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Abstract. The waiting time of passengers at transfer stations is one of the most important criteria to measure the service quality of public transportation. Because of the stochastic nature of traffic, scheduled transfers cannot always occur. This research proposes an online control framework for a bus line using holding, skip-stop and speed change tactics. We build an arc-flow optimization model enumerating all possible tactics within a time horizon. The model minimizes total passenger travel times by improving, among others, transfer times and reducing deviations from the bus schedule. Decisions are based on real-time passenger flow data and travel times. The methodology was tested on a case study of the bus system of the city of Laval, Canada. A simulation framework has been developed, integrating data on smart card transactions and bus locations, to verify the performance and results of the optimization model. Data generation in the simulation framework is improved using a training set. Different levels of uncertainty are introduced on instances of a testing set and the resulting optimal parameters are applied to a validation set.

Keywords: transit network; bus operations; bus holding; bus line synchronization; real-time control; passenger flow data.

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1. Introduction

Public Transit (PT) networks are becoming increasingly important considering concerns about climate change. PT companies and services develop inter-route, inter- and intra-modal transfers in order to achieve a better connectivity of the network and more flexible route planning. An efficient PT system can retain existing customers and attract more people to leave their cars behind and opt for public transportation.

Research shows that users are reluctant to engage in multi-segment trips if transfer times are uncertain (Ceder et al. (2013)). The level of satisfaction of users is highly dependent on waiting times, since their personal evaluation of waiting time is higher compared to other parts of a trip (e.g.: access time, in-vehicle time) Boardman et al. (2001). It is therefore increasingly important to synchronize transfers. There are multiple stages of planning and operating a PT network (e.g.: network design, timetabling, vehicle scheduling, operation, etc.) as defined in Ceder (2007). This research will concentrate on the control stage of operating a PT network. The context in which a planned and synchronized bus schedule takes place is stochastic and dynamic. Even an optimal timetable can be subject to unpredictable congestions or route incidents. This is why real-time control strategies are needed to mitigate the undesirable effects of uncertain events.

This research is based on one month of real passenger- and bus-related data provided by the "Société de Transport de Laval" (STL). It uses data from Automated Vehicle Location systems (AVL), Automatic Passenger Counter systems (APC) and Automated Fare Collection systems (AFC) and integrate it in real-time control tactics. Using this historical data, relevant time-dependent travel times, passenger demand and transfer demand are generated to input into a real-time control arc-flow model. First, the model is tested with existing non-stochastic data. Then different levels of uncertainty are introduced in a simulation framework to test the reliability of the model and to examine the relative value of the available data.

1.1. *Contributions*

To the author's knowledge, no research on real-time control strategies has been implemented using an arc-flow model. In our model, a node represents a bus arrival or a passenger arrival at a stop and at a certain time. All tactics are dependent on discrete events such as passenger arrivals, bus arrivals and transfer arrivals. A tactic cannot be implemented if no such event occurs. This limits the number of executable tactics at each stop to only a few possibilities, as opposed to tactics represented by integer variables in the literature, or rule-base models. This allows for timely resolution and thus a possible execution of proposed tactics in real-time. Moreover, different combinations of control tactics are tested with different levels of uncertainty in a rolling-horizon simulation framework. Finally, we test our methodology on a large real data set from a dense urban transit network.

2. Literature Review

Control strategies can be divided into three categories: stop control, inter-stop control, and others (Eberlein et al., 1999). Stop control strategies include tactics implemented at stops, for example holding for a certain amount of time at a stop or skipping stops. Inter-stop strategies include speed changes or traffic lights control. The last category includes tactics such as adding or removing vehicles.

2.1. *The holding problem*

The holding tactic is the easiest to implement and the literature review shows that holding, by itself, is the most effective tactic to save time (Ibarra-Rojas et al., 2015). Holding can be used to either maintain a certain headway between buses (Fu and Yang, 2002; Sun and Hickman, 2008; Daganzo, 2009; Bartholdi and Eisenstein, 2012), or to minimize waiting times (Eberlein et al., 2001; Zhao et al., 2003; Puong and Wilson, 2008).

Eberlein et al. (2001) define the holding problem as a deterministic quadratic problem and proposes an algorithm to solve it. The research proposes a rolling horizon for the holding problem. Hickman (2001) formulates the holding problem as a convex quadratic program at a number of control points. Zhao et al. (2003) define a control model based on a compromise between passengers on board and passengers further along the line, using stochastic arrivals at stops. The holding problem is also considered with bus capacity constraints using real-time bus locations in a heuristic algorithm (Zolfaghari et al., 2004). Delgado et al. (2012) implement two strategies (holding and limiting the number of passengers to be able to get on a bus at certain stops) in a deterministic optimization model considering all waiting times of passengers.

2.2. *Real-time control*

Gkiotsalitis et al. (2022) present an extensive literature review of public transport transfer synchronisation at the real-time control phase. Dessouky et al. (1999) prove the impact of real-time control in intelligent systems. In fact, having real-time information on bus locations, passenger demands, arrival times and passenger origin/destination pairs allows for timed transfers. Later, Dessouky et al. (2003) show that this information was especially useful in networks with many connecting buses.

Sun and Hickman (2005) propose a non-linear integer programming problem using two different stop-skipping tactics for real-time control and test each one's performance with different route scenarios. Real-time information on bus locations is used to predict next-stop departure times in Yu and Yang (2009), with a genetic algorithm to optimize holding times. Many studies concentrate on synchronizing transfers using real-time control. Hadas and Ceder (2008) develop a new definition of synchronized transfers and apply it to multiple consecutive transfers stops (transfer segments) rather than to single transfer points. This approach was improved in later articles using dynamic programming (Hadas and Ceder, 2010). Cats et al. (2011) introduce a dynamic transit-simulation model using real-time data on congestion, passenger demand and bus activity. The article uses the mean headway from the preceding and succeeding buses as a basis for holding tactics. In recent years, the combination of different real-time control strategies has been studied. Ceder et al. (2013) and Nesheli and Ceder (2014) propose a combination of holding and skip-stop/skip-segment in order to minimize total passenger travel time by increasing the number of direct transfers. Travel times, passenger demand and transfers are assumed to be known and are deterministic. Moreover, passenger arrivals are independent of bus arrivals. The work is continued in Nesheli and Ceder (2015) where short turning is implemented as a real-time control action. Travel times are fixed, as well as passenger arrival rates and transfers. Liu and Ceder (2016) use a tactic-based predictive control approach under dynamic and stochastic traffic environment. Finally, Gavriilidou and Cats (2019) proposes two different transfer synchronization controllers using different real-time passenger data to show the importance of passenger data on the performance on transfer control.

2.3. *Headway control*

The literature also addresses the regulation of bus headways using holding and other real-time control tactics. Fu and Yang (2002) minimize headway variation by minimizing the average waiting time at stops, not considering in-bus delays. Liu et al. (2014) implement an optimization model with holding and speed change tactics. Two objective functions are tested (minimizing headway gap or total passenger travel time) using transfers at single points or along shared corridors. Daganzo (2009) studies high frequency bus routes, shows that control is necessary to avoid bus bunching and proposes a real-time holding strategy at pre-defined control points. Bartholdi and Eisenstein (2012) present a novel approach by defining headways according to system states and behaviour, instead of using static headways. Holding times are calculated using the headway from previous bus. Ji and Zhang (2013) propose a dynamic model to regulate headways and avoid bus bunching.

