Multi-Criteria Risk-Informed Capital Renewal Planning: A Pavement Management Application

Roozbeh Rashedi*, Ph.D., P.Eng.
VP-Technology, Infrastructure Solutions Inc.

Michael Maher, Ph.D., P.Eng.
Senior Geotechnical & Materials Engineer, Golder Associates Ltd.

Xian-Xun Yuan, Ph.D., P.Eng.
Associate Professor, Department of Civil Engineering, Ryerson University

Paper prepared for presentation at the
INNOVATIONS IN ASSET MANAGEMENT
Session
of the 2020 TAC Conference

Abstract

Developing a risk-informed decision-making framework is crucial to address two major aspects of managing road networks. The first is the development of deterioration models to capture physical deterioration trends based on various road attribute combinations. The second is the development of an optimization process for capital planning that integrates risk analysis with lifecycle cost analysis, effectiveness of maintenance and rehabilitation technologies, and their network effects. This paper discusses techniques for performance modeling based on risk-informed decision-making methods with a focus on municipal pavement assets. A case study is presented to show the effectiveness of the methods presented and to discuss real-life implications.

***** Corresponding author contact: roozbeh@infrasol.ca

INTRODUCTION

Municipal roads and highway systems are among the fundamental infrastructure assets that provide a foundation to the performance of all national economies by sustaining economic development and facilitating social interaction. Preserving and maintaining pavement assets has therefore been an important yet challenging task for governments under restricted funding programs. State and local governments in the United States spent $70 billion in 2014 alone on operation and maintenance activities (ASCE 2017). The 2016 Canadian Infrastructure Report Card reports a $48 billion replacement cost for pavements currently in poor condition, and a further $75 billion replacement cost for those in fair condition (CIRC 2016). The report card states that roads present one of the largest gaps between current and target rates of reinvestment, with a current reinvestment rate of only 1.1% and a target recommended rate of investment at 2% to 3% as a percentage of asset replacement value. The 2019 CIRC (CIRC 2019) reports that since 2016 the situation has deteriorated with 39% of road assets currently in the Very Poor/Poor/Fair categories compared to 37% in 2016. With the continued downloading of road assets to lower-tier municipalities the increasing burden of operation and maintenance programs falls to city and county tax payers. Data from the Association of Municipalities of Ontario indicates that 67% of the roads in Ontario are under municipal jurisdiction, amounting to 140,000 km of pavement with a combined operating and maintenance budget in the range of $40 billion per year (AMO 2016).

When determining the cleverest way to spend an annual road budget, consideration must be given to the full toolbox of pavement preservation and rehabilitation treatments. Among various strategic approaches, preventive maintenance has received the most attention by highway agencies as a cost-effective method of extending the service life of a pavement network. Synthesis 153 on the Evaluation and Benefits of Preventive Maintenance Strategies (TRB 1989), defined preventive maintenance as “a program strategy intended to arrest light deterioration, retard progressive failures, and reduce the need for routine maintenance and service activities.” More recently, the FHWA Pavement Preservation Expert Task Group and the National Center for Pavement Preservation emphasize more the benefits of long-term strategic preservation programs. FHWA defines pavement management as "a program employing a network level, long-term strategy that enhances pavement performance by using an integrated, cost-effective set of practices that extend pavement life, improve safety and meet motorist expectations” (FHWA 2017) while NCPP defines it as “the application of engineering and fiscal management using cost-effective treatments and existing funds to control the future condition of pavement networks” (NCPP 2019).

