Risk-Based Asset Management Framework for Subway Systems

Mona Abouhamad[1] and Tarek Zayed, F.ASCE[2]

[1] Faculty of Engineering, Cairo University, Cairo University Road, Giza, Egypt

[2] Professor, Department of Building and Real Estate (BRE), The Hong Kong Polytechnic University, Hong Kong, E-mail: tarek.zayed@polyu.edu.hk

Abstract

The 2017 report card for America's infrastructure assigned a grade D to transit systems indicating they are in a poor condition with strong risk of failure. A possible solution proposed is adopting a comprehensive asset management system to maximize investments in light of the fund scarcity dilemma. This research develops a risk-based asset management framework for subway networks. A generic subway hierarchy is proposed and risk is assessed using three sub-models; failure index, consequences of failure and criticality index. Failure Index is predicted using inspection reports and Weibull reliability function. Consequences of failure are assessed based on seven criteria along financial, social, and, operational perspectives. Criticality index is introduced to assess the functional importance of a station in its location using seven attributes along three main criteria. The Fuzzy Analytical Network Process is employed to analyze experts' knowledge used in the two functional sub-models. The real case study assessment indicates two stations with high risk indices showing the necessity of an intervention action. This research presents a basis for evaluating subway infrastructure on a structural and functional basis. It assists authorities to derive an informed rehabilitation decision using a generic and consistent framework.

INTRODUCTION

Subway systems play a vital role connecting thousands of people to different destinations on a daily basis. In North America; data from both countries was consulted since they both have similar conditions pertinent to the weather conditions, years of construction, deterioration sources and other different factors affecting the infrastructure under study. The Canadian infrastructure report card (Canadian infrastructure report Card, 2016) recommended encouraging infrastructure owners to establish asset-management plans based on rates of deterioration and community service levels. Moreover, the 2017 report card for America's infrastructure assigned a grade D to transit systems indicating they are in a poor condition with strong risk of failure. A possible solution proposed by the 2017 report card is adopting a comprehensive asset management system to maximize investments in light of the fund scarcity dilemma. An ideal asset management system should include condition assessment and/or deterioration models, repair selection method, and prioritization of component for repair methodology. Risk management, on the other hand, is the decision making process where actions are taken in response to the outcome of a risk assessment. In case of subway networks; the literature demonstrates some condition assessment models, however, no functional assessment models or risk assessment models are noted. This research develops a risk assessment model for subway networks through developing the components of a risk equation; structural assessment and functional assessment.

The following section is a background to the topic; it covers the different practices adopted by subway authorities in addition to a literature review for the research work done in the subway network domain. The methodology section proceeds to illustrate the different steps of developing the proposed model. The case study section is the application of the developed model to a real life case study, results presentation and model validation. The final section is the summary and research conclusion.

BACKGROUND

The literature in subways domain is scarce with only handful models structurally assessing subway stations. Abu-Mallouh (1999) developed a model to optimize the number of stations accommodated within a given capital program for full and partial rehabilitation. (Farran 2006) developed a model to address life cycle costing for a single infrastructure element with probabilistic and condition rating approach for condition state. Semaan (2009) developed a condition assessment model to diagnose specific subway stations and assess their conditions using an index (0-10). This was further expanded by the same author (Semaan 2011) to develop a model to evaluate structural performance of different components in a subway network using performance curves for components and the entire network using reliability-based cumulative Weibull function. In a corresponding effort, (Marzouk and Abdel Aty, 2012) proposed a Building Information Modeling (BIM) system for subways including four asset management indicators for structural integrity, mechanical systems, heating, ventilation, and air conditioning (HVAC) systems and, electrical system and user-related indicators. The model however, delivered only a platform and a proposed BIM flowchart without continuing to define the proposed indicators considering them as ready inputs to an integrated BIM/Asset management model. The authors recommended the use of experts' judgement for acquiring missing information regarding subway components. Gkountis and Zayed (2015) used the Analytical Hierarchy Process (AHP) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to develop a condition assessment model for subway stations and tunnels considering structural, electrical, and mechanical components. The authors used experts' judgement to estimate defect and component's weights.

Hastak and Baim (2001) stated that in the context of subway stations; inspections are used to identify the needed assessment for rehabilitation work. However, since no federal or state regulatory is used for inspections; the development and the implementation of the inspection standards in mainly the transit management responsibility (Russel et al. 1997). Each transit authority developed its customized approach according to its management plans and rehabilitation needs. California transit authority developed an evaluation system for stations and ranked them on a scale from excellent to poor based on predefined criteria combined using a weighted average technique (Abu-Mallouh 1999). Whereas, Metropolitan Transit Authority of New York Transit developed a ranking system for condition assessment by assigning points to different functional factors. London Transit developed the Key Performance Indicator to evaluate the performance of stations from its customers' point of view using a direct evaluation of customer satisfaction through surveys and interviews. The Paris Rapid Transit Authority worked on developing a selection procedure for stations in need of rehabilitation, the model used a seven functional criteria selection procedure (Abu-Mallouh 1999). Table 1 summarizes practices used by different authorities and outlines their basic features and limitations. It can be concluded that the practices assessed stations from a functional perspective while the structural perspective was assessed using discrete inspection reports only. The reported transit management practices adopt a qualitative functional perspective to inspect and prioritize subway stations for rehabilitation. On the other hand, the academia focused mainly on structural quantitative models through condition assessment and deterioration models. While these two perspectives of assessment are vital; neither of them is inclusive. A study of one perspective is not sufficient to provide an overview of the state of the system. Nevertheless, none of the reported literature/practices integrates the functional and structural aspects of a subway station into a single model.

The Fuzzy Analytic Network Process

Saaty developed the Analytic Hierarchy Process (AHP) as a multi-criteria decision support methodology to derive relative scales of absolute numbers known as 'priorities' from judgments expressed numerically on an absolute fundamental scale (Saaty 2005). The Analytic Network Process (ANP) was developed as an extension to AHP problems with dependencies and feedback among criteria. ANP works on deriving relative priority scales of absolute numbers from a group of judgments. These judgments represent the relative influence of one of two elements over the other in a pairwise comparison, with respect to an underlying control criterion. ANP relies on the accumulated experience and knowledge of decision makers, instead of merely supplying them with data that may provide little decision support (Sarkis et al. 2006). Detailed steps for execution of ANP model are outlined in Saaty (2008).

In spite of the various advantages of ANP, the ANP-based decision model is noticeably ineffective when dealing with the inherent fuzziness or uncertainty in judgment during the pairwise comparison process. Even though using the discrete scale of 1–9 to represent the verbal judgment in pairwise comparisons has the advantage of being simple and straight forward, yet, it does not account for the uncertainty and imprecision associated with the mapping of a person's perception or judgment to a crisp number and cannot reflect the human thinking style (Kahraman et al. 2006). Fuzzy ANP was introduced to capture the 'fuzziness' or the vague and uncertainty in the evaluation of alternatives.