2.4. Dynamic models

More recently, the literature focuses on the dynamical use of real-time data. Berrebi et al. (2018) compare and evaluate different holding methods used in real life and proposed in the literature. The research shows that prediction-based methods achieve the best results when considering both holding time and headway regularity. The drawback of prediction-based methods is their sensitivity to prediction accuracy. Sánchez-Martínez et al. (2016) propose a model that considers the dynamic nature of travel times and demand and show the importance of accurate estimations of the current state of the PT network. Manasra and Toledo (2019) present a simulation framework that considers multiple and entire bus lines (as opposed to single transfer stops in the previous literature) and takes into account all stages of passenger trips (in-bus time, dwell time, transfer time and extra time if a passenger is unable to board a bus) with a capacity constraint. The model defines an optimization horizon at each step considering the actual state of the PT network.

The rest of the article is organized as follows. Section 3, describes the case study and the underlying problem. Section 4 describes the mathematical formulation of the problem. Section 5 presents our optimization model and simulation framework, as well as our tests and results. Finally, section 6 presents our conclusion and possible further work.

3. Problem description

3.1. Data presentation and pre-processing

This work is based on a full month of anonymous data on the whole network of the STL (routes, buses, passengers, transport tickets, etc.). General Transit Feed Specification (GTFS)[1] files are generated for each day of the month and are then used as inputs to our model. The data is organized as follows.

- **Stops, routes and trips:** The data contains route and schedule information on all stops and routes in the STL network. A route is a PT service associated to a bus line that follows a sequence of stops. There can be multiple daily trips along the same route.
- **Dwell times and travel times:** The case study has information on dwell times as well as planned and real travel-times across the PT network. When the real dwell time at a stop is null, the stop is skipped.
- **Passenger demand:** This research uses passenger flow information coming from AFC systems on buses and in metro stations. The STL also estimates individual trip destinations using AFC data, as defined in Trépanier et al. (2007). All origin-destination (OD) pairs are generated using this data and buses are "filled" accordingly. On the other hand, passenger information from APC systems was not used as it was not reliable.
- **Transfer demand:** Data generated by the AFC systems, allowed the reconstruction of multi-segment passenger trips. Using the information on transfer demand, this research determines synchronized transfers between buses. A synchronized transfer is when two or more buses arrive at a transfer point at the same time and allow passengers to transfer instantly. If a transfer isn't synchronized, passengers have to wait for their connecting buses. Not all transfers are synchronized.

[1] More information on the GTFS format here: https://gtfs.org/

The GTFS files described above as well as data from the GPS systems in the PT network are used as inputs for the model. The data was pre-processed to create classes of data for the modeling. These instances are used to generate graphs for the multi-commodity arc-flow model. Figure 1 illustrates how this data is used to generate instances for our model.

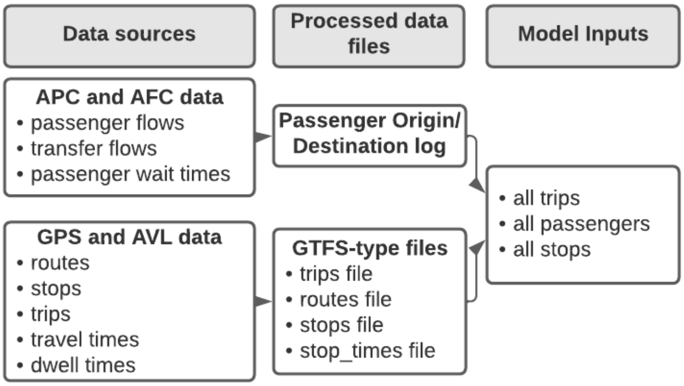

Fig. 1. Data processing and generation.

3.2. *Initial data analysis*

After pre-processing the data, an initial analysis was conducted to determine where the PT network operation could be improved. Passenger flows on all bus lines and along all route segments were analyzed. We then identified corridors with the most passengers and bus stations with the biggest passenger flows. Lines, segments and hubs with the most transfers were identified and used in this research. Finally, the differences between planned and actual travel and transfer times for all passengers were analyzed. The biggest source of delay in passenger travel times was missed or late transfers.

3.3. *Description of control tactics*

Real-time control tactics can help synchronize transfers and ensure planned transfers take place. The following real-time control tactics are implemented in order to improve travel times and transfer times.

Holding: Holding makes a bus wait for a predetermined amount of time at a certain stop. Holding is used in order to reduce bus-bunching, schedule deviation and to synchronize transfers before or at transfer points. The holding tactic can therefore impact the travel time of three groups of passengers. Firstly, holding affects passengers on board the bus who add the holding time to their travel time. Secondly, passengers on board who want to transfer will spend more time in the bus, but their transfer time decreases. Finally, passengers waiting at further stops along the route add the holding time to their waiting times for the bus.

Skip-stop/Skip-segment: Skip-stop is a tactic consisting of skipping a stop along a bus route to avoid dwell times at the stop and deceleration/acceleration time before and after the stop. The skipping of multiple consecutive stops is introduced as the skip-segment tactic in Nesheli and Ceder (2014). Skip-stop/skip-segment is a tactic devised to gain time, but it impacts passengers differently. Passengers on board that do not wish to alight on any of the skipped stops have a shorter travel time. Passengers wishing to alight at a skipped-stop, get off at the nearest stop and walk to their destination. Passengers waiting to board the bus at a skipped-stop wait for the next bus and their waiting time increases. Passengers waiting further along the line have shorter waiting times. Finally, passengers on board wishing to transfer arrive at their transfer stops faster but have longer waiting transfer times out of the bus.

Speed control: The speed control tactic consists of making a bus drive faster or slower. In this research, only the effects of speeding up are evaluated. After discussion with the PT operator, a speedup factor of 0.8 was chosen. The speed control tactic affects both passengers on the bus and out of the bus. Passengers on board have a shorter travel time. Those wishing to transfer arrive at their transfer stops faster but have longer waiting transfer times out of the bus. Passengers waiting further along the line wait less for the bus to arrive. Transferring passengers from other lines decrease their transfer time. If the bus arrives at a stop too early before its planned arrival time, passengers arriving on time miss the bus and must wait for the next one.

All control tactics can be implemented individually or at the same time. Unlike in most previous studies where tactics were applied at a few predetermined stops, here all stops are control stops. All impacts of each tactic on passenger transit times are taken into account in our model.

4. Problem formulation

This research formulates an arc-flow model to represent the bus network and evaluate the impact of real-time control tactics. The formulation contains all the implemented tactics. The model seeks to minimize total passenger travel times by improving, among others, transfer times and reducing deviations from the bus schedule. The impact of the implemented tactics is evaluated using total passenger travel time, the number of successful transfers, individual passenger travel times and passenger waiting times (in and out of the bus). This research uses a single low frequency line with many feeder lines and transfer points. Tactics can only be applied to the buses of the main line. The model calculates optimal control tactics for all stops and buses in a predefined optimization horizon. The arrival times of feeder lines are not influenced by control tactics.

4.1. Methodology

This section describes how the graphs for the arc-flow model are built and how the proposed control tactics are incorporated into the graphs. Figure 2 illustrates a simple example of a graph. This example does not contain real data for confidentiality reasons. Figure 2a) shows a graph without any control tactics. Figure 2b) shows the same case graph with the holding tactic after optimization. The number of passengers along an edge is displayed on it. The time of each node is written on top of it. The exogenous flow of a node, if non-zero, is displayed above it. The horizontal distance between nodes is proportional to the time between two nodes. The vertical distance between nodes represents the distance traveled by the bus. Arrival and departure nodes of the same stop are not aligned in the figures for the sake of clarity. This mock example contains two buses, one departing a time equal to 100 and the next departing at time 300. In the no tactics case, four passengers wish to board the first bus at stop number one but arrive at the stop after the bus has departed. Moreover, two passengers coming from a feeder line wish to transfer at stop number two and board the second bus in the horizon. They arrive too late at stop number two to be able to board the second bus. In the case including the holding tactic, we can see that new possible paths for the buses were added in the graph. The optimization model then makes decisions on the paths for each bus by minimizing the total passenger travel time.

