USING MASSMOTION TO ANALYZE CROWD CONGESTION AND
MITIGATION MEASURES AT INTERCHANGE SUBWAY STATIONS:
CASE OF BLOOR-YONGE STATION IN TORONTO

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ABSTRACT

With year after year of record ridership and future demand only expected to grow, transit infrastructure is under increasing pressure. Examining the impact of the scheduling and coordination of subway lines at interchange stations is critical to reduce crowd congestion at station facilities. There is, however, a gap in knowledge with regards to how crowd congestion is impacted by the arrival patterns of trains. The effects of arrival pattern is especially critical at interchange stations where several train lines converge. A simulation-based analysis was performed to fill this gap, that is, how passenger congestion is impacted by the arrival pattern of trains. Field data was collected at the Bloor-Yonge Toronto Transit Commission (TTC) subway station, a station known to be operating at capacity during peak periods. To perform the analysis, a model of the station was developed, calibrated and validated in the pedestrian simulator MassMotion. The congestion duration passengers experienced was examined by varying both the passenger volume and the arrival pattern of the two independent train lines. Adjusting train arrival pattern was found to have as much as a 63% reduction in experienced passenger congestion. Additional scenarios are proposed as improvements over the status quo and tested for their significance in terms of improvement in congestion time experienced.
INTRODUCTION

With rising automobile fuel costs and traffic congestion, there exists an ever-increasing demand for transit by commuters. Transit infrastructure must therefore be prepared to meet this challenge in an efficient and safe manner. Interchange stations often represent the lynchpins of subway networks. It is at these stations where large passenger flows from various lines often interact with each other while entering/exiting the station or transferring between lines. Therefore, it is imperative that crowd congestion inside these stations is kept at acceptable levels for efficient use and safe operation. One factor affecting the congestion level inside an interchange station is the arrival train pattern of the different lines serving the station. Little research has been conducted to examine the impacts of train arrival patterns on station congestion, crowd dynamics and passenger experience. This paper seeks to fill this knowledge gap by analyzing passenger congestion at the interchange station of Bloor-Yonge in Toronto as a function of the train arrival pattern, train headway and passenger boarding/alighting distribution. The adopted approach of this research involves developing a pedestrian/crowd simulation model for crowd analysis and scenario testing.

LITERATURE REVIEW

Pedestrian modelling is a relatively new field of research in transportation modelling. A wide variety of pedestrian flow models have been generated over the last 20 years, including both macroscopic and microscopic models. Hoogendoorn et al. studied the relationship between pedestrian flow and speed, and between self-organization and spatial patterns of pedestrian movement. Their work determined many important microscopic properties, in particular the importance of reaction time in decision making (1). Campanella and Hoogendoorn further worked with models to calibrate model parameters (2). In 2009 they worked on the Nomad walker model by analyzing flow regimes through narrow bottlenecks. Their work showed that microscopic models can be calibrated over many types of flow simultaneously.

Improvements in pedestrian modelling involved treating the rich intricacies of human movement. In 2003, Hughes et al. postulated that a crowd is distinct from a classical fluid because a crowd has the ability to think (3). Shao and Terzopoulos integrated motor, perceptual, behavioural and cognitive components into a pedestrian model (4). This helped develop pedestrians into individuals rather than an amorphous flow or ‘blob’ as previous work had assumed. Singh further studied that within crowd flow subgroups exist (5). Assuming agents behave exclusively as individuals is unrealistic as one would expect that friends and families would prefer to move together. Today, the application of pedestrian modelling occurs in several fields. For example, Ulicny et al. examined how crowd modelling is necessary for application in video gaming and computer-generated-images in film and television (6).

Urban applications of crowd modelling were started by Schelhorn et al. using the STREETS model (7). Pedestrian flow was examined as a function of both urban form and trip attractants. The built environment provides many opportunities for the study of pedestrian flow. Daily occurrences and unique architecture create interesting issues which impact the behaviour of pedestrians such as route choice.

