Performance Metrics and Analysis of Transit Network Resilience in Toronto

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Paper submitted for presentation at the 2016 Annual Meeting of the Transportation Research Board and publication in Transportation Research Record.

Submission Date: July 29, 2015
Word Count: Abstract (199), Paper (5051), + 7 figures/tables (1750) = 7000

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ABSTRACT

Slow expansion and inadequate upgrades of the transit network in Toronto, combined with unprecedented levels of demand, have created a daily commute for transit users which is plagued by delays and disruptions. This paper aims at examining and quantifying the resilience of the public transit network in Toronto to operational disruptions. It also attempts to identify critical points within the network, as well as the spatial impact of service disruptions. The study of resilience is a relatively new research topic, with a limited breadth of research conducted to date, especially when one considers the resilience of a public transit network. This paper intends to fill this research gap by proposing a new framework for resilience measurement and analysis.

The approach adopted in this work is a unique combination of quantitative methods founded in Graph Theory and demand-elastic methods of transportation network analysis using EMME4. The research findings revealed the critical stations in Toronto’s subway network, which if disrupted, would create major negative impacts on passenger trip times. The underlying reasons for their inherent critical nature is discussed and analyzed. In addition, this work was able to spatially quantify transit resilience by identifying both low-risk and at-risk areas within Toronto.
INTRODUCTION

Over the last decade or so, the assessment of transportation system resilience has gained traction in both transportation planning and day-to-day operations. A nascent topic within the study of transportation resilience is the development of quantitative measures of resilience to help planners and operators identify network locations of high vulnerability, devise strategies to mitigate risk and reduce the overall impact of network disruptions on travellers.

Nowhere is the study of resilience and its quantification more important and timely than the public transit system in a major metropolitan area such as Toronto where fast-paced demand growth, slow rate of network capacity building and rising occurrence of various types of incidents across the transit system have combined to threaten the integrity of the transit system and the quality of transit service offered to the public. Public transit within the City of Toronto is provided by two separate agencies, each with a defined geographic jurisdiction. They include GO Transit, which operates commuter rail services as well as inter-municipal coach buses, and the Toronto Transit Commission (TTC), which operates the underground subway lines (of which there are four) and surface-level services consisting of 11 streetcar lines and nearly 150 bus routes. Figure 1 exhibits the urban rail network of Toronto, including the GO rail network and TTC’s subway and streetcar networks. The TTC serves on average 2.76 million passengers per day. Having experienced almost three decades of government neglect to invest in transit infrastructure expansion, portions of the TTC system now operate strenuously above capacity during the peak periods. Under such difficult conditions, the system has been subject to a growing number of incidents that slow down, or even suspend entirely, transit services. In 2013, the city’s subway system alone has seen 5,864 instances of delay [1]. Such instances of delays are attributed to incidents at track level (fire, unauthorized persons), mechanical failures, unruly passengers and weather, to name a few. These incidents can result in the holding of train service for several minutes, or be so severe that the suspension of services on an entire line is necessary. In the case of suspension of service, there were 43 incidents in 2013, a significant number with far reaching impacts on the travel times of public transit users.

a. TTC Streetcar System.

![Toronto Streetcar Map](image-url)
b. TTC Subway Network

![TTC Subway Network Map]

FIGURE 1 (a) Streetcar Network Map  (b) TTC Subway Network Map  (c) GO Train System Map. Adapted from [2].

The metro system in Toronto (particularly the YUS line) operates well over capacity during the morning peak period, as evident from the unsatisfied demand unable to board the first train to arrive, and thereby left on the platform to wait for the next train. Even a small delay or disruption to train operations can have lasting effects in terms of passenger throughput and line/station congestion. The quantitative impact of such disruptions is not well understood. Qualitatively, operators and users alike know the cost of even a minor delay in terms of greatly increased travel times, due largely in part to the capacity-constrained nature of the system. While quantifying travel time increases is of prime importance, it is also critical to examine the spatial nature of disruptions. Network topology and geographical constraints are expected to play a significant role in the extent of spatial impact of a disruption. A robust metric for public transit network resilience needs to address the aforementioned questions.

This paper seeks to answer the question of how to quantify the resilience of a public transportation network. In particular, this paper will present a metric for the resilience of the Toronto
transit system, although the metric could be applied elsewhere. The selection of metrics employed within
this work was based on a thorough and comprehensive review of the literature on resilience and
associated performance measures. The literature review spanned a number of fields, which allowed for a
blending of concepts from different disciplines.