The model uses space-time dependent networks built as follows.

Nodes: A node represents a passenger arrival at a bus stop or a time for a bus to arrive at/depart from a stop. There are arrival nodes and departure nodes to distinguish when buses arrive at and leave stops. Passenger flows are represented by exogenous flows at each node.

Edges: The weight of an edge represents the time difference between the origin and destination nodes of the edge (the destination node must occur after the origin node). Dwell-times are represented by edges between arrival and departure nodes of the same stop. Travel-times are represented by edges between the

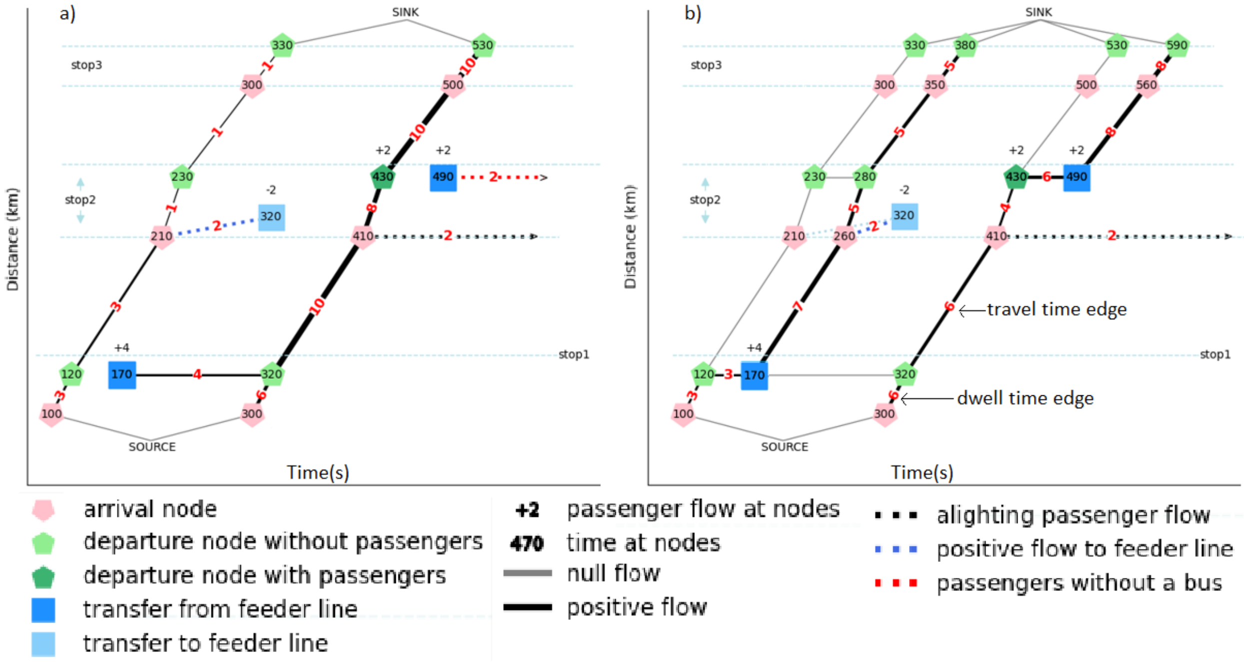

Fig. 2. Example of a graph construction. a) No tactics. b) Hold tactic.

departure node of one stop and an arrival node of the next stop (see indications on figure 2). It is possible for an edge to link two nodes from different buses (e.g.: a passenger misses their bus and has to wait for the next bus). All edges are directed and have a capacity constraint related to the capacity of the vehicles.

Graphs: A graph has source and sink nodes. The source node has an exogenous bus flow equal to the number of trips. The sink node has an exogenous bus flow opposite to the number of trips. The source node can be seen as a bus depot from which all trips depart. Graphs are built in consecutive steps for each bus trip. For each stop, the travel time, the arrival time, the dwell time and the departure time are represented in the graphs. To begin, an arrival node is created at the time of arrival of the bus at the first stop. The source node and the first stop are linked with an edge of weight equal to the travel time to this stop. The departure of the bus from the stop is represented by a departure node. The arrival and departure nodes are linked with an edge with weight equal to the dwell time at the stop. For the speed control tactic, the travel time to the stop is smaller and so the bus arrives earlier at the stop. The corresponding arrival and departure nodes are added to create an additional possible path for the bus from the source. Any passenger arriving before the departure of a bus from a stop can board the bus. Nodes with positive exogenous flows representing boarding passengers are linked to the bus paths. If any transfer passengers from other lines want to board at this stop, transfer nodes with the corresponding positive exogenous flows are created at the time of arrival of the feeder lines. On the other hand, some passengers will want to alight the bus. This is represented by a negative exogenous flow. If passengers want to transfer to another line at this stop, a transfer node with negative exogenous flow is created at the time of the departure of the feeder line from this stop. If a skip-stop/skip-segment tactic is applied, no passengers can board or alight at this stop. Passengers will then have to walk to the nearest non-skipped stop. Finally, the holding tactic is represented by the time between possible departures. Edges are added between consecutive possible departure nodes. A holding tactic can be implemented only as a waiting time between two existing nodes, e.g., a bus can wait for a transfer passenger coming to the same stop. The last node for the stop is linked to the next bus to allow passengers that missed the current bus to board the next one.

The rest of the graph is constructed by iterating these steps over the remaining stops. Starting from the first stop, all possible paths to the second stop are created and so on. The graphs built in this manner incorporate all possible tactics. The model uses these graphs as inputs to determine optimal bus paths and tactics.

4.2. Mathematical formulation

The following assumptions are made for the offline model. We have knowledge on route information, real and planned travel times, real and planned dwell times, passenger demand, transfer demand, transfer stops, bus schedules and delays. In the online application of the model, real information is not available for all stops. The missing information is generated based on historical data and available real-time data as described in section 5.1. Road congestion conditions allow the implementation of the speed control tactic. Passengers are informed of the skip-stop/skip-segment tactic before the first skipped stop. Passengers waiting to board at a skipped stop wait for the next bus. Transfer passengers that miss their transfer will wait for the next possible transfer. Passengers always choose the fastest option available to them. Passenger demand does not change because of a bus delay. Finally, passengers arrive at a stop shortly before the scheduled time of arrival of the bus, since the case study is based on a low frequency line.

We use the following notations to describe the mode parameters and variables.

Sets

N		set of nodes with s the source node and t the sink node.
N^-		set of normal and transfer nodes with negative exogenous flows, not including t
A		set of arcs (u,v)
B		set of buses
S		set of stops
A_b^s	$b \in B$, $s \in S$	set of arcs for the bus b between stops s and $s+1$
AN_b^v	$b \in B$, $v \in N^-$	for node u and for the bus b, AN_b^u is the set of arcs passengers alighting at node u take to board the bus b. There is one arc per passenger.
AM_b^v	$b \in B$, $v \in N^-$	for node u and for the bus b, AM_b^u is the set of arcs taken by passengers from the previous bus if they miss their bus and have to alight at node u. There is one arc per passenger.

Parameters

c_{uv}	$(u,v) \in A$	passenger flow capacity on arc (u,v)
w_{uv}	$(u,v) \in A$	travel time between nodes u and v.
f_v	$k \in K, v \in N$	exogenous passenger flow at node v
g_v	$k \in K, v \in N$	bus departures or bus arrivals at node v
M		bus capacity
p	$1 \leq p$	out of bus waiting times as perceived by passengers

Variables

x_{uv}	$(u,v) \in A$	$x_{uv} \in \mathbb{N}$, passenger flow on arc (u,v)
y_{uv}	$(u,v) \in A$	binary variable for the bus flow on arc (u,v)
z_{uv}	$(u,v) \in A$	$z_{uv} \in \mathbb{N}$, indicator variable equal to x_{uv} if y_{uv}=0, and 0 otherwise
x_{uv}^+	$(u,v) \in A$	binary variable. $x_{uv}^+ = 1$ if passenger flow on arc (u,v) is positive, and 0 otherwise.