Given the increasing demand placed on urban transit systems, it is required now more than ever to conduct comprehensive studies of capacity and congestion within existing systems. Planners may use
pedestrian flow models to study proposed capacity upgrades and policy changes.

In 2004, Hoogendoorn et al. examined the impact of gates on the flow for several rail stations in Lisbon, Portugal (8). Similar to the work presented in this paper, Hoogendoorn looked at level of service and congestion levels using the flow model NOMAD. Of note in that study was how Hoogendoorn examined the transfer flows as a separate portion of the study. The analysis of congestion and level of service for transferring passengers are factors which were also examined in this work. Where this paper differs, is the study of how arrival pattern of trains impacts the aforementioned, rather than how gates shaped congestion.

Due to the population density and high transit use in China, Zhao et al. examined whether existing infrastructure was adequate to meet high demand times, such as increased flow due to a concert or sporting event (9). Their work was motivated by Beijing’s preparations for the 2008 Olympic Games. Using Legion, flow was analyzed for efficiency and service quality. Unlike Bloor-Yonge, no transfer stations were examined in Zhao’s work. Continuing with the Chinese studies, Chen et al. looked at the station capacity and passenger flow on the Beijing subway line. Their work determined the practical passenger capacity and distribution of passengers throughout the line (10). Using statistical regression, they proposed using automatic gate machines and selecting passages to guide flow in order to help meet future demand. Chen also discovered poor platform distributions resulted in congestion, similar to those experienced at the Bloor-Yonge station. Passengers tended to congregate near entrances and exits. The authors proposed double-decker island style stations to improve distribution. Close to Beijing lies the southern city of Hong Kong, home to the MTR, an expansive transit system. Lam et al. looked into the effects of crowding at two MTR train stations (11). The study focused on the impact of train dwell time and the congestion and crowding experienced by passengers. Lastly, in 2009 Du et al. modelled the walking time of subway transfer passengers (12). Their work looked at optimizing the train arrival times between lines such that passengers reached their destination platform as the train was arriving. With regards to specific station architecture, Seer looked into the bottle neck capacities at choke points such as stairs and escalators.

With regards to MassMotion—the simulation software used in this work—several studies were conducted in 2011 to ensure the parameters used for agent behaviour were appropriate (13). One of the key parameters which has an influence on agent movement is the agent speed profile. This parameter is randomly generated within a pre-set range as explained in the work conducted by Peacock et al. (14). Agent speed during simulation is a function of congestion and the degree of slope of the floor. Speeds are adjusted by a factor for going up and down ramps or stairs in accordance with work conducted by Fruin (15). The agent walk speed distribution was validated using egress simulations for high-rise buildings. Further validation of the MassMotion modified social forces algorithm was conducted using the Transbay Terminal in San Francisco in 2011 (16). The accurate and realistic results (as evidenced by the aforementioned calibration studies) produced by MassMotion were large motivators for selecting this software suite.

Of note is the limited number of published works on both MassMotion and the TTC. Also, very little work has been done on the study of train arrival patterns. In particular, almost no work has been done to
study the congestion implications of train arrival pattern at a transfer station. This research proposes to fill the knowledge gaps.

**DATA COLLECTION**

**Station Description**

The Toronto Transit Commission (TTC) is the public transportation agency for the City of Toronto operating an integrated network consisting of buses, streetcars, Wheel-Trans (a door to door accessible bus service) and an extensive subway system. The busiest subway station is the Bloor-Yonge interchange station which serves as a convergence point for 25,000 commuters heading to the CBD from the outskirts of Toronto during the morning peak hour alone. Bloor-Yonge is the meeting point of the Bloor-Danforth (BD) line, which runs east-west, and the Yonge-University Spadina (YUS) line which runs north-south. The station is currently operating at capacity during the morning peak period, typically between 8:00 AM to 9:30 AM. As ridership is expected to increase it is imperative that an analysis be conducted to examine crowd behaviour in order to make policy and operations related decisions in the future.