LITERATURE REVIEW
The study of system resilience is a relatively new field of research. In the wake of increasing climate
instability and security threats, incorporating aspects of resilience into system planning and operations is
gaining traction across a range of disciplines. The word ‘resilience’ has a wide variety of definitions and
is often synonymous in the literature with 'robustness', 'reliability', 'redundancy' and 'adaptability', among
others. Resilience has been studied in a large number of fields including sociology, psychology,
engineering, ecology, business, and economics.

The past decade has seen a few research efforts focused on the quantification of resilience.
Heaslip et al. [3] [4] put forth the idea that resilience is cyclical in nature. Initially, the resilience of the
system is diminished after a disruption, but it returns gradually with time post-disruption. Serule et al. [5]
expanded upon that work by attempting to quantify the recovery of systems as a proxy for resilience.
murray-tuite [6] also contributed to the quantification of resilience through the application and
examination of different traffic assignment regimes.

A number of research efforts have sought to produce indices of resilience so as to rank-order
network components and compare similar networks with respect to resilience. For example, Li Zhang et
al. [7], Scott et al. [8], Sullivan et al. [9], and Adams et al. [10] produced a number of indices of
resilience, which incorporated various network properties, both pre and post disruption. A summary of
their indices in addition to others can be found in Table 1.

Jenelius and Mattsson [11] developed a methodology for determining the vulnerability of road
The Importance of a link is a function of the increase in weighted travel time that occurs when that link is
disrupted. The researchers further applied their framework in 2005 to a more detailed analysis of the road
network in Sweden [12].

**TABLE 1 Summary of Resilience Indices in the Literature**

<table>
<thead>
<tr>
<th>Source</th>
<th>Metric</th>
<th>Index Approach and Application</th>
</tr>
</thead>
<tbody>
<tr>
<td>Li Zhang et al.</td>
<td>Measure of Resilience (MOR)</td>
<td>Intermodal transportation system, with focus on freight movement. MOR is a ratio of travel speed pre and post disaster</td>
</tr>
<tr>
<td>Nagurney et al.</td>
<td>Relative Total Cost Index</td>
<td>Applied to the road network to contrast assignment best-practices. The index is the ratio of increase in total cost of the network, in terms of travel, to a disrupted state</td>
</tr>
<tr>
<td>Scott et al. [8]</td>
<td>Network Robustness Index (NRI)</td>
<td>Applied to the road network; examined the relationship between volume, capacity and link criticality. NRI is a measure of link criticality, in terms of the impact on the network when disrupted</td>
</tr>
<tr>
<td>Adams et al. [10]</td>
<td>Risk Priority Number (RPN)</td>
<td>Operational resilience of road corridors; examined the cost of taking alternative routes during a disruption. RPN accounts for the probability and severity of a disruption on a segment</td>
</tr>
</tbody>
</table>
Department of Homeland Security (DHS) [14]  Resilience Index for Transit Stations  Screening process examining the elements of transit stations that contribute to resilience given natural disasters

Jenelius et al. [12]  Link Importance and Exposure  Applied to the road network to determine the critical links by examining the cost of link disruption

Miller-Hooks et al. [15]  Resilience Index  Applied to freight operations; tested an optimal set of post-disaster scenarios and recovery mechanisms

Chang et al. [16]  Transportation System Performance Index  Applied to freight operations; examined link accessibility and network coverage

A rich stream of research in transportation network analysis has adopted concepts and approaches borrowed from the field of Graph Theory. In a recent study, Derrible and Kennedy [17] outlined the applications of Graph theory to transit network design, providing an inventory of the work done to-date using Network science and Graph theory.

Osei-Asamoah and Lownes [18] looked at the structural resilience of complex networks (with a focus on transportation networks) by calculating a number of structural indices. Such metrics are computationally simple to perform and allow for ease of comparison between networks.

Ip and Wang [19] [20] have conducted several research efforts regarding transportation network resilience using Graph theory. In their earlier work, they represented the transportation network as an undirected graph. Their metric for resilience for a particular node was based on the number of independent paths from the node in question to all other nodes.

