmed that our approach could generate solutions to effectively reduce the travel delay of commuters and the number of commuters who could not board a bus. In this paper, we considered only the cases when the travel demand and available capacities of existing buses are deterministic and derived from historical data. However, these parameters are actually subject to uncertainty. Hence, one potential direction of future work is to integrate uncertainty into our optimization model, which could be quantified by fitting a distribution to the data provided by the smart card records.

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