Bloor-Yonge station consists of three levels (concourse (accessed from street level), YUS tracks, BD tracks). The levels are connected via ten staircases and escalators and two elevators. Access to the station can be done at either end of the YUS platform, and at the west end of the BD line via the concourse level (Figure 1, stairs/escalators: 1,6,7,8,9,10,11). The major flows during the peak hour are transfer flows between the YUS line and the BD, with the majority going from the east/westbound to southbound (via stairs/escalators: 4 and 5). Other transfer flows (BD northbound and vice versa) use stairs/escalators numbered 2 and 3.
FIGURE 1 Adapted from (17) shows stairs/escalator labels and Bloor-Yonge station layout

Southbound and northbound trains have their own platforms, whereas BD trains (east and west) share a common island platform.
Data Collection Process

Data was collected manually by 16 persons due to a lack of any automated passenger count system. Collection occurred from July 19 to July 21 in 2011 using iPhone and Android counting applications which logged time-stamped counts. The peak period of data collected was between 7:45 AM and 9:15 AM. Since all points of interest could not be observed simultaneously, July 19th involved determining flows through segregated passages and stairs as a means of determining speed-density relationships, the next day involved determining all people on stairs and escalators, in addition to when trains arrived and the final day on determining boarding and alighting distributions. Post-collection, the data was examined to ensure that similar passenger behaviour was observed on the 20th and the 21st. The analysis showed that in fact, behaviour was similar. With regards to boarding and alighting, only northbound and southbound trains were analyzed, the former observed from 7:50AM to 8:30AM and the latter from 8:35AM to 9:15AM. In addition, on July 21st, the dwell time for each northbound and southbound train was recorded.

Data collected for passengers on stairs and escalators was aggregated into 10-second intervals. Although two elevators exist within the station, no data was collected with regards to their use as they move only a small fraction of the flow which travels through the station during the peak period.

Additionally, personnel measured the step length, number of steps and the number and length of landings for all the stairs in the station. The measurement of the offset of the stairs and escalators from the shear walls was also recorded. These physical characteristics were used for construction of a scale model.

Data Analysis and Extraction

In order to determine representative train loads for analysis, the data collected needed to be processed. To determine transfer flows between directions, a careful analysis was conducted based on train arrival times and observed flows. For example, the flow up stairs/escalator four and five was known (east-west (EW) flow). Thus, examining a period of time when no southbound train was at the platform allowed one to determine how much of the EW flow was headed up to the north concourse and how much was headed up to the south concourse, via stairs and escalators 7 and 8 respectively. The proportion of the flow of EW passengers which split between the southbound platform and concourses was determined. The same practice was applied on the northbound platform side using appropriate stairs/escalators and for a west and eastbound train. With train loads (the number of passengers boarding/alighting at Yonge and Bloor station) determined, an OD matrix was generated for all movement of passengers through the station.

MODEL CONSTRUCTION

MassMotion is a 3D microscopic pedestrian modelling software package developed by Oasys, a division of Arup. The software uses a modified Social Forces algorithm, where agents are modelled as particles whose movement is determined by ‘social forces’, including an attractive force to their destination and repulsive forces produced by stationary obstacles and other agents. MassMotion is a next generation simulator, where the modeller does not need to define an agent’s path. Instead, agents determine a path based on minimizing a cost (time) function, navigating automatically between specified origins and destinations by taking into account free and obstructed space, and the presence of other agents. This allows an agent to react to dynamic conditions, like the presence of congestion. Originally developed in
2005, the software has been used around the world, including the redesign of Union Station in Toronto and JetBlue T5 at JFK Airport.

Construction of a model in MassMotion involves building up the 3D geometry on top of an imported CAD file in a full 3D environment. Other required inputs include a pedestrian origin-destination matrix and gate timings to simulate train doors. Basic agent characteristics (size, walking speeds) were set at the defaults, which are based on values recorded in the literature, but can also be customized if needed. Agent size is a value determined from the calibration of MassMotion. Walking speed is a random variable which is normally distributed by default. Agents can also be programmed to perform a series of actions as they move to their final goal. Using these methods, detailed below, a scale 3D model of the station was generated.