Leu et al. [21] used Melbourne as a case study for the network analysis of resilience. The public transportation network of Melbourne was represented as an undirected graph, nodes and links were disrupted, and resilience was calculated based on a concept called topological integrity. Roughly, this can be described as how the shortest paths change within a network given service disruptions.

Outside of transportation engineering, there has been far reaching applications of network science to study the resilience of various network types, including: power grids [22, 23], the internet [24, 25], supply chain management and communications [26, 27].

Assessment of the Literature

Of note is the relatively small number of studies which examined the resilience of a public transit system explicitly. There is a further lack of research which examines public transportation disruptions in the North American setting. The vast majority of research conducted to date looked at road networks in isolation. A critical observation of the literature reveals that there is no single universal definition, nor metric for resilience. The definition of resilience is highly context dependent, and by extension, the quantification of resilience can vary greatly between applications. It is further observed that there exist two general approaches regarding how to quantify resilience. The first is based on demand-insensitive Graph Theory concepts while the second approach involves incorporating the concepts of demand variability and network topology via simulation. It is therefore proposed in this study to utilize metrics from both approaches in order to quantify the resilience of Toronto’s transit network as accurately and comprehensively as possible.
METHODOLOGICAL APPROACH

As shown in the literature review, structural metrics of a graph could serve as a strong basis for analyzing the resilience of a complex network. Therefore, the application of approaches based on Graph Theory will be undertaken on a graphical representation of the Toronto transit network. However, a network science approach is bounded by a strict set of limitations, especially in the context of analyzing a public transit system. Transit systems are home to a number of different modes with vastly different properties (e.g. speed, headway, etc.). In addition, the behaviour of commuters on a transit network is influenced in no small part by the characteristics of the transit lines they utilize. Therefore, this work will augment the quantitative methods of Graph Theory with demand-elastic methods of transportation network analysis, resulting in a hybrid approach to measuring and investigating the resilience of Toronto’s transit network.

Graph Theoretic Measures of Resilience

The Graph theoretic measure of resilience used in this study is based upon the work of Osei-Asamoah et al. [18], as discussed in the literature review. Additionally, the concept of topological integrity is borrowed from the work of George Leu et al. [21].

The application of Graph theory requires an accurate and comprehensive directed graph. One such graph, \( G = (N, E) \) where \( N \) represents the nodes and \( E \) represents the edges, was created for the TTC surface and metro system. Nodes \( (N) \) consist of surface transit stops and metro stations, and links \( (E) \) represent the connecting roads or underground tunnels which join the stops and subway stations respectively. The graph representing the TTC network was generated in NetworkX via Python scripting. The graph includes all TTC surface stops and subway stations, as well as all links hosting TTC services. The generation of lines and stops is based on the General Transit Feed Specification (GTFS) data and information provided by the TTC.

The selection of NetworkX was based on its inherent suitability with regards to handling complex networks. NetworkX is an open source tool and has been applied in a number of studies of real-world networks [28, 29].

Network resilience in this study is measured by the impact of node disruptions (i.e. removal) on the performance of the network. Node disruptions are considered under two unique strategies, defined as ‘targeted’ and ‘random’. In both cases, after a node is removed from the network, the Global Efficiency (GE) is calculated. The targeted removal is based on the rank-ordered Betweenness-Centrality (BC) value of the nodes. That is, the nodes with higher BC values are removed first (hence, targeted) until all nodes are removed from the network. With regards to the random removal, nodes are removed at random until all nodes have been removed. Random removals are simulated 15 times with a rotating random seed.

The BC of a node or link is a measure of how central that element is in the network. The concept was first proposed by Freeman [30] and has found applications in ranking node and link importance in different types of networks. BC is a global measure of node/link load and importance, and is therefore preferred over a more local measure such as connectivity.

The BC of a node, \( v \), is defined by the following equation:

\[
BC(v) = \sum_{s \neq v \neq t} \frac{d_{st}(v)}{d_{st}}
\]

Where:

- \( d_{st} \) is the number of shortest paths from node \( s \) to node \( t \);
- \( d_{st}(v) \) is the number of shortest paths from nodes \( s \) to \( t \) which travel through node \( v \); and
Normalized values of BC range from a minimum of 0 to a maximum of 1.

The GE of a network, first proposed by Latora and Machori [31], is a measure of the exchange of information within a network. Osei-Asamoah et al. [18] explained that GE quantifies how flow is exchanged between nodes in a transportation network.