A complete asset management plan and a good pavement preservation strategy should also incorporate the risk aspects of the network. Risk can be integrated into a comprehensive pavement management solution for many reasons, which range from uncertainties associated with cost or performance models to failure to achieve defined serviceability targets (Saha & Ksaibati 2016; Alberti & Federico 2019). Due to practical reasons and implementation difficulties, risk assessment is generally performed as a qualitative method (Wang et al. 2011). A multi-criteria analysis (MCA) is proposed to be used to improve the subjective nature of the qualitative risk assessment process. MCA is useful particularly when dealing with decision-making problems that involve multiple objectives and constraints (criteria). A wide range of MCA methods were developed in 80s and 90s and since 2000 have become more widely considered in various domains. MCA techniques are diverse in both the kinds of problem they address and in the techniques they employ. Examples of some of the more widely used MCA methods include: Analytical Hierarchy Process (AHP) (Saaty 1990; Saaty 2008), fuzzy AHP (van Laarhoven and Pedrycz 1983), multi-attribute utility theory (Keeney and Raiffa 1993), and

Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) (Lai et al. 1994). MCA techniques can be employed to help overcome the limitations of human judgment by imposing a systematic and structured approach to evaluate criteria and their relative importance. To provide the ability to incorporate multiple factors or conflicting objectives MCA can consider compensatory or dominance relationships among multiple attributes (Lai et al. 1994). This paper presents the application of the Delphi and Analytical Hierarchy Process (AHP) for risk assessment and discusses an optimized capital planning approach to devise effective capital renewal plans. Scenarios from a real-life case study compare the results of using risk tolerance constraints as part of the optimized capital planning.

RISK INDEX FORMULATION

The concept of risk and risk-based asset management has become more prominent in recent years. The concept of risk, however, can vary depending on the domain of application and the methodologies used for risk assessment. In an ideal world, risk is typically defined by Eq. 1 as the combination of Probability of Failure (PoF) and Consequence of Failure (CoF) in monetary terms. The formula can be further extended by incorporating concepts such as Risk Mitigation or Vulnerability.

$$Risk(\$) = PoF \times CoF(\$) \qquad \text{ideal risk fomula} \qquad (1)$$

The ideal risk formulation is typically aligned with quantitative risk assessment methods that are based on detailed numerical calculations on probability distributions associated with various risk events and monetary implications on the consequences of failure (Shahtaheri et al. 2017). Pure quantitative risk analysis is, however, a challenging task for many organizations. It requires massive amounts of high quality data to assign reliable probability estimates. There are often complex modeling processes involved, such as traffic demand modeling, network hydraulic capacity analysis, climate impact, etc., to assess the probability and impact of various failures on network performance. In addition, objective monetization of failure and performance is not easy due to the subjective and often controversial assignment of cost on soft factors such as social cost, traffic delays, community impact, loss of life, etc. Due to these difficulties, in practice, organizations often use a variation of the ideal risk formula that represents risk in terms of the Criticality Index (CrI) and the Likelihood of Failure (LoF) associated with different assets (Eq. 2). The practical approach transfers the ideal formula from a cardinal to an ordinal system. Rather than assigning exact numeric values to probability and consequence, the practical formulation uses various assignments for the level of Criticality and Likelihood of Failure. For example, four levels of criticality and likelihood can be specified based on the descriptions in Tables 1 and 2. These definitions and the number of levels can be adjusted and refined depending on the application and requirements for the analysis.

$$Risk\ Index = f(CrI, LoF) \qquad \text{practical risk fomula} \qquad (2)$$

Table 1: Sample Asset Criticality Levels

Criticality Level	Criticality Index	Description
Not Critical	1	Asset failure cost would be moderate and the loss of asset would have minor impact to the community.
Slightly Critical	2	Asset failure cost would be moderate and the loss of asset would have moderate negative impact to the community.
Critical	3	Asset failure cost would be moderate and the loss of asset would have substantial negative impact to the community.
Extremely Critical	4	Asset failure cost would be extremely expensive and the loss of asset would be critical to the community.

Table 2: Sample Likelihood of Failure Levels

Likelihood Level	LoF Index	Description
Very Low	1	Asset failure is not likely. Asset is in the beginning of its service life and in excellent/good condition.
Low	2	Asset failure is not likely. Asset is in its early service life and in good condition.
Moderate	3	Asset failure probability is moderate. Asset is in mid service life and in fair condition.
High	4	Asset failure is probable or imminent. Asset is at the end of service life and in poor or very poor condition.