The locations of the stopped trains (both BD trains and YUS trains) at the station platforms were approximated. This is because in real life the stopping locations vary from train to train because of the variable dynamic performance of trains and driver behaviour. Given that the variation in stopping location is within a few meters, an assumption of a fixed train stopping location was implemented. The difference of a few meters would have a negligible impact on pedestrian flow.

The southbound platform is home to a unique installation, a crowd control barrier, installed in late 2009 (18). The barrier is temporary in nature, only being present during the morning peak period. It separates passengers alighting from a southbound train from those wishing to board. The barrier forces patrons down towards the southern end of the platform, whereas without the barrier the majority would pool towards the north end. Stairs and escalators were modelled based on the collected data regarding number of steps, height, width, landings, etc.

**MODEL CALIBRATION**

Using the aforementioned data collected during the summer of 2011 the model was calibrated. Calibration consisted of the following measures:

- Adjusting stair/escalator distance and queue functions.
- Adjusting train-passenger distributions for the BD line (convergence, $\varepsilon < 10\%$).
- Altering Agent properties: body radius, direction bias, and shuffle factor.

The model was considered calibrated when it met the following criteria as per the Federal Highway Administration (FHWA) guidelines for applying traffic microsimulation modelling software (19):

1. Observed flows and modelled flows on the various stair/escalator combinations were within 10%; and
2. Visual inspection of a MassMotion simulation rendered realistic agent behaviour.

**Escalator Distance and Queue Penalty Functions**

To ensure accurate splits of agents between the stairs and escalators, the functions which govern their perceived cost was altered. Given that in the default settings of MassMotion, escalators present a lower cost than stairs, most agents would take the escalator. The escalator’s distance function was increased to
represent a relatively higher cost for taking the escalator. Also, as the arrival rate of passengers exceeds
the service rate of an escalator, a queue begins to form. By increasing the cost of waiting time in this
queue for escalators, more agents could be diverted from only taking the escalator to a more realistic split
between both the stairs and the escalator. Escalators were also set to a capacity of 120 people per minute
(17). The escalator distance/queue penalty function parameters when set at 10.465 m and 6.919 (unit
less), respectively.

**BD Line Passenger Distribution Adjustment**

Exact pedestrian paths through the station are unknown. For calibration, passenger boarding and alighting
distributions amongst the six train cars (for east and westbound) was adjusted to match observed flows
with modelled flows through the various stair/escalator zones.

No data was collected for the boarding and alighting distributions of eastbound and westbound trains.
This was due to the collection of said data being impractical given the station layout. To assign values for
these trains, a delicate procedure of balancing stair/escalator flows was conducted. By trial and error,
simulations were run with varying boarding/alighting distributions and the observed flows on stairs and
escalators were compared with the modelled values.

An assumption of a commuter population was made with regards to the BD line passengers. Under this
assumption, we assumed that passengers would board a train into the surrounding cars that would allow
them to exit near their destination stair/escalator. This assumption is a fairly good one, as during the
morning peak, which is what is modeled, the vast majority of passengers would be commuter and hence
would plan and optimize their routes. It should also be noted that even during the peak period, it is
unlikely that passengers are unable to board a car which would allow them to alighting closest to their
destination stair/escalators.

**Agent Properties**

Values such as body radius and shuffle factor were adjusted to ensure that agents were able to behave in a
realistic manner during simulation. By reducing body radius, agents can more smoothly tackle corners
and will occupy less space and thus can move past one another more easily. The shuffle factor accounts
for how fast agents are able to move side to side and it is a function of their forward velocity. A high
shuffle factor enables agents to move through crowds with less effort. The default values for the body
radius, directional bias and shuffle factor are 0.20 m, 0 (i.e. no preference) and 0.1, respectively.
However, the calibrated values for our model were set at 0.18 m, 1 (i.e. keep right) and 0.1. Reducing the
body radius implies that agents squeeze in closer to each other, as experienced in a highly congested
station. Typically in North America, people keep to the right when walking and driving, and accordingly
agents in our model were given a directional bias that is in line with this behaviour. The shuffle factor was
unadjusted as it is a relatively untested portion of MassMotion, and thus experimentation with it is not
advised (16).