GE of a network is defined as:

$$GE = \frac{1}{N(N-1)} \sum_{s \neq t} \frac{1}{Z_{st}}$$

Where:

- $Z_{st}$ is the length of the shortest path between node $s$ and node $t$;
- $N$ is the number of nodes in the network; and
- The GE value obtained is normalized (min 0, max 1) by dividing by the GE of an ideal network where all node pairs are connected.

To further expand the scope of resilience analysis, the concept of topological integrity, as adopted from Leu et al. [21] was applied. It involved determining the number of non-overlapping sub-graphs, both before and after a node is disrupted. Prior to a disruption, the graph studied here is fully connected, in the sense that one can get from any node in the network to any other node. After the removal of a node (i.e. a disruption) the graph may be split into several disconnected sub-networks. The probability that a random node removal results in the network becoming sub-divided into $k$ pieces was calculated.

**Demand Elastic Resilience Measure**

To define, quantify and ultimately apply a practical metric of resilience, one must include the aforementioned transit network properties and build upon the existing graph theoretic metrics (such as GE or BC). To meet such an end, simulation will be undertaken to examine the impacts of disruptions on trip-makers using EMME (“Equilibre Multimodal, Multimodal Equilibrium”). For over 40 years, EMME has evolved into a comprehensive package for modelling travel demand on transportation networks. Currently, it is used widely across Canada, and in particular it is the software of choice for the regions in the GTHA (including Toronto, the focus of this study).

**EMME Network Model of Toronto**

The network model used in this work was produced by the Travel Modelling Group (TMG) at the University of Toronto, representing the entire GTHA in the year 2012. The model contains all the transit services and lines which operate during the morning peak period, and their appropriate frequencies, scheduled departures, etc.

Transit demand was generated from the 2011 Transportation Tomorrow Survey (TTS). This survey, conducted every 5 years, is a phone-based survey of approximately 5% of the households located in the GTHA. The TTS data includes information on the modes of both access and egress to and from transit. Furthermore, the TTS data has the transit routes used by the survey respondents. Since this paper is an analysis of the resilience of the TTC network in Toronto, the TTS transit demand matrix was limited to only those trips that begin or end inside the City of Toronto.

This work has adopted a modified transit assignment model that considers the idiosyncrasies of
the transit assignment problem in Toronto [32]. The calibrated model, known as the Congested Fare-Based Transit Assignment (FBTA), is sensitive to congestion, which is a key consideration in the capacity constrained system in Toronto. Furthermore, FBTA incorporates fares in the path-selection algorithm. To denote that congestion is experienced by trip-makers and subsequently converted to a value of time, the trip cost of the FBTA model is defined in terms of the ‘perceived congested’ minutes of travel.

Importance Measure

As outlined in the literature review, Jenelius et al. [12] define the Importance of node $k$ as the aggregated travel cost increase, $c_{ij}^k - c_{ij}^0$, over all OD pairs incurred when $k$ is disrupted. Travel demand, $x_{ij}$, is used as a weight to account for the volume and severity of a disruption being proportional to the volume of passengers passing through a given node.

$\text{Importance} (k) = \frac{\sum_i \sum_{j \neq i} x_{ij}(c_{ij}^k - c_{ij}^0)}{\sum_i \sum_{j \neq i} x_{ij}}$

Where:

- $x_{ij}$ is the demand from origin node $i$ to destination node $j$; and
- $c_{ij}^k$ is the cost of travel from node $i$ to node $j$ given node $k$ is disrupted, $c_{ij}^0$ is the base case.

The above equation represents the impact of a node disruption as a function of the travel demand that utilizes or passes through that node. The concept of Importance is therefore a measure of the ability of the transit network to provide an efficient means of transportation. The inputs (travel time, and demand volume) to calculating the Importance of a node are readily quantifiable, and are easily understood by planners, operators and system users at all levels.