Mikhailov & Singh, (1999) & (2003) used the Fuzzy Preference Programming (FPP) technique to derive crisp priorities, including the criteria weight and the alternatives scores from crisp, interval and fuzzy judgments. The FPP is applied to increase ANP capabilities in dealing with inconsistent and uncertain judgments through considering crisp comparison judgments as interval judgments with equal lower and upper bounds. In addition, FPP provides an appropriate index to measure the inconsistency of human judgments especially when the decision maker's performance is strongly inconsistent (Yu et al. 2007).

Fuzzy Preference Programming (FPP) adopts the concept of α–cuts to decompose fuzzy numbers into a number of intervals, adequately representing the initial fuzzy sets. The method finds priorities for each α-level cut, which are further aggregated in crisp local and global priorities (Mikhailov 2003). Fuzzy judgments are decomposed using α-cuts and through applying FPP method, thus, a sequence of crisp priorities $W\ (\alpha_1)$, corresponding to each α-cut level can be obtained; the results are then aggregated to find final crisp values of priorities shown in Equation (1) (Mikhailov et al. 2003).

$$W\ (\alpha_1) = (W_1\ (\alpha_l), W_2\ (\alpha_l) \ldots W_n\ (\alpha_l))^T \qquad \text{Equation (1)}$$

$$l=1, 2, 3 \ldots L \qquad 0 =< \alpha_1 < \alpha_2 < \cdots < \alpha_l=1$$

FANP handles the uncertainty in quite a different manner than that of regular ANP with sensitivity analysis. Fuzzy ANP accommodates the subjectivity of human judgment as being expressed in natural language which entails 'fuzziness' in real-life problems.

Risk Assessment Models

An ideal asset management system should include condition assessment and/or deterioration models, a repair selection procedure, and prioritization of component for repair methodology. Risk management is the decision making process where actions are taken in response to the outcome of risk assessment. Risk based asset management models have been implemented in the literature in various fields to quantify and assess the overall risks associated with different systems (Opila et al. 2011).

A failure risk model for buried pipes was developed by (Kleiner et al. 2004); Baris (2010) developed a risk assessment model at an individual pipe level by combining probability of failure determined by statistical deterioration modeling of sewer pipes and consequence of failure determined by examining geographical, physical, and functional attributes of sewer pipes in the light of expert knowledge. Hahn el al. (2002) used six mechanisms to predict probability of failure for sewers. While Fares (2008) developed a risk model for water main failure that evaluates the risk associated with each pipeline in the network. Seattle Public Utilities calculated the risk of failure in monetary terms (Martin et al. 2007). The Edmonton office of Infrastructure developed a risk assessment process to assess the scale and likelihood of different infrastructure failures related to current funding shortfalls. They concluded that adopting a risk assessment methodology helps identify a concrete course of actions and provides decision-makers with a tool to determine the potential impacts of not investing in specific infrastructure projects (City of Edmonton Office of Infrastructure 2003).

RESEARCH METHODOLOGY AND MODEL DEVELOPMENT

The developed methodology aims at combining structural and functional perspectives of a subway network into a single risk assessment model. The structural integrity is assessed through a failure index sub-model whereas the functional perspective is assessed through the consequence of failure and criticality index sub-models. The output of the three sub-models is then integrated into a risk index model using 30 rules extracted from experts' knowledge. This section starts by presenting the network hierarchy used through the analysis and proceeds with the sub-models and risk model development.

Subway Hierarchy

A generic subway network hierarchy is presented in Fig. 1. A typical subway line is composed of a number of station buildings. They operate by means of their composing systems such as electrical, mechanical, security and communication, and, structural. This research focuses only on the operational risk failure derived from the structural systems in a network. Therefore, the structural system is identified as a composition of stations, tunnels and auxiliary structures. These are composed of the elements located at the lowest level of the hierarchy. This hierarchy will be the basis of calculations through model development and its associated sub-models.

Failure Index Sub-Model

The Failure Index (FI) sub-model builds upon the performance model developed by (Semaan 2011). Semaan (2011) used reliability-based cumulative Weibull function to evaluate the structural performance of different components in a subway network and develop performance curves for subway components and the entire network. Reliability-based cumulative Weibull function takes a probabilistic approach that yields a reliability index, which is the inverse of the probability of failure. Therefore, FI can be estimated as the inverse of the reliability and is shown in Equation (2)

$$\mathrm{FI}_f = 1 - R(t) = 1 - e^{-\left(\frac{t-\alpha}{\tau}\right)^{\delta}} \qquad \text{Equation (2)}$$

Where,

R (T) = Reliability, t = Time, δ = deterioration parameter, α = location parameter, τ= scale parameter, δ= and e = exponential.

Different system configuration requires different calculations for failure index values. The series-parallel reliability technique (Hillier and Lieberman 1972) entitles that any system is composed of components outlined in parallel, in series, or, in a combination of both. A system in parallel is a redundant system where components work simultaneously. The word redundant here refers to the manner of operation of the station system. The station system operates in parallel, accordingly, the stations system will only fail if all its components (stations) fail. This is the logic used to calculate the different failure index values. A subway network is composed of lines, stations, and auxiliary structures; the failure index is calculated for each system based on the configuration shown in Fig. 2.

Station System (STA): In a subway station system, the slab and stairs are redundant systems and can be considered as a parallel system. The wall system is a series system in which if any wall "fails" to perform, the whole station becomes unsafe, and thus does not perform. Failure index of a station system can be computed using Equation (3)

F_{STA} = 1- [(1- $\prod_{i=1}^{n} F_{STEi}\, F_{STIi}$)*(1- $\prod_{i=1}^{n} F_{SEi}\, F_{SIi}$)*(1- $\prod_{i=1}^{n}(1 - F_{WIi})(1 - F_{WEi})$)]

Equation (3)

Where,

F_{STAj} = Failure index of station j, F_{STE} = Failure index of exterior stairs, F_{STI}= Failure index of interior stairs, F_{SE}= Failure index of external slab, F_{SI}= Failure index of internal slab, F_{WI}= Failure index of internal wall, F_{WE}= Failure index of external wall, and, i=1, 2 … n = station floor.

Tunnel System (TUN): A tunnel system operates in series in which it fails if any of its components fail, therefore, FI values are calculated using Equation (4)

$F_{TUN} = 1 - (1 - F_D) * (1 - F_w) * (1 - F_s)$ Equation (4)

Where;

F_{TUN} = Failure index of tunnel, F_D = Failure index of Dome, F_w = Failure index of wall, F_s = Failure index of slab.