Objective

$$\min \sum_{(u,v)\in A} w_{uv} x_{u,v} + \sum_{(u,v)\in A} w_{uv}(p-1) z_{u,v} \tag{1}$$

Constraints

$$\sum_{(v,w)\in A} x_{vw} - \sum_{(u,v)\in A} x_{uv} = f_v, \forall v \in N \setminus N^-, v \neq t \tag{2}$$

$$\sum_{(v,w)\in A} x_{vw} - \sum_{(u,v)\in A} x_{uv} = f_v + \sum_{(u,w)\in AN_b^v} (1 - x_{uw}^+) - \sum_{(u,w)\in AM_b^v} (1 - x_{uw}^+), \forall b \in B, v \in N^- \tag{3}$$

$$\sum_{(v,w)\in A} y_{vw} - \sum_{(u,v)\in A} y_{uv} = g_v, \forall v \in N \tag{4}$$

$$x_{uv} \leq c_{uv} y_{uv}, \forall b \in B, s \in S, (u,v) \in A_b^s \tag{5}$$

$$x_{uv} - c_{uv} y_{uv} \leq z_{uv}, \forall (u,v) \in A \tag{6}$$

$$z_{uv} \leq x_{uv}, \forall (u,v) \in A \tag{7}$$

$$x_{uv} - x_{uv}^{+} M \leq 0, \forall (u,v) \in A \tag{8}$$

$$0 \leq x_{uv} - x_{uv}^{+}, \forall (u,v) \in A \tag{9}$$

$$y_{uv}, x_{uv}^{+} \in \{0,1\}, \forall (u,v) \in A \tag{10}$$

$$0 \leq x_{uv}, z_{uv}, \forall (u,v) \in A \tag{11}$$

Eq. 1 describes the objective function of the model, minimizing total passenger travel times as perceived by passengers. This includes in-bus and out-bus travel times. The first sum in the objective function represents total passenger travel time. The second sum in the objective function represents the additional cost perceived by passengers of waiting out of bus. Constraints 2 ensure flow conservation for passenger flows. The incoming flow of a node, added to the number of passengers wishing to board/alight at a node must be equal to the number of passengers leaving a node. Constraints 3 update flows for alighting passengers. If a passenger didn't board the current bus, then they cannot alight from the current bus. Passengers that missed their bus will board and alight from the next possible bus and are added to the alighting flows for the next bus. Constraints 4 ensure that each bus takes a single path. The source node has a positive exogenous bus flow equal to the number of buses departing from the origin of the bus line. The sink node has a negative bus flow equal to the opposite of the source node. Constraints 5 ensure that passengers cannot travel between stops without being on a bus. A bus can travel empty. Constraints 6 and 7 ensure the relationship between variables x, y and z. If $y_{uv} = 1$ then $z_{uv} = 0$ and if $y_{uv} = 0$ then $z_{uv} = x_{uv}$. The variable z is used to linearize the product between the variables x and y. In reality, $z_{uv} = x_{uv}(1 - y_{uv})$. Constraints 8 and 9 ensure that if $x_{uv} > 0$ then $x_{uv}^{+} = 1$ and if $x_{uv} = 0$ then $x_{uv}^{+} = 0$. Constraints 10 describe that a bus can either travel on an edge or take another edge. Two buses cannot take the same path at once. Finally, constraints 11 indicate that passenger flows must always be non-negative.

5. Experiments

This section describes all the experiments made in this research and presents our results. Firstly, we describe the simulation framework and discuss the data generation for the instances used in the simulations. All possible combinations of parameters for the simulation framework are tested and the performances of the model are compared for each case. Five scenarios are used for the simulated network. The first case is the case without optimisation. In the second scenario only the holding tactic is applied. The third scenario combines the holding and skip-stop/skip-segment tactics. The fourth scenario combines the holding and speed control tactics. The last scenario combines all three tactics.

All coding is in Python and the Python MIP[2] package is used to solve all instances of the optimization problem. The results presented in this research are based on the data of line 70 of the STL network, but the code works for any other line of the PT network. Line 70 is a line with 91 stops and 30 different feeder lines. Transfers occur at many different stops along line 70, but most feeder lines transfer in 5 major transfer stops along the line.

5.1. Simulation Framework

In this research a simulation framework is designed to test and validate the results from the deterministic optimization model. Figure 3 illustrates the simulation framework. The simulation evaluates a dynamic optimization algorithm. The discrete-event simulation runs a re-optimization every time a bus reaches a stop within the current optimization horizon. First, the optimization horizon is redefined. The optimization horizon consists of all the buses and stops that will be included in the current step of the simulation. It contains the next few stops on the main line of the bus trip currently being optimized. The optimization horizon also includes the previous and next buses on the main line. Finally, the optimization horizon includes buses on feeder lines potentially transferring at the next few stops of the main line. Then data for the re-optimization is collected and generated as described in section 5.3. The data generation is based on historic data as well as available real-time data. We use real data for all stops that have already been visited. Passengers that missed their bus or transfer are also taken into consideration. The generation type for the data can be changed between steps of the simulation. Then a graph corresponding to the generated information is built and the associated optimization problem is solved. The solution describes control tactics for all stops in the optimization horizon. We apply the inter-stop speed control tactics for the next stop of each bus. Finally, the stop control tactics are applied to the first stop that is reached in the current optimization horizon. As soon as a bus reaches a stop in the optimization horizon, a new step is started in the simulation. All other control actions are re-evaluated in the next iteration of the simulation.

Manasra and Toledo (2019) apply holding and speed control to a stop that has just been reached. This method does not allow for sufficient time to inform the bus drivers of the tactics to be implemented. For this to be possible, the calculations need to be made between stops. If the calculations are made once a stop is reached, they must be intended for tactics starting from the next stop. In this research, there are on average 150 nodes and 200 arcs in the optimization in each step. The mean computation time per step of the simulation is 0.3 seconds. This short computation time allows for a timely implementation in real-time.

5.2. Data sources

The data used in the case study of this research originates from the bus network of the Société de transport de Laval, Canada, a city of 436,000 inhabitants. The network has 46 bus lines and about 1,000 stops. Data comes from the Automated Vehicle Location systems (AVL), the Automatic Passenger Counter systems

[2] Package available here: https://www.python-mip.com/

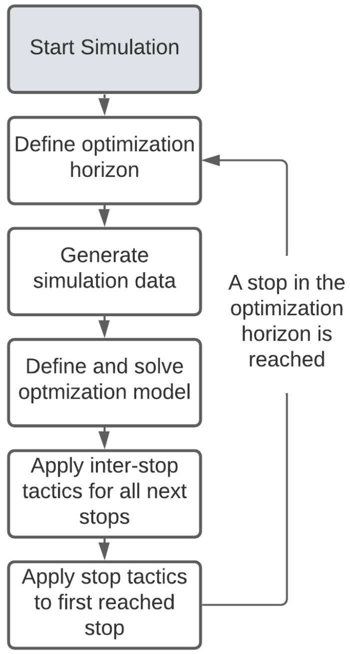

Fig. 3. Simulation framework for the optimization model testing and validation

(APC) and the Automated Fare Collection systems (AFC). The case study in our research differs from most experiments in the literature for the following reasons. Firstly, the STL has a team of data scientists working on improving the level of service and daily operations. The STL already implements different tactics and communicates with bus drivers when they are behind schedule or when they are running early. From its AVL, the STL also has real-time information on bus bunching and can give instructions to drivers on how to mitigate the effects of such delays on passengers. This means that the 'no optimization' scenario in our case study presents a well monitored and dynamically controlled bus network. Secondly, by using the STL smartphone application, passengers have access to real-time data about the positions and time of arrival of buses. In this network, and particularly for the case of the low frequency line 70, passengers can plan their trips before leaving using the most up-to-date information about the state of the bus network. Only trips that are likely to be successful will be offered to passengers planning multi-legged trips. Transfers that are too short and risky (less than a few minutes transfer time between buses) will not be included in the options available to users on the application. Finally, the information on passenger arrivals and transfers is exact and comes from smart card data (AFC). Hence, we do not model passenger arrivals. All stages of each passenger's trip are taken into account: waiting at stops, in bus travel time, in bus waiting time, waiting for transfers, walking time if skipped stops. Any improvements made in the model and simulations are calculated precisely for each passenger in the system (with or without transfers).