The Importance of the 69 TTC subway stations are calculated based on the simulation of service disruptions within EMME for the AM peak period (weekday service, 6:00 AM – 9:00 AM)

Service Disruptions in EMME

Given the static nature of EMME, only a subset of disruptions to the TTC network could be simulated. In contrast to the graph theory approach described before, only TTC subway stations were considered for disruption in EMME. The choice to target only the subway network was made in light of the computational requirements to run even a single EMME simulation. Focusing on TTC subway stations exclusively allowed for a more detailed and complete analysis. Furthermore, the subway system represents a critical lynchpin in the Toronto transit network, where disruptions are commonplace and the impacts severe. The static properties of EMME require that any modelled disruption be maintained for the analysis period, thus representing an all-or-nothing event. As a result, dynamic disruptions, or small-scale operational disruptions such as delayed trains could not be considered. Therefore, in accordance with the definition of Importance, and given the confines of the modelling platform of choice, a service disruption at a given subway station is assumed to result in service suspension for a portion of the line, the extent of which is defined by the presence of crossover tracks. Trains are assumed to be turned back upstream and downstream of the disrupted portion of the line. Crossovers can be described by way of an example, as shown in Figure 2.
a. Spatial Impact of Track Crossovers

![Diagram of train crossovers]

FIGURE 2 (a) Impact and (b) Location of Train Crossovers. Adapted from [2].

b. Location of all Crossovers by Line

**Yonge-University Line**
- South of Downsview Station
- South of Wilson Station
- North of Spadina Station
- South of St. George
- East of Union Station
- North of Bloor Station
- South of St Clair Station
- South of Eglinton Station
- South of Lawrence Station
- South of York Mills Station
- South of Sheppard-Yonge Station
- South of Finch Station

**Bloor-Danforth Line**
- East of Kipling Station
- East of Islington Station
- East of Jane Station
- East of Keele Station
- East of St. George Station
- West of Woodbine Station
- East of Victoria Park Station (double crossover was re-installed - not yet operational)

**Scarborough RT Line**
- East of Kennedy Station (on westbound track) (often used as a terminal station)
- West of McCowan Station (often used as a terminal station)

**Sheppard Line**
- East and west of Sheppard-Yonge Station
- East of Bayview Station
- West of Don Mills Station
In the case of a disruption at Sherbourne station (purple star), trains will turn back at St George and Broadview stations. As a result, a total of four stations would experience service suspension due to the particular location of track crossovers.

**Exposure Measure**

Jenelius et al. [12] developed a metric built upon Importance called Exposure. Exposure is defined by the following equation:

\[
Exposure(m) = \frac{\sum_{k} \sum_{i \in V} \sum_{j \neq i} x_{ij}(c_{ij}^k - c_{ij}^0)}{L \sum_{i \in V} \sum_{j \neq i} x_{ij}}
\]

Where:

- \(x_{ij}\) is the demand from origin node \(i\) to destination node \(j\);
- \(c_{ij}^k\) is the cost of travel from node \(i\) to node \(j\) given node \(k\) is disrupted, \(c_{ij}^0\) is the base case;
- \(L\) is the number total number of possible disruption scenarios; and
- \(V\) is the set of origin nodes within the Planning District (PD) \(m\).

The exposure of a municipality or district \(m\) is defined here as the increase in travel time aggregated over all origin nodes \(i\) in the district and all destination nodes \(j\) in the entire network. Thus, given a random station failure somewhere on the TTC subway system, the expected increase in travel cost is given by the formula above. \(L\) is number of possible disruption scenarios that could occur in the network and \(V\) is the subset of origin nodes located within the district \(m\).

Given the above formulation, the expected Exposure of the 16 PDs which represent Toronto (Figure 3) are calculated. The disruption scenarios to be considered, \(L\), are those of the assumed service suspensions described previously.
RESULTS

This section presents the application of the multi-faceted approach described in the previous section to quantifying and evaluating the resilience of the transit network in Toronto. The results of the Graph theory metrics of resilience are presented in Figure 4.

a. Node Disruption Strategies – Graph Theory Approach

![Network Performance Measure Response to Random and Targetted Node Removal](image)
b. Topological Integrity – Graph Theory Approach

The performance of the network under a targeted removal strategy (Figure 4 (a)) represents a worst case scenario. Based on the aforementioned BC values, the nodes of the network are rank-ordered and removed sequentially. A node with a higher BC value is more central to a network and thus is more critical, hence its removal would have a more drastic impact on network performance.

Figure 4 (a) shows a great deal of information about the network response to node removal. In general, both targeted and random node disruptions result in reduced network performance. Under both strategies, the GE drops by approximately 50% after about 15% of the nodes are disrupted under the targeted scenario and after 20% under the random removal regime. The GE reaches a minimum of zero under both regimes but this occurs after about 85% node removals under the targeted case, as opposed to closer to 95% node removals under the random case.