Auxiliary structures System (AS): These systems operate in series in which it fails if any of its components fail, therefore, FI is calculated using Equation (5)

$F_{Aux\ St} = 1 - (1 - F_w)$ (1- $F_{TS} * F_{BS}$) Equation (5)

Where;

$F_{Aux\ St}$ = Failure index of auxiliary structure, F_W = Failure index of walls, F_{TS} = Failure index of top slab, and, F_{BS} = Failure index of bottom slab.

A Line System: is composed of all stations, tunnel, and auxiliary structure systems operating on the line. These systems together operate in series whereas; the composition of each system operates in parallel. The stations systems are redundant system, they operate in parallel and will fail to operate when all stations in a line fail. Likewise, a line failure occurs when all tunnels on the line fail to operate. Same applies for the auxiliary structure, operating is parallel in a line systems. On the other hand, the three systems operate in series. If any of the systems fails entirely that means the subway line is in a failure status and can no more function effectively. The line hierarchy is shown in Fig. 2 (a) and is computed using Equation (6)

$F_{line\ i} = 1 - [(1 - \prod_{n}^{i=1} F_{STA_i})*(1 - \prod_{n}^{i=1} F_{TUN_i})*(1 - \prod_{n}^{i=1} F_{AUX_i})]$ Equation (6)

Where;

F_{line} = Failure index of line, F_{STA} = Failure index of station, F_{TUN} = Failure index of tunnel, $F_{Aux\ St}$ = Failure index of auxiliary structure, and i=1, 2 … n = number of systems in a line.

Subway Network; a subway network is composed of all the lines operating in the network. It can be concluded that the lines in a network operate in parallel. Hence, the network only fails when all the lines operating in the network fail. This can be computed using Equation (7) and concluded from Fig. 2 (b).

$F_{Net} = \prod_{n}^{i=1} F_{Linei}$ Equation (7)

Where;

F_{Net} = Failure index of network, F_{Linei}= Failure index of line.

Consequences of Failure Sub-Model

A generic risk management system should identify failure index and Consequences of Failure (CoF) to be combined later to produce a representative risk index. A formal review of failure consequences diverts attention away from maintenance tasks having little or no effects and focuses on maintenance tasks that are more effective. This ensures the maintenance spending is optimized and guarantees the inherent reliability of equipment is enhanced (Gonzalez et al. 2006). Indirect impacts of failure of a subway station include, but are not limited to, service disruption, passenger delay, loss of reputation, loss of revenue in addition to other socio-economic impacts reflected as the extent to which the failure affects adjacent services and customers benefiting from the service and the ease of providing an alternative service. However, only a fraction of the expected CoF can be monetized whereas most of the expected indirect CoF are difficult to monetize and measure (Muhlbauer and W Kent. 2004). One way to overcome the difficulty inherent in these calculations is measuring CoF using indices, which facilitates comparing between expected CoF and highlights areas of higher failure impacts.

This research determines factors affecting CoF calculations in terms of tangible and intangible impacts which revealed a wide spectrum of consequences occurring at element and station levels. A station is composed of a number of elements operating simultaneously; based on the location of the element and its nature, the element failure might cause total, partial, or no station closure. This suggests CoF are element-dependent, Fig. 3 outlines the CoF model. Based on literature and experts' knowledge, Consequences of failure are broadly grouped into financial, social, and, operational impacts of failure. It is noted that some factors could fall under two different perspectives simultaneously.

The defined impacts of failure along different categories are interdependent; hence, the effect of a single impact cannot be measured independently without considering how other impacts affect and are affected by its occurrence. Therefore, Fuzzy Analytical Network Process is selected to obtain relative weights of these factors. FANP addresses the interdependency inherent in the relation between these factors and accounts for the uncertainty caused by using expert knowledge. Fig. 4 demonstrates the main criteria and attributes considered in the consequence of failure sub-model. For each subway element, the consequence of failure index ($\mathrm{CoF_i}$) is computed using Equation (8)

$$\mathrm{CoF_i} = \mathrm{CW_i} * \mathrm{Ss_i} \qquad \text{Equation (8)}$$

Where;

CoF_i= Consequence of Failure Index, CW_i = Criteria weight obtained using questionnaire survey and FANP, Ss_i = Severity score calculated from network data and inspection reports, i= elements operating per station.

Financial Impacts

Financial impacts represent the direct tangible impacts of failure measured in terms of cost of maintenance, repair, or, replacement of the failed component(s). In addition to the expected revenue loss due to partial or total station failure or service interruption, assessed in the operational impacts of failure. User traffic frequency, measured in social impacts of failure, is also a factor of revenue loss. Revenue loss is calculated using Equation (9);

$$RL = T_f * Fr * TTR/365 \qquad \text{Equation (9)}$$

Where;

RL= Revenue Loss, T_f = User traffic frequency, Fr= Commute Traffic fare, and, TTR= Time to repair (indays)

Operational impacts

Operational impacts of failure are those involving managerial decisions; they include time to repair and ease of providing alternative. The time to repair is the total time required to return the failed component into a functioning state. Ease of providing alternative is also a major concern since providing an alternative quickly and easily minimizes the impact of failure and the social costs incurred from this failure. Ease of providing alternative is mainly a factor of the available shuttle buses in case of a station failure. Therefore, it is measured in terms of number of bus stops adjacent to the failed station (in case an alternative is required)

Social impacts

Social impacts of failure are the direct social consequence of failure incurred by the customers. They are measured in terms of the user traffic frequency, interruption rate, and service continuation. The magnitude of the social impacts of failure is directly proportional to the number of users using this station and the adjacent businesses to which this station connects. The interruption rate refers to the frequency of interruptions occurring at that station per year. Station reputation reflects the customer dependability on the station as a main means of transportation for daily trips. The service continuation refers to whether this interruption will cause total station closure, partial closure, or can be repaired without station closure and service interruption.

Station closure depends mainly upon the location of the failing component in the network hierarchy. Referring to the systems analysis approach; if a component operates in a series system, then its failure will cause closure to the station (either partial or total) based on the component criticality. Whereas in a parallel system, failure of a component does not require closure of the station since the system can still function effectively. It is stressed that in our analysis we only consider operational failure in which serious injury or death is not expected, in which case, the station will be fully closed since the human life is the most valuable and cannot be compared with any consequence.

Examining consequence of failure revealed a level of interdependency between attributes and sub-attributes. None of the specified attributes can be considered independent; hence, cause and effect loops flow between them. This is the type of interdependency precisely modeled by ANP. Furthermore, these attributes convey a degree of fuzziness and subjectivity derived from using experts' knowledge, thus, FANP will be utilized to develop the model and address the interdependency inherent in the relation between these factors. In order to determine the overall consequence of failure for each station the following steps are adopted:

- From literature review, inspection reports and experts feedback identify consequence of failure of different elements,
- Categorize consequence of failure according to their Social, Operational, and Financial Impacts,
- Using pairwise comparison and FANP, estimate Consequence of failure Weights(CW_i) .
- Using expert feedback, station configuration and historical data, compute the Severity Scores (Ss_i) ,
- Compute total Consequence of Failure score (CF_i) per element using Equation (10),

$$\mathrm{CF_i} = \mathrm{CW_i} * \mathrm{Ss_i} \qquad \text{Equation (10)}$$

- Using system configuration, aggregate consequence of failure for different elements per station, whenever required.