5.3. Data generation

The real data provided by the STL is used as a basis for the instances generated in the simulations. The month of data is divided into three working sets. The training set consists of the first twenty-four days of the month (or eighty percent of the data set). The testing set contains three weekdays of the remaining week (or 10 percent of the data set) and is used to find the best parameters for the simulations. Finally, the remaining three weekdays of the data set are used for the validation set (ten percent of the data set). A

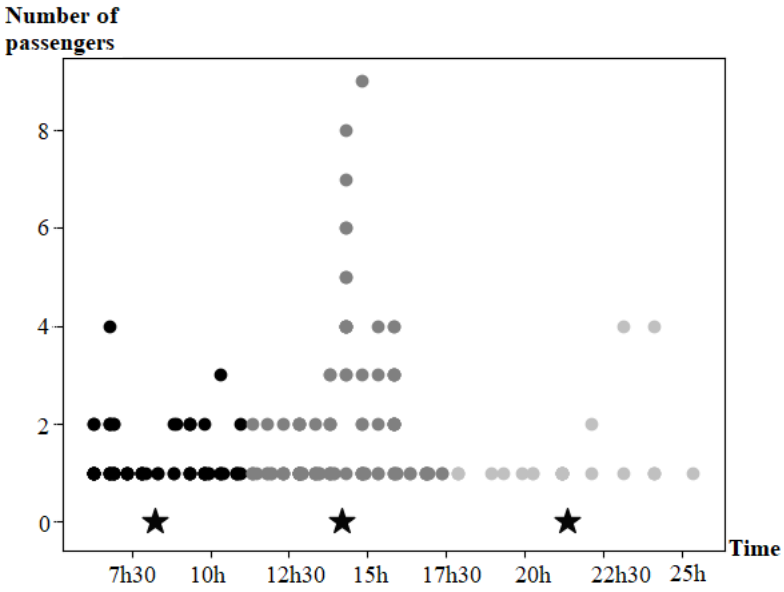

Fig. 4. Clustering of the number of passengers boarding at a specific stop.

second validation set is used consisting of three days of data on line number 42, a busier line of the STL bus network.

Before the simulations, the data of the training set was clustered for dwell times at each stop, travel times between each pair of consecutive stops, number of boarding/alighting passengers at each stop, number of boarding/alighting transfer passengers at each stop and finally, headways between buses. The data is clustered using K-means algorithm. The clusters are based on the time of occurrence. For example, dwell times happening around the same time of the day are in the same group. Extreme data points were removed from all clusters (e.g., dwell times significantly higher than all other dwell times in the same cluster). An example of clustering for the number of passengers boarding at a stop of line 70 is shown in figure 4. There are 3 clusters, depending on the time of day. The time stops at 25 hours because the service ends after midnight.

Bus trips are then generated using these clusters. First a set of consecutive bus trips is chosen from the testing or validation set and a planning horizon is defined. Then the same number of trips covering the same planning horizon will be generated iteratively to be used in the simulation. When generating bus trips, there are multiple types of data generation for each component of the trip. Type "real" returns the real data from the bus trips in the testing set. If all the components of the trip are generated using real data, the simulation gives the same results as the deterministic model (perfect information scenario). Type "mean" generates the mean of the data points of the cluster corresponding to the time of the day of the generated event. Type "sample" draws randomly from the cluster corresponding to the time of the day of the generated event. Finally, type "planned" returns the planned value of the corresponding event. Boarding and alighting passengers are generated separately and not as origin/destination pairs. Feeder line arrival times can also be generated using the current delay at the time of the simulation, the expected delay calculated at the time of the simulation, the planned arrival time or the real arrival time. Table 1 shows what type of data generation is possible for each of the components of the generated instances.

First, the optimal simulation parameters were determined by testing all parameters on buses of the testing set. The optimal parameters for our simulation framework are presented in Table 2. The best results were obtained using the real values for all data types (corresponding to the perfect information scenario).

Table 1. Types of data generation for each component of the trip

Generated Data	Real	Mean	Sample	Planned

Nevertheless, the second-best parameter was chosen for the data types for which real information is not available in real-time (e.g., boarding/alighting (transfer) passengers, dwell times, travel times, arrival times of feeder lines). The generation of dwell times had little impact on the performance of the optimization model. The travel times between pairs of stops had little variation for instances in the same cluster. Planned headway times were well respected by the PT operator and were in most cases equal to the real headways. The number of alighting/boarding (transfer) passengers had the biggest impact on the decisions made in the simulations. The integer mean of the number of passengers boarding/alighting at each stop proved to give the best results. Finally, the predictions of arrival times of feeder lines using available real-time data gave results close to tests with the real values of the data. After the optimal parameters were determined, we tested all instances of the validation set with the optimal simulation parameters. Finally, the optimal parameters and the simulation were tested on another line altogether.

Table 2. Optimal types of data generation for each component of the trip

Generated Data	Optimal Generation Type
Dwell times	Mean
Travel times	Mean
Headway times	Planned
Boarding/alighting passengers	Mean
Boarding/alighting transfer passengers	Mean
Arrival time of feeder lines	Current Delay

5.4. *Results*

Figure 5 shows the distributions of passenger travel times in the experiments. Buses were clustered in five groups depending on the time of day (early morning (before 7AM), morning rush hour (7AM to 10AM), midday (10AM-4PM), evening rush hour (4PM to 8PM) and end-of-service (after 8PM)). For all buses, passenger travel times are divided into waiting for the bus to arrive (with or without transfer), travelling in bus, waiting in bus due to holding tactics, waiting for a connecting bus of a feeder line (if there is one) and walking (in cases of skipped-stops). Figure 5 presents the distribution of passenger travel times when only the holding tactic is allowed. We compare passenger travel times for the no tactics case with the online simulation holding case and the perfect information, offline holding case. Both the simulation and perfect information cases of the model perform better than the no optimization case when there are some missed transfers to improve. Nevertheless, we can see that the simulations perform worse in cases where there were no missed transfers. When the model has perfect information, no tactics are needed when there are no missed transfers. In the simulation case, some predictions about the number of transferring passengers were inaccurate, inducing needless holding time. In general, the simulations activate more holding time than the perfect information offline optimal case. This is due to some inaccuracies related to the data generation in the simulation framework. Figure 6 presents the difference in individual travel times between the simulation