To validate the model, the modelled and observed flows were examined. Figure 2 shows the flow
comparison for a particular stairs/escalator combination. As illustrated, the model results replicate closely
the observed flows. Similar results were obtained for other stair/escalator combinations in the station.
FIGURE 2 shows the comparison of flow along a defined staircase/escalator between the model and collected data.

**TRAIN ARRIVAL SCENARIOS**

An analysis period of 30 minutes was chosen for this study. This allowed for a sufficient number of trains to arrive at the station, and was a reasonable length for simulation computation time. A sensitivity analysis was conducted to examine the impact of train arrival patterns on the congestion passengers experienced within Bloor-Yonge station. To conduct the analysis, some parameters needed to be held constant. Based on the gathered data, the average headway of trains during the morning peak period was two minutes and thirty seconds (20), this value did not vary between lines or between directions. This headway was applied to all directions for the duration of the study and remained constant. The average dwell time of a train during this same period was found to be 45 seconds; this value was applied to all scenarios and held constant throughout the analysis.

Sample train loads by direction were determined from the 2011 data. They were calculated by dividing the total passengers (by direction from the 2011 data) by the number of trains in that direction.

With train loads determined and fixed and holding dwell time and headway constant, the arrival pattern of the four lines was offset relative to one another in order to create twenty-five unique scenarios. Given that northbound and southbound trains have separate platforms and their flows do not interact since they use separate station architecture, these two lines were offset together and they are assumed independent of
each other. Unlike the north and southbound directions, the BD line shares a common platform, and as a result their flows interact as they move through the station.

Scenario Nomenclature

All scenarios begin at 8:00 AM and run for 30 minutes. Offsets of train arrival are relative to 8:00 AM and relative to eastbound trains which arrive at 8:00 AM and every two minutes and thirty seconds thereafter. The westbound and north-south linked trains are offset relative to the eastbound ones and relative to each other by 30-second increments. The staggering of arrival pattern is designed to determine which configuration produces the best and worst congestion for passengers (and transferring passengers) in the station. Given the 2 min-30 sec headway, and 30-sec offset increments, 25 unique scenarios for train arrivals were created. They ranged from all the lines arriving at the same time, to all the lines offset by the maximum amount (i.e. two minutes).

Volume Analysis

The train volumes based on the 2011 data effectively represent the station running at capacity as evidenced by the overflow demand experienced daily. To examine the sensitivity of volume on congestion, the 25 train arrival patterns were additionally run using train volumes of 80% of capacity and 50% of capacity, with the OD matrices adjusted accordingly. Simulations run at even 110% of capacity rapidly broke down and produced no meaningful results and hence were omitted from this paper.

Implementation of Automatic Train Control (ATC) Scenario

Of the 25 train arrival patterns, one scenario will produce the lowest congestion for passengers and one will produce the highest amount of congestion time. These represent the best and worst case arrival patterns respectively. These extreme scenarios will be further tested under the implementation of ATC for the subway lines. Transit systems using ATC have reported a reduction in headway of trains to as low as one minute and thirty seconds (21). Implementation of ATC would allow for more passengers to move through the station as trains arrive less full, more frequently and hence platforms would clear more readily. For the ATC simulations, train loads were adjusted lower to account for more frequent train service and hence lower load factors on the trains. The assumption for the lower loads is that passenger arrival rate during the peak hour is approximately uniform.