To explain the two concepts, we use a simple car accident example. To determine the risk associated with driving a transport truck well over the speed limit on a highway as compared to diving an economy car slightly over the speed limit using the ideal quantitative assessment method, we first need to collect considerable amount of historical data on accidents on the highway under investigation. Using the accident data, a probability distribution can be developed based on driving speed. This distribution, however, might need to be further extended to consider the type and condition of the vehicle, time of day, level of traffic, weather conditions, or even the drivers' age and experience. As seen in this example, quantifying PoF can be quite complicated and requires a multitude of variables to determine reliable probability functions, even for a small problem. The next step using the ideal case is to determine the consequence of failure in monetary terms. This can be easily achieved by determining the value of the vehicles. However, when assigning other social costs, such as personal injuries or emotional distress, the monetization process becomes more complex. Using the practical risk index calculation approach, we can assign a higher criticality to the transport truck as compared to the economy car, since its failure (or accident) is expected to be more costly. Also, the likelihood of failure (or accident) is higher in the first case since the driver is speeding significantly above the speed limit. This simple logic can replace the complex calculations needed to assign a monetary value or a probability distribution. This simplification, however, has its own limitations and care must be taken not to oversimplify a problem.

In general, the CrI-LoF approach results in a qualitative risk assessment process that is highly dependent on expert opinion and past experience to replace the requirement to collect detailed high quality data and perform complex analysis of network performance under risk events. A purely qualitative risk analysis can also be problematic due to lack of consistency and the high level of subjectivity in the assessment. This can lead to unreliable results by ignoring key inputs or inconstant subjective assignment of weightings. To avoid the pure subjectivities involved in the CrI-LoF approach, a semi-quantitative process is proposed by using multi-criteria analysis methods. To ensure that expert opinion and all key contributing factors in the analysis are captured, a Delphi surveying method is recommended. Also, to arrive at proper weighting and consistency in the analysis, a Fuzzy Analytical Hierarchy Process (FAHP) is proposed to be used as part of the risk assessment process.

RISK ASSESSMENT USING MULTI-CRITERIA ANALYSIS (MCA)

One of the important parts of performing the risk assessment process is to select influential factors for criticality calculations. As discussed in the previous section, one of the main advantages of using a semi-quantitative analysis based on MCA methods is the ability to substitute complex network modeling and lack of high-quality data with expert opinion. In this process, however, a strong consensus among experts' opinions is required to ensure all significant influential factors are incorporated. To capture expert opinion properly, a Delphi method is proposed to be used to identify the key influential factors and their relative importance. The Delphi technique was developed in the 1950s by the Rand Corporation for the US Air Force to obtain the most reliable and statistically significant consensus among experts using a series of questionnaires with controlled opinion feedback (Linstone and Turoff 1975; Chan et al. 2001). The Delphi is used for a systematic communication and feedback process to arrive at a consensus among experts on an uncertain and often intangible issue in the form of relevant statistical data. Delphi is an iterative forecasting procedure characterized by anonymity, iteration with controlled feedback, and statistical response (Dickey and Watts 1978). The following Delphi process is proposed to be used to determine critically influential factors:

1. **Selection of an eligible expert panel:** The success and reliability of the Delphi method and its results depend on the expert panel involved. To identify an eligible panel of experts a set of selection criteria is used. Only experts who have extensive experience in three out of four areas described below are selected to participate in the survey process.
    a. Experts who have extensive experience in public works departments and road construction or operation activities.
    b. Experts currently or previously involved in the asset management or pavement management process.
    c. Experts with extensive knowledge of risk assessment and network performance measures.
    d. Experts with knowledge of municipal council priorities and community concerns and inputs related to asset performance and management issues.