Consequence of failure considered in this research are quite diverse, to overcome the difficulty inherent in these calculations, consequence of failure are measured through indices. This facilitates comparison between expected consequences and highlights areas of higher impact of failure. FANP will be used as the main analysis tool to obtain CoF criteria weights. Triangular fuzzy numbers were selected for their wide applicability and ease of comprehension by decision makers. A fuzzy scale of $\tilde{1}$ to $\tilde{9}$ is used to represent subjective pairwise comparison of the selection process (equal to extremely high) in order to capture the vagueness of the comparison process. The scale and its reciprocal are shown in Table 2.

Following the FANP calculation scheme, the consequence of failure estimation sub-model is structured as a network of clusters and nodes. The clusters include financial, operational, and social impacts of failure. The financial impacts cluster includes nodes for maintenance and rehabilitation cost and revenue loss. The operational impacts cluster includes nodes for time to repair and ease of providing alternative. The social impacts of failure cluster include nodes to user traffic frequency, degree of service continuation (total /partial/ none) and interruption rate. The factors' weight as well as the stations' evaluation in terms of these impacts was done qualitatively in light of experts' knowledge. In addition, the factors selected and their credibility was refined by checking with experts and improving the selected impacts accordingly.

Criticality Index Model

This research introduces criticality for the scope of subway networks as the Criticality index. The subway network breakdown structure is assessed differently, the element is selected such that its criticality level is dominant and diverse enough to prevail over other network components. Consequently, subway stations are selected to be the focus of criticality analysis. Systems and subsystems share the same major role of delivering the service; however, their criticality is derived from their respective locations in stations that vary in criticality according to several factors. From this discussion, the concept of criticality propagation is introduced; criticality level propagates upwards and downwards in a hierarchy of a subway network such that they acquire the same criticality level as the stations where they operate. Similarly, a line criticality is computed as the sum of criticality indices of stations existing on this line. For interconnecting systems such as tunnels and auxiliary structures, C_R is computed as the higher index of the two corresponding stations through which this system connects.

Factors contributing to station C_R are identified through historical data, experts' knowledge and by consulting current structure and map of several subway networks. Station criticality is a complex decision based on different attributes defined as; number of lines, number of levels, station use whether end or intermodal, and station proximity to different attraction locations. C_R factors defining a station differ in significance, thus, a weight component is introduced to the C_R equation to accommodate the subjective variability in attributes weight. Attribute scores are computed based upon the network under examination and individual station information. Station criticality is defined in terms of three main factors and seven sub factors or attributes. Amongst attributes identified, the station location is the most diverse. For further details about this model, the reader is referred to (Abouhamad and Zayed 2013b). Station criticality attributes are strongly connected, hence, cause and effects loops flow between them. Therefore, FANP with application to Fuzzy Preference Programming is used to compute the attributes weight. The Criticality Index model is outlined in Fig. 5.

Criticality Index per station (C_R) is computed using Equation (11)

$$C_R = \sum_{i=1}^{n} C_R wi * C_R s \qquad \text{Equation (11)}$$

Where; C_R= Criticality Index per station, $C_R wi$= Criticality attributes weights calculated using questionnaire surveys and FANP, $C_R S$= Criticality scores calculated using current network data, and i=1,2, …,n, n= criticality attributes

Risk Index Model

Risk by definition is a combination of failure index and the severity of adverse effects (Lowrance 1967). While risk refers to both positive and negative probable impacts. Only negative impacts were considered in this model. When studying the risk level, it should be noted that elements with similar failure index might show wide variation in terms of consequences of failure and vice versa. In addition, critical elements with high consequences of failure usually compose a smaller portion of the overall network. Accordingly, focusing only on these elements would result in an unbalanced management practices since unexpected failures may occur in less-critical elements, which constitute the majority of the network. Furthermore, a comprehensive risk assessment should consider the relative importance of different components and systems of a subway network. A criticality index is introduced to measure the relative importance and consider it in the risk index development. Consequently, a new term is added to the risk equation, named as the criticality index (C_R). Several methods exist to compute the risk index value, ranging from simple straightforward multiplication to more sophisticated computation of risk matrix.

The Fuzzy Rule Based (FRB) technique was selected to compute the risk index in this research. This method permits users to integrate their experience into the decision support system through using "if-then" rules. Fuzzy sets allow for a more precise presentation of element's membership particularly when it is difficult to determine the boundary of the set as crisp values. An FRB consists of a set of if-then rules defined over fuzzy sets (Masulli et al. 2007). The rules are usually created using "expert knowledge" (Castillo et al. 2008). The relationship between different fuzzy variables is represented by if-then rules of the form "If antecedent…… Then Consequent". In cases where the antecedent has more than one part, the fuzzy operator is applied to obtain one number representing the consequence for the antecedents of that rule. This is the number used afterwards to obtain the output function. The Mamdani fuzzy inference system (Mamdani and Assilian 1975) uses the min-max composition as defined in Equation (12)

$$\mu_{C_K}(Z) = \max\left[min\left[\mu_{A_K}\left(input\ (x)\right), \mu_{B_K}\left(input\ (y)\right)\right]\right] k \qquad \text{Equation (12)}$$

Where;

μ_{C_K} ,μ_{A_K} , μ_{B_K} are the membership functions for output "z" for rule "k",X and y are inputs.

The proposed model is performed using MATLAB® fuzzy logic toolbox, where, the antecedent and the consequent are fuzzy propositions. Mamdani algorithm based on experts' knowledge is used to construct the rule base. The model combines FI, CoF, and C_R expressed as triangular membership functions. The min-max composition is used and the defuzzification was done using the Centre of Area method. The fuzzy risk equation solves Equation (13) and is shown in Equation (14)

Risk Index = Failure Index* Consequence of Failure * Criticality Index Equation (13)

Ri: IF FI is Xi and CoF is Yi and C_R is Zi then Risk is Li Equation (14)

Where, i= 1, 2, 3 ….k , Xi. Yi, Zi, and Li are linguistic constants as defined in model, k = number of rules

The threshold for risk values are set based on the maximum allowable FI and CoF values. This eliminates the major drawback of a risk matrix in differentiating between the two extreme cases of high FI with low CoF and vice versa. It also ensures the highest priority is given to elements with most emerging rehabilitation need whether derived from high FI or high CoF. Based upon feedback from experts, CoF is categorized into three levels based upon the combined effect of failure on financial, social, and operational levels. Criticality serves to define stations into normal stations with moderate importance and critical stations with higher criticality. The entire data incorporated in the risk index calculations is reserved for a detailed analysis of each station. The membership functions were selected based on literature review and unstructured interview with subway experts. A set of 30 rules (5 rules for FI, 3 for CoF and 2 for C_R) was generated to develop the Risk Index.