Southbound Platform Utilization

Passenger boarding and alighting distributions for the arrival pattern scenarios are based on the 2011 collected data, and represent how passengers currently utilize the available platform space. A known issue on the congested southbound platform is crowding toward the northern end. This has impact on passenger flows and it causes congestion. Similar to the ATC scenario, the best and worst case arrival patterns were further tested with the southbound boarding distribution being uniform along the length of the platform. This test represents a policy change in which TTC would enforce a defined passenger boarding behaviour. The basis for this analysis is that passengers will experience less congestion when utilizing all available station capacity.
Determining the Level of Passenger Congestion

MassMotion records the level of service (LOS) A-F time experienced by all agents during the simulation. The LOS metric employed by MassMotion is in accordance with the work of Fruin. For each arrival pattern, the total amount of time at LOS F was determined for each direction. LOS F represents a scenario in which people are densely packed, shoulder to shoulder and front to back. Given that Bloor-Yonge station effectively operates at capacity during the morning peak, commuters will likely experience the less severe conditions associated with LOS D or E frequently. Commuters will also experience some periods at LOS F, especially at areas where opposing flows converge, or station architecture restricts movement, e.g. stairs/escalators. Hence, a period of LOS F represents a serious breakdown in the operation of the system, a point when congestion in terms of people per unit area is highest. During these periods of LOS F is when safety concerns are paramount and the marginal cost on the system for each additional user is highest. For example, emergency egress from a station operating at or around LOS F poses a serious risk for those inside the station. Therefore, it follows that reporting LOS F time per passenger as a measure of congestion provides valuable information to system planners. These four values were then divided by total amount of passengers for that direction to determine the average LOS F time per passenger by direction. A system average LOS F time per passenger was determined by generating a weighted average with respect to directional flow amounts.

Further refinement of the data allowed for the average LOS F time per passenger of strictly transfer flows to be determined. The transferring of passengers from the YUS to the BD line and vice versa represents the largest flow during the morning peak period. It is imperative to analyze how the train arrival pattern and subsequent proposed policy changes impacts this subset of the population.

RESULTS

The congestion contours for the 25 unique train arrival scenarios across all volume levels are depicted in Figure 3. The z-values on the graph denote the average amount of time a passenger experiences (in seconds) LOS F-type conditions as they move through the station. The x-y plane denotes train arrival offset relative to the constant eastbound train.

a. System Congestion for volume level: 100% Capacity
b. System Congestion for volume level: 80% of Capacity

![System Congestion for 80% Capacity]

FIGURE 3 Station Congestion Surfaces for the 25 train arrival scenarios at the three volume levels.

c. System Congestion for volume level: 50% of Capacity

![System Congestion for 50% Capacity]
a. Passenger Congestion for all Eastbound Originating Passengers

b. Passenger Congestion for Eastbound Terminating Passengers (those who leave at Bloor-Yonge)
c. Passenger Congestion for Eastbound Transfer Passengers (those who transfer north or south)

**Passenger Congestion for Eastbound to Southbound Transfer Flows**

![Graph showing passenger congestion levels for different offsets and volume levels.]

FIGURE 4 Passenger Congestion for Passengers Transferring Between Eastbound and Southbound, Volume Level: Capacity.

Given that Bloor-Yonge is a transfer station, it would be valuable to study how the arrival patterns impact those passengers which terminate at the station and those which are transferring through the station. Therefore, Figure 4 further investigates the eastbound direction by showing how the train arrival pattern affects those aforementioned groups in particular. Similar to Figure 3, z-values denote the average amount of time a passenger is congested.

The arrival patterns that produced the highest and lowest average congestion time for passengers are shown in Table 1. In addition, the relative standard deviation and range of values for all the scenarios (for each volume level) is also tabled. Further analysis was conducted on the best and worst case scenarios by examining the impact of implementing ATC and an adjustment in platform distribution. The results of these implementations are also found in Table 1 for comparison.
Table 1: Results for the Best and Worst Case Train Arrival Patterns