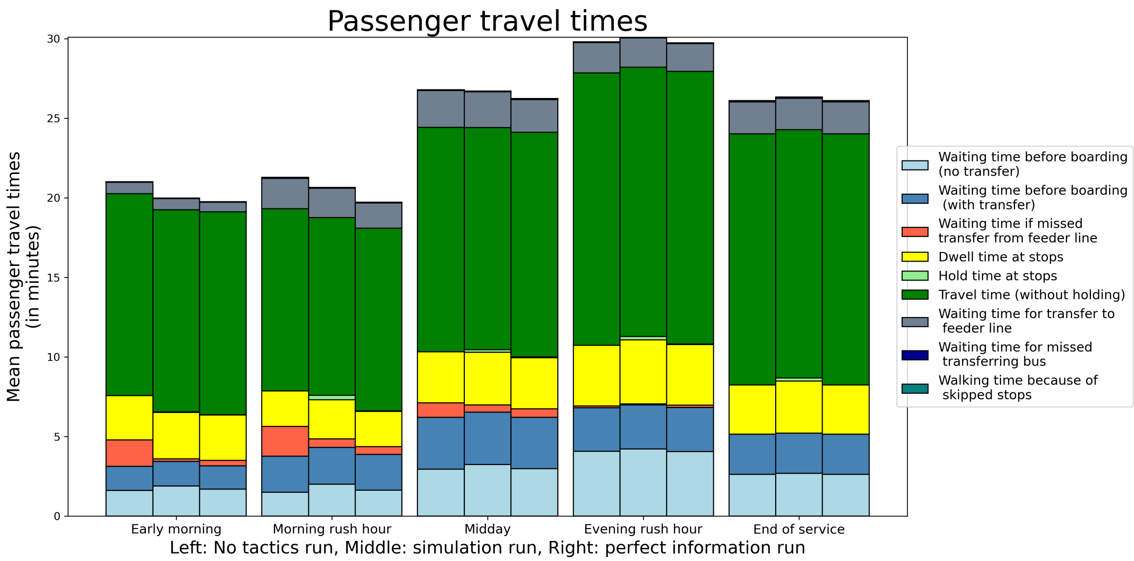

Fig. 5. Passenger travel time distributions for all buses. Holding only.

case and the optimal case of the holding only scenario. We compare individual travel times using boxplots. We can see that most individuals have a very small variation in travel times, and that the time gains are made for the few individuals that managed to get their transfer after applying tactics. Figure 6 also presents the percentage of passengers with successful or missed transfers and the percentage of passengers that missed their bus (not counting missed transfers). Finally, table 3 summarizes this information.

Table 5 summarizes passenger travel times for the case with holding and skip-stop tactics. We can note that the additional walking time due to skip-stop tactics is minimal. When looking at individual passenger travel time variations for the case with holding and skip-stop tactics, we can note that the boxplots remain compact. This indicates that time gains are again mainly explained by turning missed transfers into successful transfers. Passenger travel time gains because of skipped stops are minimal. Table 6 presents the passenger travel times for the holding with speed control tactic case. We note that the speed control tactic case has overall passenger travel times smaller than the skip-stop tactic case. We note that the speed control tactic was less effective than the skip-stop tactic in increasing the number of successful transfers. Moreover, there was a bigger variation in individual passenger travel times due to the decrease in in-bus travel time. Finally, table 7 presents the passenger travel times for the holding with skip-stop and speed control tactics case.

Figure 7 presents the bus travel times for holding tactic only, comparing the no tactics case, the online simulation framework case and the offline perfect information case. Figure 7 also presents the percentage of stops at which tactics are applied for each cluster. We note that the differences in mean bus travel times are minimal between the three cases. Moreover, holding tactics are applied to a very limited number of stops. Table 4 further summarizes these results. Table 8 summarizes bus travel times for the case with holding and skip-stop tactics, and shows the percentage of stops with different tactics. In this case, the skip-stop tactics compensate for any additional time added by the holding tactic. The skip-stop tactic is used more often than the holding tactic. Table 9 presents the bus travel times the holding with speed control tactics case. It also shows the percentage of stops where tactics were applied. The speed control tactic was applied to a large proportion of stops (more than 30%). This was compensated by more holding time when the bus had to wait for transfer passengers, or in order not to be too early compared to the schedule. Finally, table 10

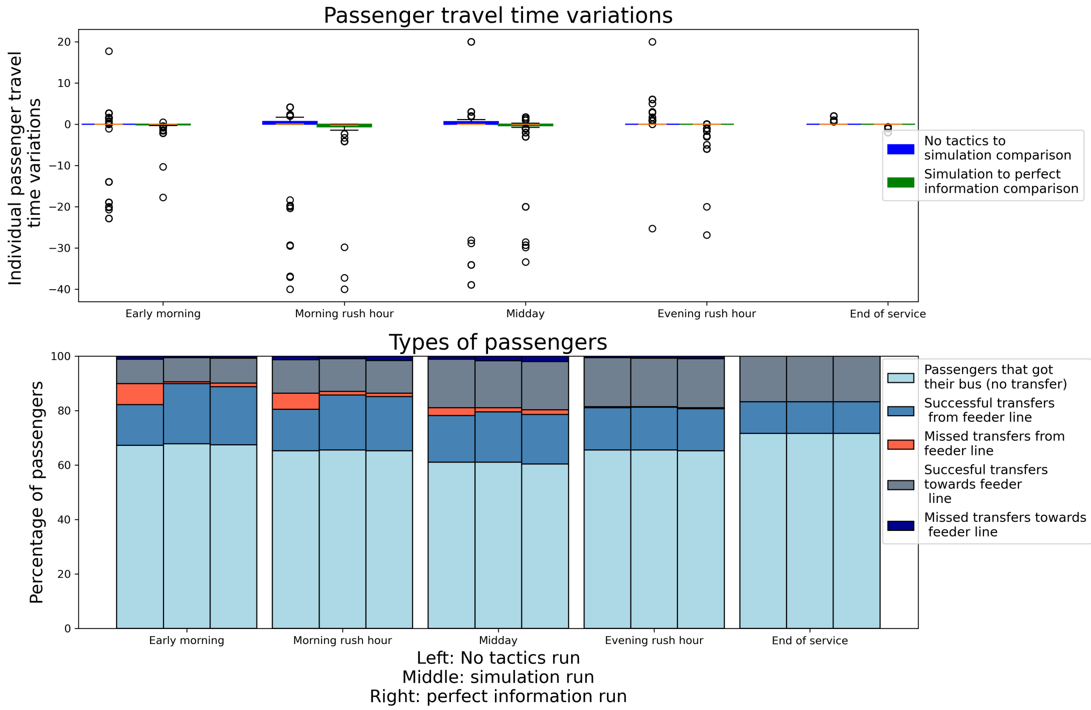

Fig. 6. Passenger travel time variations for all buses and percentage of passenger transfers. Holding only.

presents the bus travel times for the holding with skip-top and speed control tactics case. It also shows the percentage of stops where tactics were applied.

6. Conclusion

Real-time control is a crucial part of planning for PT operators. The waiting times of passengers and the reliability of transfers significantly influence the service quality of PT. This research concentrates on improving transfers times and reducing travel times by using real-time control tactics. The methodology is based on a case study of the city of Laval, Canada with a month of data from their PT network data. A deterministic arc-flow model is developed to integrate three different real-time control tactics: holding, skipping stops/skipping segments and speeding up. Firstly, the model is tested using real data from the case study. Then, to simulate real-time operations, a stochastic simulation framework generating data with different levels of uncertainty is created. This research evaluates five cases in the simulation framework: no tactics, holding only, holding with skip-stop/skip-segment, holding with speed control and finally holding combined with both speed control and skipping stops. For each run of the simulation, the results of the simulation are compared to the results of the perfect information, deterministic case. The model is tested on a large number of instances to determine optimal data generation parameters in the simulation framework. Finally, more simulation runs are made to validate the optimal parameters of the simulation and the results of the model.