Case Study and Model Implementation

An actual case study was conducted on a sub network in a metro system in Canada to validate the model and proof its robustness. The subway under study is one of the oldest networks in North America, with 68 stations spreading on four lines and covering the north, east, and centre of the city of Montreal. Six stations (SEG 1 to SEG 6) on three different lines are analysed in the model with one station being the interconnecting station. SEG 1 to SEG 3 fall on the same line given the name Line A, SEG 4 and SEG5 both fall on the second line B. SEG 6 falls on line C whereas, SEG 2 is the interconnecting station for the three lines. Stations were selected from literature (Semaan 2011) and based upon availability of inspection reports for different indices calculations.

Data Collection

The developed framework required data collection at different stages. The probability of failure sub-model is developed based on the analysis of a segment of a subway network in Canada. Data sources include inspection reports provided by Ministry of Transportation (MoT) operating the network and literature review. The consequence of failure and the criticality models required incorporating expert knowledge and engineering judgment along two stages; attributes selection and weights calculations. The variability of experts' feedback was enriching to this model; considering the novelty of the topic and scarcity of literature in this area. The fuzzy rules of the risk index model together with the membership functions are also developed by means of experts' input. Data collection therefore was gathered using inspection reports, structured and unstructured interviews, and a questionnaire survey.

Structured and unstructured interviews were held with experts from operations and structural department in (MoT) along the various stages of the model development. The main purpose was understanding the problem beforehand and ensuring the developed model represents the real-life problem and incorporates the various conflicting factors. The credibility of the designed survey was also confirmed during interviews after which some modifications were incorporated.

Inspection reports

MoT inspection reports contain a wealth of information pertaining to the different systems and elements operating within the network, their history, characteristics and location. It is noted that the inspection history is irregular and very detached. Discrete inspections were done on different station buildings between the years (1992-2005), which is the range of inspection reports provided. No specific inspection scheme can be identified; some stations have up to 3 inspection reports whereas others have none. A station renovation program was executed in 2005 and aimed at renovating all stations constructed in the year 1966. Consequently, maintenance and rehabilitation actions performed on elements in 2005 are assumed to improve the overall performance to 90% of total performance. In addition, the remaining service life after the maintenance and rehabilitation (M&R) action is assumed 90 years proportional to the revised performance. It was also noted that there was no complete inspection report on the network level for any given year. Nevertheless, the information required for the framework development was extracted from the report including; (1) Station building systems' year of construction, (2) Structural plans, (3) Elements configuration, (4) Station characteristics, (5) Number of floors and exits per station, (6) M&R action performed (if any) and year of action, (7) Range of M&R actions, repair cost, time to repair, and, cost breakdown.

Questionnaire survey

The consequences of failure and criticality models required conducting pairwise comparisons between goals, attributes, and, main criteria while considering the level of interdependency between them. A questionnaire was constructed for that purpose, a sample questionnaire is shown in Fig. 6.

The questionnaire contains the pairwise comparison matrices of the model. Seven pairwise comparison matrices conducted on three levels, a) Main criteria comparison with respect to goal, b) Main criteria comparison with respect to each other, and c) sub-criteria comparison with respect to main criteria. Three open ended questions were provided to ensure the flexibility of including respondents' comments. Any feedback relevant to the research was accounted for in the questionnaire through regular updating. Nevertheless, some of the answers, albeit important, were out of scope of the research and could not be accounted for. These answers, however, translate the importance of the topic and the wide gap existent needed to be covered.

Interviews

The third type of data collection is through interviews. Structured and unstructured interviews were undertaken throughout the research with civil and operations engineers and managers in MoT. The purpose was to ensure the practicality of the model for real life analysis and credibility of proposed attributes. Feedback from experts was also required to construct membership functions for the inputs and outputs from the fuzzy model and establish the relation between the model variables. Data collection and analysis is discussed in details in another paper.

Sub-Models output

Failure Index (FI) is calculated using year 2014 as the base for calculations. The subway system hierarchy together with the equations presented earlier were used to compute FI values for elements at the lowest level of the hierarchy then aggregated upwards to compute the integrated FI values for stations, tunnels and auxiliary structures, identified as a segment (SEG).

A questionnaire survey was launched to gather the required data for CoF and Criticality models' development. The questionnaire conducted pairwise comparisons between attributes, sub-attributes and goals for each of the two sub-models. It also contained open ended questions for experts to provide their knowledge on model development and suggest any required modifications. The output of the questionnaires are local and global weights for attributes in CoF and C_R models. Further details about the resultant weights can be found in (Abouhamad and Zayed 2014). FANP calculations are done using MATLAB® software and FPP as a prioritization tool.

Scores for CoF attributes were obtained from literature review (Farran, 2006) and current information of Montreal subway. Sample calculations for CoF index are seen in Fig. 7. As stated earlier, CoF are calculated for elements at the lower level of the hierarchy then aggregated upwards. It is evident that CoF are highly affected by FI value for each system since all the factors accounted for in the model are directly proportional with FI value. Calculations for C_R were done for the entire Montréal subway network (68 stations). Two stations with maximum and minimum criticality levels were set as thresholds for normalizing the index for the six stations under study. Criticality index is defined as the functional role a station plays and thus is calculated on stations level. A tunnel criticality index is taken as the higher value for the two connecting stations, while auxiliary structures acquire the criticality index of corresponding subway station. This explains the constant C_R value per segment as seen in Fig. 7. Unlike FI and Cof where values are upwards aggregated, for an element level analysis, C_R values for a given element are the same as the station where it operates.

Risk Index Model

The probability of failure values and consequence of failure scores aggregated to stations level is combined with the criticality scores in a fuzzy rule based risk index model. MATLAB® fuzzy tool box is used perform the operations using fuzzy membership functions and fuzzy rules extracted from expert feedback. The fuzzy rules presented in Table 3 are used to construct a fuzzy expert system capable of assessing the level of risk of any given station. The "Risk system" done by the Mamdani method has three inputs. Probability of failure having five membership functions, consequences of failure having three membership functions, and criticality index having two membership functions. The system operates by means of thirty rules as indicated in the figure and the output of the system is the risk index represented on a scale of five membership functions. Fig. 8 illustrates the membership functions for the three sub-models and the risk level as identified by experts.

The input variables have a total of ten categories; five for probability of failure, three for consequence of failure and two for criticality index. Therefore thirty rules were entered into the risk mode. Fig. 9 shows a sample of rule configuration for thr risk index model. The rules to be fired are highlighted in yellow and the resultant risk level is defined in blue. The fuzzy risk model is graphically represented by the fuzzy risk surface shown in Fig. 10. Table 4 presents the expected risk index for each system.