<table>
<thead>
<tr>
<th>Volume Level</th>
<th>Best Arrival Pattern (Direction: Offset)</th>
<th>Worst Arrival Pattern (Direction: Offset)</th>
<th>System Congestion Per Passenger(s)/Std Dev (s)</th>
<th>Relative Standard Deviation (%)</th>
<th>Range (min/max)</th>
<th>ATC Scenario-System Congestion Per Passenger(s)/Std Dev (s)</th>
<th>Uniform Southbound Boarding Distribution-System Congestion Per Passenger(s)/Std Dev (s)</th>
<th>Simulation runs, N</th>
</tr>
</thead>
<tbody>
<tr>
<td>100% Capacity</td>
<td>W: 1 min N/S: 1 min</td>
<td></td>
<td>61.9/7.7</td>
<td>17.1</td>
<td>28.3/10.0</td>
<td>50.8/7.7</td>
<td></td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>W: 2 min N/S: 0 min</td>
<td></td>
<td>109.1/7.8</td>
<td></td>
<td>30.9/5.1</td>
<td>96.1/8.2</td>
<td></td>
<td>10</td>
</tr>
<tr>
<td>80% Capacity</td>
<td>W: 1.5 min N/S: 1 min</td>
<td></td>
<td>38.4/4.5</td>
<td>24.6</td>
<td>22.9/0.81</td>
<td>33.1/1.9</td>
<td></td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>W: 2 min N/S: 0 min</td>
<td></td>
<td>84.4/6.5</td>
<td></td>
<td>17.0/0.46</td>
<td>63.9/5.3</td>
<td></td>
<td>10</td>
</tr>
<tr>
<td>50% Capacity</td>
<td>W: 2 min N/S: 1 min</td>
<td></td>
<td>14.6/1.0</td>
<td>24.7</td>
<td>3.9/0.31</td>
<td>12.7/1.7</td>
<td></td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>W: 2 min N/S: 0 min</td>
<td></td>
<td>39.3/0.75</td>
<td></td>
<td>5.0/0.25</td>
<td>33.4/0.58</td>
<td></td>
<td>10</td>
</tr>
</tbody>
</table>

Pairwise hypothesis testing of alternatives was conducted to determine whether the implementation of ATC or the policy change for the southbound platform had a significant impact on the congestion time experienced by passengers.
TABLE 2 Hypotheses Testing for Proposed Alternatives

<table>
<thead>
<tr>
<th>Volume Level</th>
<th>Best Arrival Pattern (Direction: Offset)</th>
<th>Hypothesis Testing for ATC Implementation</th>
<th>Hypothesis Testing for Uniform Southbound Boarding Distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Worst Arrival Pattern (Direction: Offset)</td>
<td>ATC a significant reduction in congestion?</td>
<td>Test Value&lt;sup&gt;1&lt;/sup&gt;</td>
</tr>
<tr>
<td>100% Capacity</td>
<td>W: 1 min N/S: 1 min</td>
<td>8.9</td>
<td>61.9-28.3 = 33.5</td>
</tr>
<tr>
<td></td>
<td>W: 2 min N/S: 0 min</td>
<td>6.6</td>
<td>78.2</td>
</tr>
<tr>
<td>80% Capacity</td>
<td>W: 1.5 min N/S: 1 min</td>
<td>3.3</td>
<td>15.4</td>
</tr>
<tr>
<td></td>
<td>W: 2 min N/S: 0 min</td>
<td>4.6</td>
<td>67.3</td>
</tr>
<tr>
<td>50% Capacity</td>
<td>W: 2 min N/S: 1 min</td>
<td>0.75</td>
<td>10.7</td>
</tr>
<tr>
<td></td>
<td>W: 2 min N/S: 0 min</td>
<td>0.55</td>
<td>34.3</td>
</tr>
</tbody>
</table>

1. Test Value<sup>1</sup> = \( t_{(1–\alpha)\cdot (n+m−2)} \cdot s_p \cdot \frac{\sqrt{\frac{1}{m} + \frac{1}{n}}}{\sqrt{\frac{1}{n+1} + \frac{1}{n+2}}} \)

DISCUSSION OF RESULTS

Examining Figure 3 reveals an interesting finding. Across all volume levels the contours exhibit a peak for the scenario in which westbound trains are offset by two minutes, and north and southbound trains arrive with eastbound trains. Visual inspection of this scenario reveals that at this arrival patterns flows from trains interact at some key choke points in the station causing large amount of congestion.