The results show that an improvement in total travel times, in individual travel times and in the number of successful transfers is made for any type of data generation compared to the no tactics case. The best

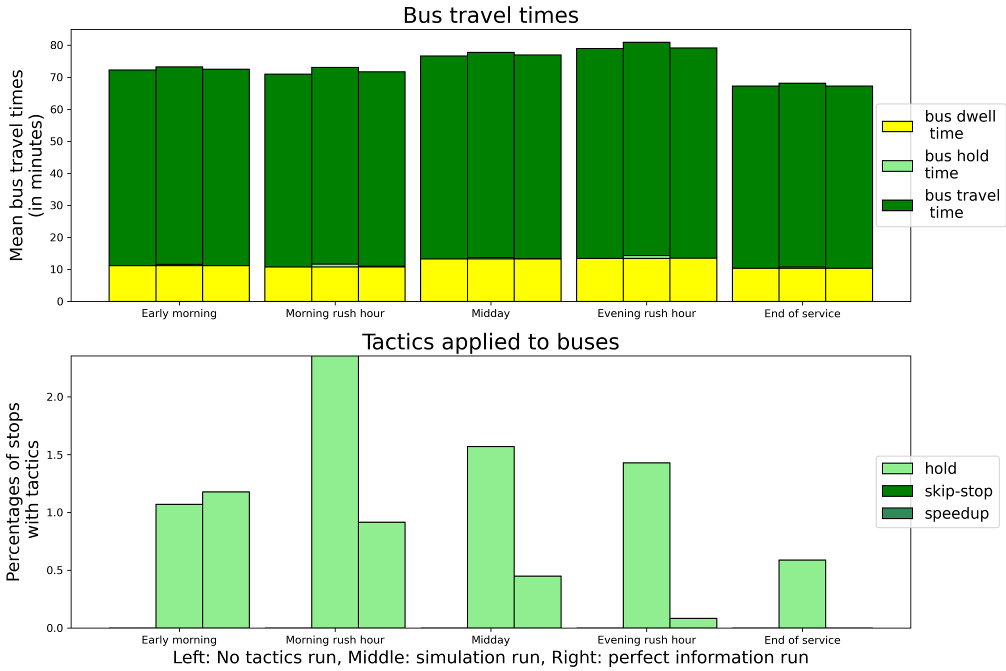

Fig. 7. Bus travel time and percentage of stops with tactics. Holding only.

improvements occur in the cases when buses are in advance compared to their planned schedules. In these cases, small holding times allow for great improvements in passenger travel times.

The performance of the model is limited by the assumption that passengers do not leave the system but wait for the next bus. In an urban environment, it is unlikely that a passenger will always wait 20 to 30 minutes for the next bus. For future research, the performance of the model could be improved by an in-depth analysis of travel origin/destination pairs. In that case, boarding and alighting passengers could be generated together and not separately. Moreover, the research on a single main line could be expanded to multiple lines in the bus network.

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Table 3. Average passenger travel times (holding only).

Time of day	Case	Wait for boarding	Wait for transfer (boarding)	Missed transfer (boarding)	Dwell time	Hold time	Travel time	Wait for transfer (alighting)	Missed transfer (alighting)	Walking time if skipped stop	Total time	Passengers with missed boarding transfers(%)	Passengers with missed alighting transfers (%)
Early morning	No Tactics	1.6	1.5	1.7	2.8	0.0	12.7	0.7	0.0	0.0	21.0	7.7	1.1
Early morning	Online	1.9	1.5	0.2	2.9	0.0	12.7	0.7	0.1	0.0	20.0	0.7	0.6
Early morning	Offline	1.7	1.5	0.3	2.9	0.0	12.7	0.6	0.0	0.0	19.8	1.3	0.7
Rush hour AM	No Tactics	1.5	2.3	1.9	2.2	0.0	11.4	2.0	0.1	0.0	21.3	6.0	1.3
Rush hour AM	Online	2.0	2.3	0.5	2.5	0.3	11.2	1.9	0.1	0.0	20.7	1.3	1.0
Rush hour AM	Offline	1.6	2.3	0.5	2.2	0.0	11.5	1.6	0.1	0.0	19.8	1.3	1.7
Midday	No Tactics	2.9	3.3	0.9	3.2	0.0	14.1	2.4	0.2	0.0	26.9	2.9	1.2
Midday	Online	3.2	3.3	0.4	3.3	0.2	14.0	2.3	0.3	0.0	27.0	1.6	1.7
Midday	Offline	3.0	3.2	0.5	3.2	0.1	14.1	2.1	0.2	0.0	26.4	1.7	2.0
Rush hour PM	No Tactics	4.1	2.7	0.1	3.8	0.0	17.1	1.9	0.0	0.0	29.8	0.4	0.6
Rush hour PM	Online	4.2	2.8	0.1	4.0	0.2	16.9	1.9	0.1	0.0	30.2	0.2	0.7
Rush hour PM	Offline	4.1	2.8	0.1	3.8	0.0	17.1	1.8	0.0	0.0	29.8	0.4	0.9
Night	No Tactics	2.6	2.5	0.0	3.1	0.0	15.8	2.1	0.0	0.0	26.1	0.0	0.0
Night	Online	2.7	2.5	0.0	3.3	0.2	15.6	2.1	0.0	0.0	26.3	0.0	0.0
Night	Offline	2.6	2.5	0.0	3.1	0.0	15.8	2.1	0.0	0.0	26.1	0.0	0.0

Table 4. Average bus travel times and tactics (holding only)

Time of day	Case	Dwell time	Hold time	Travel time	Total time	Stops with hold(%)	Skipped stops(%)	Stops with speedup(%)
Early morning	No Tactics	11.2	0.0	61.1	72.3	0.0	0.0	0.0
Early morning	Online	11.2	0.4	61.7	73.3	1.1	0.0	0.0
Early morning	Offline	11.2	0.0	61.4	72.5	1.2	0.0	0.0
Rush hour AM	No Tactics	10.8	0.0	60.2	71.0	0.0	0.0	0.0
Rush hour AM	Online	10.8	0.9	61.4	73.1	2.4	0.0	0.0
Rush hour AM	Offline	10.8	0.2	60.7	71.7	0.9	0.0	0.0
Midday	No Tactics	13.2	0.0	63.4	76.6	0.0	0.0	0.0
Midday	Online	13.2	0.5	64.0	77.8	1.6	0.0	0.0
Midday	Offline	13.2	0.1	63.7	77.0	0.4	0.0	0.0
Rush hour PM	No Tactics	13.4	0.0	65.6	79.0	0.0	0.0	0.0
Rush hour PM	Online	13.4	0.9	66.6	80.9	1.4	0.0	0.0
Rush hour PM	Offline	13.5	0.0	65.6	79.1	0.1	0.0	0.0
Night	No Tactics	10.4	0.0	56.9	67.2	0.0	0.0	0.0
Night	Online	10.4	0.4	57.4	68.1	0.6	0.0	0.0
Night	Offline	10.4	0.0	56.9	67.2	0.0	0.0	0.0

Table 5. Average passenger travel times (holding and skip-stop)

Time of day	Case	Wait for boarding	Wait for transfer (boarding)	Missed transfer (boarding)	Dwell time	Hold time	Travel time	Wait for transfer (alighting)	Missed transfer (alighting)	Walking time if skipped stop	Total time	Passengers with missed boarding transfers(%)	Passengers with missed alighting transfers (%)
Early morning	No Tactics	1.6	1.5	1.7	2.8	0.0	12.7	0.7	0.0	0.0	21.0	7.7	1.1
Early morning	Online	1.6	1.4	0.2	2.8	0.0	12.6	0.8	0.0	0.0	19.4	1.1	0.5
Rush hour AM	No Tactics	1.5	2.3	1.9	2.2	0.0	11.4	2.0	0.1	0.0	21.3	6.0	1.3
Rush hour AM	Online	1.5	2.1	0.2	2.2	0.1	11.3	1.9	0.0	0.0	19.3	0.6	0.6
Midday	No Tactics	2.9	3.3	0.9	3.2	0.0	14.1	2.4	0.2	0.0	26.9	2.9	1.2
Midday	Online	2.6	2.9	0.2	2.7	0.1	13.6	3.1	0.1	0.0	25.4	0.7	0.8
Rush hour PM	No Tactics	4.1	2.7	0.1	3.8	0.0	17.1	1.9	0.0	0.0	29.8	0.4	0.6
Rush hour PM	Online	3.6	2.6	0.0	3.5	0.0	17.0	2.2	0.1	0.0	29.0	0.2	0.6
Night	No Tactics	2.6	2.5	0.0	3.1	0.0	15.8	2.1	0.0	0.0	26.1	0.0	0.0
Night	Online	2.4	2.4	0.0	3.0	0.1	15.7	2.1	0.0	0.0	25.7	0.0	0.0