In the case of random disruptions, the loss in GE is quite steep until about 30% of the nodes are removed, after which the rate of decline in GE is markedly less. It should be noted that under both scenarios, the GE of the network drops considerably after the removal of a relatively small percent of the total nodes. This rapid loss of efficiency in transfer between nodes is perhaps due to the lack of adequate redundancy built into the network, affecting resilience adversely. A more robust network would exhibit a shallower curve for GE loss when plotted against node removal.

The results from Figure 4 (b) are somewhat more positive in terms of analyzing the resilience of the network. Based on the frequency distribution, it is apparent that the removal of a random node is not likely to break the network into two or more disconnected sub-graphs. Figure 4 (b) also shows that the maximum number of disconnected sub-graphs which can occur due to a node failure is three, yet with very small likelihood for the network to decompose into two or three disconnected sub-graph.

A topological integrity based analysis can be used as a proxy for the resilience of the network, as it is a good indicator for a severe network breakdown. An event which causes the network to become severed represents a total failure in the ability of the transit system to operate. Users who desire to travel from an origin in one of the disconnected sub-graphs to a destination in another sub-graph can no longer complete their trip using the transit network. The benefit of such analysis is that it allows one to observe
possible network vulnerabilities, i.e. which nodes in particular, if disrupted, would result in the formation of disconnected sub-graphs.
a. Station Importance Values
b. PD Exposure Map

FIGURE 5 (a) TTC Subway Station Importance Map. (b) Expected Exposure of the 16 PDs constituting the City of Toronto (Trip Perceived Congested Minutes/Trip).
Figure 5 (a) shows that the stations on the Yonge portion of the YUS line have the highest Importance values, that is, they would result in the greatest increase in travel time over all OD pairs if disrupted. Other notable stations of high Importance are Yonge-Bloor and St George, the critical transfer stations from the BD line to the YUS line. These transfer stations serve as the interchange points for trip-makers commuting from the east and west ends of the GTA respectively. It is at these two stations where passengers must transfer from the BD line to the YUS line in order to complete their trips (most of which terminate in PD 1 during the AM peak).

Figure 5 (b) shows the Exposure of the 16 PDs given a random failure on the TTC subway system, for trips originating from that PD. Expected Exposure is the average increase in travel time for trip-makers originating from a specific PD over all possible disruption scenarios. As postulated at the onset of this work, network resilience is strongly impacted by network topology. Station Importance calculations strongly support this argument, the evidence of which can be found in the large difference in Importance values based on the location of the disruption relative to other transit services in the network. The concept of Exposure, as discussed in the methodology, measures the demand-weighted increase in travel time per trip that begins in a particular PD and ends anywhere else in the network. The impact of a service disruption can therefore be studied in terms of the cost to particular areas of Toronto. Based on the subway network topology and the location of high-quality transit alternatives, one expects that the fringe PDs (i.e. PDs 8, 9, 10, 11, 12, 15 and 16) would be the most exposed, the primary reasons being that these PDs have sparse trip origin demand and few good alternatives to make transit trips.

As evident from the Exposure map, on average, the most exposed PDs are 12, 5 and 16. Trip-makers travelling from PD 12 or 5 have an average increase in demand-weighted travel time of 69.7 and 62.2 Trip-Perceived Congested minutes per trip, respectively. A few service suspensions might result in immense increases in demand-weighted travel time, chiefly service disruptions impacting the stations between Yonge-Bloor and Lawrence. In fact, the top 5 most impactful disruptions involve service suspensions on the YUS line north of Bloor-Danforth line and south of Finch station. It is no surprise then to find that trip-makers who originate east of the YUS line (PD 5, 12) can be greatly impacted by the average service disruption. Trip-makers originating from PDs 11 and 4 are more advantageously positioned in the event of the failure of the YUS line. Spatially, these residents are closer to the functional University-Spadina line (Figure 1 (b)) and thus we see these PDs are less exposed. The impact of the Don Valley Parkway, which snakes north-south through Toronto, likely also contributes to the relatively greater increase in travel time for those trips originating in PD 4 and 12.