It is interesting to note from these contours that the transferring passenger surface exhibits essentially the same shape (peaks and troughs) as the total passenger plot. This implies that the congestion experienced by those passengers who do not transfer have little impact on the congestion the system experiences, as suggested by Figure 4 (b) and (c). A congestion mitigating strategy should target specifically the transferring flows since these passengers largely dictate the congestion levels at the station. Additional plots for eastbound transferring passengers for the other volume levels, and westbound/southbound transferring passengers exhibit the same behaviour.

Congestion is sensitive to the volume of passengers. Lower congestion is experienced when fewer people (i.e. 50% capacity volume) move through the station. At the higher volume levels, more people experience higher congestion and thus congestion is less sensitive to the arrival pattern, as evidenced by the relative standard deviation in Table 1. At the lower volume levels, there are less people and longer and
more frequent periods of low congestion, hence when an arrival pattern does produce congestion, it spikes
the values. This is again evident based on the relative standard deviation in Table 1. It is also implied
from the shape of the surface contour in Figure 3 (c), which shows high peaks relative to the other
contours. While one might expect that the train arrival pattern in which all trains arrive at the same time
would result in the worst congestion, this is not the case. In fact, at all volume levels the same particular
arrival pattern produced the worst congestion. The lesson learned here is that congestion is not strictly a
function of the train arrival pattern (although this is still a critical factor), but the station architecture also
largely contributes. Certain arrival patterns, in particular W: 2 min, N/S: 0 min offset, result in passenger
flows to meet at pinch-points within the station, thus resulting in congestion. Notable points of high
congestion within the Bloor-Yonge station are the bases of stairs and escalators, due to queuing which
occurs when people begin to board the escalator and, at the north end of the southbound platform, where
people tend to congregate waiting to go southbound, near the stairs/escalator labelled 7 (refer to Figure 1).

Implementation of ATC to reduce headway to one and a half minutes, and the implementation of a more
uniform utilization of the southbound platform resulted in significant improvements in the average
congestion time passengers experienced (Table 2). These results were expected and can be readily
explained. Using ATC results in more trains in all directions that are operated at a lower capacity factor.
As a result, the spikes in demand placed on station facilities in less, there is less queuing at stairs and
escalators, less friction from opposing flows meeting and quicker platform clearance. By making the
boarding distribution on the southbound platform more uniform, there is less conglomeration at the northern
end, which as mentioned before, is a critical area. Passengers now can more freely move on the platform
and less congestion is experienced.

Currently the TTC is in the process of upgrading the subway system in order to facilitate the use of ATC
(18). Furthermore, as mentioned before, a crowd-control barrier has been in place on the southbound
platform since late 2009 and is intended to direct passengers to more fully utilize the southbound platform
(18), but unfortunately this barrier is not strictly enforced.

CONCLUSION

This paper sought to determine how passenger congestion is impacted by both volume and the arrival
pattern of trains in an interchange station, via a case study of a major transfer hub in Toronto. Currently,
the TTC operates the subway system without coordination amongst its various lines and little if any
research has been done to study the impact of such practices. In order to perform the analysis, a scale
model of the station was developed in the pedestrian simulator, MassMotion, calibrated to data collected
during the morning commute peak-period. Simulation analysis showed that adjusting the arrival pattern
of trains had significant impact on the level of crowding and the efficiency of flow within the station,
most pronounced for transferring agents. Up to a 43% reduction of congestion was found between the
best and worst case scenarios when at capacity, with greater reductions (up to 63%) when pedestrian
volume was lower. In addition, the implementation of automatic train control, allowing for an increased
level of frequency and reliability, was also found to significantly reduce the level of congestion. The
methods used in this study can be applied by policy makers and transit operations planners to help
maximize the available capacity within stations or better understand the impacts of train operation
decisions on station efficiency.
This study focused on analyzing situations where the station and network were operating under normal conditions, and also considered the station in isolation. Moving forward, additional research could be conducted in how congestion is impacted by delays on one or more lines, thus causing a build-up of passengers in the station. Lastly, understanding the network effects of changes to congestion at key stations represent an exciting and relatively untapped area of research for microsimulation modeling.

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REFERENCES