STA 4 had the highest risk index as expected; this is the combined effect of high probability of failure, consequence of failure, and criticality index as shown. It is noticed that the tunnel and auxiliary structure in the same segment share the same C_R level yet their risk index is very low (0.25 and 0.351) respectively. This is clearly due to the low probability of operational failure of the two systems derived from low PoF and CoF. This resultant risk value is only available through a fuzzy risk model where the criticality index is triggered to action and increases the risk index only in case of high probability of failure and/or consequence of failure. STA 6 comes next with an expected risk index of 0.5. This risk index is mainly affected by the moderately high PoF in spite of low CoF and C_R values. This also is attributed to the fuzzy risk model which triggers the expected risk index value based on an interrelated decision system just like a human expert. The risk index for the remainder elements is considered within acceptable range (0 – 0.35) since they all have low combinations of PoF, CoF and C_R values. The detailed risk report for the two stations is shown in Table 5.

STA 4 has a high risk index and thus higher degree of rehabilitation priority, however, actual data regarding STA 4 rehabilitation is not available. STA 6 is currently undergoing rehabilitation actions which conforms to its calculated risk index and PoF values. Rehabilitation actions are scheduled on weekends only to minimize service interruption which confirms the moderate risk index. All model data is used for a detailed report including expected system risk index, monetary consequence of failure defined by revenue loss ($CAD) and repair cost ($CAD). The report also specifies level of service continuation being total, partial or none, the expected time to repair based on the selected rehabilitation strategy, and the user traffic frequency existent per station in case of no interruption at all. In our case study, STA4 and STA6 were the only stations with a triggered rehabilitation action and considerable risk index.

Discussion:

Each time a budget decision is taken to renovate an element and spend a specific amount of budget, risk assessment is informally utilized. Unfortunately, this process is poorly documented in the subway asset management domain. In addition, the process is mostly subjective based on the decision maker and lacks the structure and consistency of a decision making tool. This is the main gap this research targeted addressing. However, it is important to realize what this model can and cannot do; therefore some important notes are highlighted in the following paragraphs.

1. The framework adopts an intelligent simplification approach. The subway framework was simplified enough to balance between a comprehensive model covering the most vital risk aspects while maintaining a simple and easy to implement model. As per experts' comments, the main cause of a lack of a decision making tool is the vast level of complexity, therefore this model is developed to be comprehensive yet easy to comprehend.

2. The probability of failure sub-model addresses the loss of integrity of an element indicating the element failed to successfully perform its intended function and no more meets its delivery requirements, hence, operational failure. This failure indicates loss of reliability of the targeted component.

3. The indexed versus the monetary consequences of failure have long been in comparison. This research conducted the consequences of failure model using the indexed approach. While monetary consequences of failure are easy to calculate for financial and operational impacts of failure, the case is different for social impacts of failure. Monetizing social impacts requires translating the different attributes to their dollar values. Due to lack of historical operational failure data, a valid data base was not available to adequately quantify

different consequences of failure attributes. The other route is using experts' knowledge; this can only be done with the complete cooperation and help of multi-discipline and multi-sector experts which was not possible in this research. However, an indexed model has its own advantages; it allows for incorporating incomplete knowledge and updating the model when new data emerges and this allows including a wider spectrum of information. According to (Muhlbauer, 2004), indexed models are especially useful when there is need to consider multiple factors simultaneously where complete knowledge is unavailable. In addition, even if quantification of risk factors is imperfect; results are usually able to portray a reliable picture of elements where risk is relatively lower or higher.

4. Factors contributing to station criticality were identified through historical data, experts' knowledge and by consulting current structure and map of several subway networks. In the authors opinion; all the considered factors are crucial to station criticality. None of the attributes considered can be identified as less important, hence, the authors believe none of the attributes can be eliminated and thus, the number of attributes cannot be decreased. Nonetheless, while the authors did their best to make the model inclusive, adding more relevant factors will make the model more comprehensive and thus more accurate.

The scalability of this model should be addressed as well. This framework is generic enough to serve as a starting point for best practices for subway networks. However, applying this model on a full scale requires working in conjunction with different departments in a subway network authority to ensure all the possible information is adequately captured and considered in the model. This model should continuously evolve as new data or attributes emerge.

The current research presents a novel framework for assessing risk index on asset and network levels in subway. However, some limitations to the model are noted, most of which are pertinent to the data scarcity problem;

- The weights of consequence of failure and criticality models attributes require more expert feedback to be verified. Moreover, the weights should be validated by a team of designated experts assigned to the project,
- The proposed framework should be validated using a larger data set with more precise information. A wider data set means more variability,
- The model addresses operational failure derived from failure in structural systems only. A more comprehensive approach is studying the other systems and integrating them into the framework.

The proposed model, however comprehensive, yet some recommendations and potential future work is presented to better enhance the model and increase its reliability.

- Failure of other systems like mechanical, electrical, and security and communication should be integrated into the probability of failure model for a more comprehensive failure analysis,
- Develop a web-based software tool to make the model available for public authorities use and collect data for better model enhancement accordingly.
- Addressing different categories of risk of failure including events external and internal to the organization. Events external to the organization include naturally occurring events, external impacts and, external aggression.
- Using the developed risk index to conduct a benefit cost analysis for short and long term asset management. A formal benefit cost analysis can be used as a base for prioritization.

- The probability of failure sub-model is mainly based on visual inspection reports. Further research in this area is required to compute probability of failure based on other methods such as non-destructive techniques.

CONCLUSION

The research beforehand presents a compiled effort to develop a network level risk assessment scheme for subway networks. A wide gap exists between models developed in academia so far and those implemented by subway authorities. First, none of the models studied networks from a functional point of view nor there is any documented effort to analyze risk level on an element or station level. Second, only two of the available models studied the subway from a network perspective rather than an asset perspective. This triggered the current research to develop a chain of sub-models and models aiming at clarifying the risk assessment procedure for subway networks on asset and network levels. The current practices adopted for selecting stations for rehabilitation is considered a black box where no specific algorithm can be identified. This disadvantage is the main advantage of the current model.

A generic subway hierarchy is proposed and risk is assessed through measuring probability of failure, consequence of failure and functional importance of subway stations integrated to the network level. Probability of failure is predicted using reliability-based Weibull function and inspection report for different structural elements. Aggregation to network level is done using parallel-series network technique. Seven criteria are used to assess consequence of failure along financial, social, and, operational perspectives. A criticality index is introduced to the classical risk equation to assess the functional importance a station plays in its location. Where; criticality is assessed using seven attributes along three main criteria. Integration of risk equation components is done using the fuzzy inference engine to ensure incorporating the experts knowledge into the decision making process. Relative weights of consequence of failure and criticality models attributes are calculated using experts feedback provided through a survey and the fuzzy analytical network process.