**DISCUSSION**

The analysis of realistic disruption scenarios using EMME garnered note-worthy results. Given the high utilization and central locations of Yonge-Bloor and St George interchange stations, it was largely expected that a disruption at either station would have the greatest impact on trip-maker commute times. The results show, however, that other stations might result in more dire consequences to commute times in the event of service suspension, with Lawrence station being the most critical. It is interesting to note that based on 2013 TTC disruption data, service delays at Lawrence station represented 11.2% of the total delay minutes experienced by the system. The high Importance value of Lawrence station can be explained in terms of the AM trip demand pattern, trip-maker routing options, and TTC network robustness.

The nature of the AM peak period demand is such that there is considerable demand originating from the Finch terminus of the YUS line and heading south towards downtown Toronto. Hence, a disruption at Lawrence station interrupts the travel pattern of a great many trip-makers.

The two largest contributors to the Importance value obtained for Lawrence station include factors associated with expected trip-maker behaviour and the extent of the TTC network’s robustness. In
the event of a service suspension at Lawrence station, passengers from the north of Toronto and outlying
areas are unable to complete their trip on the Yonge portion of the YUS line. Observing the results of the
simulation reveals that trip-makers would be required to switch over to the University-Spadina portion of
the YUS line in order to travel south. Given that the YUS line, particularly its eastern Yonge line, is
already operating at or above capacity, a loss of a portion of this line has a profound impact on travel
times, and this is echoed in the Importance value of not just Lawrence, but for many of the stations on the
Yonge portion of the YUS line.

Just how those trip-makers would switch over to the University-Spadina portion is an important
point for discussion and ties directly into the overall resilience of the TTC network. In order to transfer
from the disrupted portion of the YUS line to the operating portion to the west, the vast majority of trip-
makers would board buses which run predominantly east-west. Unfortunately, these bus lines operate at
very high load factors during the AM period. The additional demand of passengers from the disrupted
subway line would create great delays. These delays would become so severe that some trip-makers
would likely prefer walking to the next station to the south on Yonge where subway service is available in
order to continue their trip. Figure 6 shows the redistribution of post-disruption passenger volumes. The
thickness of each bar represents the total volume on the associated link segment. The colour code used is
described as follows. The differences in volumes between the base case and the disrupted case are
calculated, with positive values (i.e. when volume was higher in the base case, or pre-disruption) shown
as red bars and negative values (i.e. when the transit volume was higher in the disrupted scenario) shown
as green bars. The difference in relative thickness between the bars indicates the total volume on those
routes. It is apparent from Figure 6 that many passengers have switched modes, and in some cases elected
to walk.

Contrasting the relative Importance between Lawrence and the more highly utilized downtown
stations allows one to make interesting conclusions regarding the resilience of the Toronto transit system.
In PD1, transit users have far more options in order to complete their trip, most notably the streetcar
network (Figure 1 (a)). The result of such network redundancy is that disruptions in the downtown core
are far less severe than in areas where few other transit options exist. It is proposed that the greatest
indicator for the relative Importance of a station is the lack of high-quality alternative transit services.
FIGURE 6  Passenger Volumes under the Case of Service Suspension at Lawrence Station.
CONCLUSION

This research study has proposed a quantitative method to analyze the operational resilience of the multi-modal public transportation network of Toronto. The multi-pronged approach applied here was formulated based on graph theoretic approaches taking into consideration the unique properties that characterize a public transit system. In addition, the concepts of Importance and Exposure were applied using the software EMME to examine the impacts on passenger volumes and travel times.

This paper has demonstrated that the resilience of the transit network in Toronto can be quantified by considering network topology, transit service attributes and trip-making behaviour. The methodology adopted in this work has provided new insights into the magnitude of resilience existing in a public transportation network. Although the results of this work are specific to Toronto (given its specific OD pattern and network topology), the techniques employed and the analysis conducted could be applied to any sufficiently detailed transit network. For the Graph Theory part, the application requirements are as simple as having a directed graph representing the transit network under investigation. Further, the findings of this work serve to highlight the importance of having a detailed and accurate model to simulate complex real-world scenarios.

Critical network locations, which would have an enormous impact on network functionality if disrupted, were identified and analyzed. Transit planners can seek to optimize a constrained budget by targeting improvements towards the areas identified in this work, which should help strengthen the resilience of the network as a whole.

ACKNOWLEDGEMENTS

The authors are grateful to the Province of Ontario for funding this work through the Ontario Graduate Scholarship.
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