Table 6. Average passenger travel times (holding and speedup)

Time of day	Case	Wait for boarding	Wait for transfer (boarding)	Missed transfer (boarding)	Dwell time	Hold time	Travel time	Wait for transfer (alighting)	Missed transfer (alighting)	Walking time if skipped stop	Total time	Passengers with missed boarding transfers(%)	Passengers with missed alighting transfers (%)
Early morning	No Tactics	1.6	1.5	1.7	2.8	0.0	12.7	0.7	0.0	0.0	21.0	7.7	1.1
Early morning	Online	1.1	1.4	0.7	2.8	0.3	11.5	0.9	0.0	0.0	18.7	3.3	0.7
Rush hour AM	No Tactics	1.5	2.3	1.9	2.2	0.0	11.4	2.0	0.1	0.0	21.3	6.0	1.3
Rush hour AM	Online	1.5	2.2	0.9	2.2	1.6	9.3	2.0	0.1	0.0	19.7	2.6	1.5
Midday	No Tactics	2.9	3.3	0.9	3.2	0.0	14.1	2.4	0.2	0.0	26.9	2.9	1.2
Midday	Online	2.4	2.8	0.5	3.2	0.8	12.1	3.0	0.1	0.0	24.8	1.5	0.6
Rush hour PM	No Tactics	4.1	2.7	0.1	3.8	0.0	17.1	1.9	0.0	0.0	29.8	0.4	0.6
Rush hour PM	Online	3.4	2.6	0.3	3.8	0.5	15.3	2.5	0.0	0.0	28.4	0.8	0.8
Night	No Tactics	2.6	2.5	0.0	3.1	0.0	15.8	2.1	0.0	0.0	26.1	0.0	0.0
Night	Online	2.0	2.2	0.0	3.1	0.4	14.3	2.7	0.0	0.0	24.7	0.0	0.0

Table 7. Average passenger travel times (holding, skip-stop and speedup)

Time of day	Case	Wait for boarding	Wait for transfer (boarding)	Missed transfer (boarding)	Dwell time	Hold time	Travel time	Wait for transfer (alighting)	Missed transfer (alighting)	Walking time if skipped stop	Total time	Passengers with missed boarding transfers(%)	Passengers with missed alighting transfers (%)
Early morning	No Tactics	1.6	1.5	1.7	2.8	0.0	12.7	0.7	0.0	0.0	21.0	7.7	1.1
Early morning	Online	1.2	1.4	0.8	2.8	0.4	11.9	0.8	0.1	0.3	19.7	5.4	1.8
Rush hour AM	No Tactics	1.5	2.3	1.9	2.2	0.0	11.4	2.0	0.1	0.0	21.3	6.0	1.3
Rush hour AM	Online	1.5	1.9	0.9	2.0	1.0	11.0	1.2	0.0	0.3	20.8	3.6	1.2
Midday	No Tactics	2.9	3.3	0.9	3.2	0.0	14.1	2.4	0.2	0.0	26.9	2.9	1.2
Midday	Online	2.2	3.4	0.9	2.6	0.5	12.4	3.5	0.1	0.5	26.1	2.2	0.9
Rush hour PM	No Tactics	4.1	2.7	0.1	3.8	0.0	17.1	1.9	0.0	0.0	29.8	0.4	0.6
Rush hour PM	Online	2.4	2.2	1.0	3.4	0.2	16.0	2.5	0.1	0.8	28.6	3.3	1.5
Night	No Tactics	2.6	2.5	0.0	3.1	0.0	15.8	2.1	0.0	0.0	26.1	0.0	0.0
Night	Online	1.6	1.8	1.0	3.0	0.6	14.3	3.2	0.0	0.2	25.7	3.8	0.9

Table 8. Average bus travel times and tactics (holding and skip-stop)

Time of day	Case	Dwell time	Hold time	Travel time	Total time	Stops with hold(%)	Skipped stops(%)	Stops with speedup(%)
Early morning	No Tactics	11.2	0.0	61.1	72.3	0.0	0.0	0.0
Early morning	Online	11.2	0.2	61.1	72.5	1.5	4.0	0.0
Rush hour AM	No Tactics	10.8	0.0	60.2	71.0	0.0	0.0	0.0
Rush hour AM	Online	10.5	0.3	60.5	71.3	1.9	4.7	0.0
Midday	No Tactics	13.2	0.0	63.4	76.6	0.0	0.0	0.0
Midday	Online	11.6	0.3	62.3	74.2	1.4	6.4	0.0
Rush hour PM	No Tactics	13.4	0.0	65.6	79.0	0.0	0.0	0.0
Rush hour PM	Online	12.6	0.0	64.9	77.5	0.3	6.4	0.0
Night	No Tactics	10.4	0.0	56.9	67.2	0.0	0.0	0.0
Night	Online	10.1	0.1	56.6	66.9	0.3	2.5	0.0

Table 9. Average bus travel times and tactics (holding and speedup)

Time of day	Case	Dwell time	Hold time	Travel time	Total time	Stops with hold(%)	Skipped stops(%)	Stops with speedup(%)
Early morning	No Tactics	11.2	0.0	61.1	72.3	0.0	0.0	0.0
Early morning	Online	10.9	1.6	58.7	71.3	4.1	0.0	30.16
Rush hour AM	No Tactics	10.8	0.0	60.2	71.0	0.0	0.0	0.0
Rush hour AM	Online	10.9	3.1	59.9	73.9	5.6	0.0	33.38
Midday	No Tactics	13.2	0.0	63.4	76.6	0.0	0.0	0.0
Midday	Online	12.8	2.1	61.5	76.4	4.5	0.0	36.2
Rush hour PM	No Tactics	13.4	0.0	65.6	79.0	0.0	0.0	0.0
Rush hour PM	Online	12.8	1.7	61.3	75.8	2.9	0.0	45.13
Night	No Tactics	10.4	0.0	56.9	67.2	0.0	0.0	0.0
Night	Online	10.3	0.8	54.8	66.0	4.5	0.0	39.61

Table 10. Average bus travel times and tactics (holding, speedup and skip-stop)

Time of day	Case	Dwell time	Hold time	Travel time	Total time	Stops with hold(%)	Skipped stops(%)	Stops with speedup(%)
Early morning	No Tactics	11.2	0.0	61.1	72.3	0.0	0.0	0.0
Early morning	Online	9.8	2.5	60.8	73.0	4.3	5.9	16.03
Rush hour AM	No Tactics	10.8	0.0	60.2	71.0	0.0	0.0	0.0
Rush hour AM	Online	9.8	3.6	63.8	77.2	5.2	7.3	14.82
Midday	No Tactics	13.2	0.0	63.4	76.6	0.0	0.0	0.0
Midday	Online	10.1	2.5	61.2	73.8	4.9	7.4	16.47
Rush hour PM	No Tactics	13.4	0.0	65.6	79.0	0.0	0.0	0.0
Rush hour PM	Online	12.3	0.6	64.9	77.8	1.6	10.5	22.0
Night	No Tactics	10.4	0.0	56.9	67.2	0.0	0.0	0.0
Night	Online	9.8	1.5	57.0	68.2	2.9	5.6	18.24