Experts were asked to provide the relations by which probability of failure, consequence of failure, and criticality indices can be integrated to construct a risk index model that can be used to prioritize stations based on their operational risk level. This resulted in a total of 30 rules that were entered into the fuzzy model and used to develop relations and finally construct a risk surface. The developed model was used on an actual case study in Montreal for a sub network composed of six stations along three interconnected lines. The model ranked two stations as having the highest risk index and accordingly the highest rehabilitation priority. The results are validated through the current rehabilitation actions undergoing the station ranked with a high operational risk index. The fuzzy risk index model used provides a numerical representation for the risk level which better represents the case and facilitates the analysis.

The proposed model is comprehensive since it assesses risk with its components on asset and network levels yet, it is easy to implement and understandable. The model was constructed using feedback from multiple subway experts in different countries to be applied to a generic subway network, which makes the initial model generic enough to be applied to different case studies. The model can be easily adopted by different transportation authorities through updating the number of lines/stations per lines, stations and line composition, and the most relevant consequence of failure and criticality attributes as seen appropriate for any designated case study. The model interface is made user-friendly and data requested is easily understood and retrieved by authority personnel which makes model practical and functional. The model is believed to help public authorities assess different elements in a network and take an educated decision of their rehabilitation priority.

DATA AVAILABILITY STATEMENT

Data generated or analyzed during the study are available from the corresponding author by request. Information about the *Journal*'s data-sharing policy can be found here: http://ascelibrary.org/doi/10.1061/(ASCE)CO.1943-7862.0001263.

REFERENCES

Abouhamad, M. and Zayed, T. (2014). *A Functionality-Based Methodology for Ranking Subway Systems for Rehabilitation*, In B.H.V. Topping, P. Iványi, Proceedings of the Twelfth International Conference on Computational Structures Technology, Civil-Comp Press, Stirlingshire, UK, Paper 110, doi:10.4203/ccp.106.110.

Abouhamad, M., and Zayed, T. (2013a). *Multiple perspective consequence of failure estimation of subway stations*, Proceedings of the 4th Construction Specialty Conference, Canadian Society of Civil Engineers (CSCE). Montreal, Canada.

Abouhamad, M. and Zayed, T. (2013b), *Criticality-based model for rehabilitationg subway stations*. Proccedings of the 30th International Symposium of Automation and Robotics in Construction and Mining (ISARC 2013). Montreal, Canada.

Abu-Mallouh, M., (1999). *Model for station rehabilitation and planning (MSRP) (Doctoral dissertation)*, Polytechnic University, Civil Engineering, USA.

ASCE. (2017). *Report Card for America's Infrastructure*. American Society of Civil Engineering, http://www.infrastructurereportcard.org/transit/. Accessed December 26, 2017.

Baris, S. (2010). *Infrastructure Management and Deterioration Risk Assessment of Wastewater Collection Systems, (Doctoral dissertation)*, University of Cincinnati, Ohio.

The Canadian infrastructure report Card: Informing the future (2016). http://www.canadainfrastructure.ca/downloads/Canadian_Infrastructure_Report_Card_EN.pdf Accessed December 26, 2017.

Canadian Urban Transit Association, CUTA. (2012). *Transit Infrastructure Needs for the Period* 2012-2016, < http://www.cutaactu.ca/en/index.asp> (March 27, 2012).

Castillo, O. and Melin, P. (2008), Type-2 Fuzzy Logic: Theory and Applications. Springer Publishing Company, Incorporated.

City of Edmonton Office of Infrastructure. (2003). *Edmonton's Infrastructure Strategy Overview*. Edmonton: Office of Infrastructure.

Fares, H., (2008). *Evaluating the Risk of Water Main Failure Using a Hierarchical Fuzzy Expert System*, *Master Dissertation*, Concordia University, Montreal , Canada.

Farran, Mazen. 2006. *Life cycle cost for rehabilitation of public infrastructures:application to Montreal metro system*. *Master Dissertation*. Concordia University, Montreal, Canada.

Garuti, C. & Sandoval, M. (2005). *Comparing AHP and ANP Shiftwork Models: Hierarchy Simplicity v/s Network Connectivity*. Proccedings of the 8th International Symposium of the AHP. Hawaii, USA.

Gkountis, I. and Zayed, T. (2015). Subway Infrastructure Condition Assessment. *Journal of Construction Engineering and Management*, 141(12), 04015042.

Gonzalez, J., Romera, R., Perez, J. C. & Perez, J. (2006). *Optimal railway infrastructure maintenance and repair policies to manage risk under uncertainty with adaptive control*. Madrid, E-Archivo, el Repositorio Institucional de la Universidad Carlos III. <http://www.temoa.info/node/200579>. (May, 8 2012).

Hahn, M. A., Palmer, R. N., Merrill, M. S. & Lukas, A. B. (2002). Expert System for Prioritizing the Inspection of Sewers: Knowledge Base Formulation and Evaluation. *Journal of Water Resources Planning and Management*, 128(2), 121-129.

Hastak, M. and Baim, E. 2001. Risk Factors Affecting Management and Maintenance Cost of Urban Infrastructure. *Journal of Infrastructure Systems*, 7(2), 67–76.

Hillier, F.S. and Lieberman, G.J. (1972). *Introduction to Operation Research*. Holden-Day.

Kahraman, C., Ertay, T. & Buyukozkan, G.(2006). A fuzzy optimization model for QFD planning process using analytic network approach. *European Journal of Operational Research*, 171(2), 390-411.

Kleiner, Y., Sadiq, R., & Rajani, B. (2004). Modeling failure risk in buried pipes using fuzzy Markov deterioration process. *In Pipeline Engineering and Construction: What's on the Horizon?* (pp. 1-12).

Lowrance, W. 1967. Of acceptable risk: Science and the determination of safety. Los Altos: William Kaufman Inc.

Mamdani, E. H., & Assilian, S. (1975). An experiment in linguistic synthesis with a fuzzy logic controller. *International journal of man-machine studies*, 7(1), 1-13.

Martin, T., Johnson, D., & Anschell, S. (2007). Using historical repair data to create customized predictive failure curves for sewer pipe risk modeling. *In Proc., Leading Edge Conference on Strategic Asset Management.*

Marzouk, M., & Abdel Aty, A. (2012). Maintaining subway infrastructure using BIM. *In Proc., Construction Research Congress 2012: Construction Challenges in a Flat World* (pp. 2320-2328). Reston, VA: ASCE

Masulli, F., Mitra, S., & Pasi, G. (Eds.). (2007). *Applications of Fuzzy Sets Theory: 7th International Workshop on Fuzzy Logic and Applications, WILF 2007, Camogli, Italy, July 7-10, 2007, Proceedings (Vol. 4578).* Springer Science & Business Media.

Mikhailov, L., & Singh, M. G. (2003). Fuzzy analytic network process and its application to the development of decision support systems. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews),* 33(1), 33-41.

Mikhailov, L. (2003). Deriving priorities from fuzzy pairwise comparison judgements. *Journal of Fuzzy Sets and Systems*, 134(3), 365-385.

Mikhailov, L. Singh, M.G. (1999). Comparison analysis of methods for deriving priorities in the analytic hierarchy process, *1999 IEEE International Conference on Systems, Man, and Cybernetics, 1999. IEEE SMC '99 Conference Proceedings.*vol.1, 1037-1042.

Muhlbauer, W Kent. (2004). *Pipeline risk management manual: ideas, techniques, and resources*. Gulf Professional Publishing.

Opila, M. C. & Attoh-Okine, N. (2011). Novel Approach in Pipe Condition Scoring. *Journal of pipeline systems engineering and practice*, 2(3), 82–90.

Russel, H., Gilmore, J., and TCRP. (1997). *Inspection policy and procedures for rail transit tunnels and underground structures—Synthesis of transit practice 23,* National Research Council, Washington, D.C.

Saaty, T. (2005). The Analytic Hierarchy and Analytic Network Processes for the Measurement of Intangible Criteria and for Decision-Making. *In: J. Figueira, S. Greco & M. Ehrogott, eds. Multiple Criteria Decision Analysis: State of the Art Surveys*. Springer New York, 345-405.

Saaty, T. (2008). The Analytic Hierarchy and Analytic Network Measurement Processes: Applications to decisions under Risk. *European Journal of Pure and Applied Mathematics*, 1(1), 122-196.

Saaty, T. L. (2001). *Decision Making with Dependence and Feedback; The Analytic Network Process*. 2nd ed. Pittsburgh(PA): RWS Publications.

Saaty, T. L. (2012). *Super Decisions Software Guide*, 4922 Ellsworth Avenue: Creative Decisions Foundation.

Sarkis, J. & Sundarraj, R. (2006). Evaluation of enterprise information technologies: a decision model for high-level consideration of strategic and operational issues. *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews*, ,36(2), 260-273.

Semaan, N. (2006). *Subway station diagnosis index (SSDI) : A condition assessment model. (Master Dissertation).* Concordia University, Montreal, Canada.

Semaan, N. (2011). *Structural Performance Model for Subway Network. (Doctoral Dissertation)*, Concordia University, Montreal, Canada.

Table 1 Summary of Practices Applied by Subway Authorities

Subway Authority	Program implemented	Limitations
Société de Transport de Montréal	Applied two consecutive programs: "Réno-Stations I" and "Réno-Station II" to prioritize stations' rehabilitation.	Considered stations separately without considering the whole network,
	The Structural deterioration identification was based upon expert visual inspection.	Ranked stations without actual evaluation of the condition or deterioration of the stations,
	The inspector assigned each condition a score based on a predefined scale and measured the physical condition (CEM) and the performance condition (CEP).	Rehabilitation based on a simple selection procedure of the station age and expert knowledge only.
California Train Transit System	Developed a five-level evaluation system of stations and ranked them from excellent to poor.	Did not consider the subway as a network,
	The rank was done based on 10 criteria and the scores were combined using the weighted average approach.	It ranked stations without actual evaluation of the physical and structural condition of the station.
Metropolitan Transit Authority of New York Transit	Developed a ranking system for condition assessment.	Ranked stations without actual evaluation of the station deterioration level,
	Different factors were considered, and each station was ranked according to its priority, by allocating points to the different factors	Did not predict the future rating,
		A station level and not a network level model.
London Transport	Developed the Key Performance Indicator (KPI)	Did not measure the subway elements failure over time,
	The KPI evaluated the performance of the station from its customers' point of view through direct surveys and interviews.	Considered stations separately without considering the whole network,
	A (0-10) evaluation scale based upon 23 items	Ranked stations without actual evaluation of the condition or deterioration of the station.
Paris Rapid Transit Authority	Developed a selection procedure for stations in need of rehabilitation. The study assigned used a seven-criteria selection procedure.	Stations ranked using seven nonfunctional criteria without actual evaluation of the condition or deterioration of the station.

Table 2 Linguistic Scale of Relative Importance

Linguistic Scale used	Triangular fuzzy scale	Triangular fuzzy reciprocal scale
Equal Importance	(1,1,1)	(1,1,1)
Moderate	(2,3,4)	$(\frac{1}{4},\frac{1}{3},\frac{1}{2})$
Strong	(4,5,6)	$(\frac{1}{6},\frac{1}{5},\frac{1}{4})$
Very strong	(6,7,8)	$(\frac{1}{8},\frac{1}{7},\frac{1}{6})$
Absolute	(9,9,9)	$(\frac{1}{9},\frac{1}{9},\frac{1}{9})$

Table 3 Probability of Failure and Associated Risk Level

Probability of failure	Associated risk
-0.3,0,0.3	Negligible
0.2,0.35,0.5	Minor
0.4, 0.55, 0.7	Significant
0.6, 0.75, 0.9	Critical
0.8, 1, 1.2	Serious

Table 4 Risk Index Calculated Using FRB

Station	Element	PoF	CoF	Criticality Index	Risk Index
STB 1	Station	0.250	0.133	0.368	0.243
	Tunnel	0.117	0.133	0.368	0.0898
	Aux Structure	0.086	0.133	0.368	0.0875
STB2	Station	0.000	0.307	0.883	0.25
	Tunnel	0.180	0.307	0.883	0.25
	Aux Structure	0.000	0.307	0.883	0.25
STB3	Station	0.268	0.093	0.487	0.356
	Tunnel	0.180	0.093	0.487	0.215
	Aux Structure	0.000	0.093	0.487	0.215
STB4	Station	0.673	0.343	0.743	0.821
	Tunnel	0.164	0.083	0.743	0.25
	Aux Structure	0.226	0.083	0.743	0.351
STB5	Station	0.224	0.106	0.493	0.325
	Tunnel	0.149	0.106	0.493	0.221
	Aux Structure	0.000	0.106	0.493	0.221
STB6	Station	0.513	0.279	0.252	0.5
	Tunnel	0.000	0.033	0.252	0.0822
	Aux Structure	0.000	0.033	0.252	0.0822

Table 5 Detailed Risk Report for STA 4 and STA 6

Station Name	STA 4	STA 6
Probability of Operational Failure	0.673	0.513
Consequences of Failure	0.343	0.279
Criticality Index	0.743	0.252
Risk Index	0.821	0.5
Revenue Loss ($CAD)	$583,779	$526,706
Repair Cost ($CAD)	$225,000	$225,000
Service continuation	Weekend interruption	Weekend interruption
Interruption Rate	Total (1)	Total (1)
Time to repair (days)	65	50
User Traffic (annual)	1092714	1281651