2. **Designing the survey and sending the first-round questionnaire:** In the first round, the purpose of the survey is clearly explained, and the experts are informed that there would be two more rounds of questionnaires. Experts are asked to provide 5 to 10 influential factors that have to be included as part of criticality assessment for road networks (or any other asset type). Factors are divided into two categories: physical attributes and socio-economic factors. A list of potential factors based on previous research is also provided to the experts as background.

3. **Analyzing first round results**: Survey results are carefully studied and influential factors are ranked based on the frequency of suggestion by the expert panel. The top 10 factors under each category are selected and used for the next Delphi round.

4. **Delphi round two:** In the second round, the selected influential factors are presented and experts are asked to assign a relative importance value to each factor on a 4-level scale:1) not important; 2) slightly important; 3) important; 4) extremely Important.

5. **Analyzing second round results**: Based on the second-round results, influential factors were eliminated if over 60% of the experts agreed that they are 'not important'.

6. **Delphi round three:** The result of the second round in terms of percentage values of anonymous votes for the relative importance levels for each influential factor are presented and the experts are asked to reconsider the previously assigned relative importance based on the overall results and the other anonymous expert opinions.

7. **Analyzing the final results:** Based on the final round results, those factors that have over 60% votes on being 'important' or 'extremely important' are selected to be used as part of the criticality assessment process and are shown in Table 3. It is noted that the cutoff point percentage and the importance level can be adjusted depending on the availability of data and the comprehensiveness required for risk assessment. In general, a lower cutoff percentage and relative importance level will result in more factors being involved in the risk assessment process and consequently requiring more data and time.

Table 3: Influential factor results based on Delphi analysis

Influential Factor	Category	Extremely Important (% of experts)	Important (% of experts)	Slightly Important (% of experts)	Not Important (% of experts)	Selected Factor
Functional Class	Physical	80%	20%	0%	0%	Yes
Roadside Environment	Physical	0%	20%	40%	40%	No
Service Type	Physical	0%	10%	50%	40%	No
AADT	Physical	90%	10%	0%	0%	Yes
Surface Type	Physical	0%	10%	40%	50%	No
Bus Route	Physical	10%	60%	30%	0%	Yes
Maintenance Standard	Physical	70%	10%	20%	0%	Yes
Access to School	Socio-economic	10%	80%	10%	0%	Yes
Access to Health Services	Socio-economic	30%	50%	20%	0%	Yes
Urban Development	Socio-economic	0%	10%	40%	50%	No
Tourism	Socio-economic	0%	10%	30%	60%	No
Council Priority	Socio-economic	10%	50%	30%	10%	Yes
Cycling Route	Socio-economic	0%	20%	70%	10%	No

To determine the criticality influential factor weights for risk index calculations, the result of the Delphi analysis is fed into an Analytical Hierarchy Process (AHP). AHP is used to convert subjective assessments of the relative importance values by the expert panel into a set of consistent numeric weights. A pair-wise comparison matrix is developed on the basis of a ratio scale to arrive at weights for the competing factors. Table 4 shows the numeric preference scales used to develop a pair-wise comparison matrix. For example, if a judgment is made that factor A is moderately more important than factor B, then a preference index of 3 is assigned to factor A and the reciprocal of the index (i.e., 1/3) is assigned to B.

Table 4: Pair-wise comparison preference weighting

How important is criterion A compared to B?	Preference Index
Equally important	1
Moderately more important	3
Strongly more important	5
Very strongly more important	7
Extremely more important	9
Intermediate values	2, 4, 6, and 8

Using the AHP method, a hierarchical structure is developed to capture key criteria and their relationships to arrive at the desired outcome as shown in Figure 1. The main goal at the top of the hierarchy is to determine the risk index. As discussed, risk index is determined based on two criteria: criticality index and likelihood of failure. Criticality is linked to two levels of subset criteria comprising physical attributes and socio-economic factors. At the fourth level, all identified influential factors based on the Delphi analysis are used. Likelihood of failure is linked to current and historical condition data and the condition assessment methodologies. The last level shows all the road segments in the network that are being evaluated.

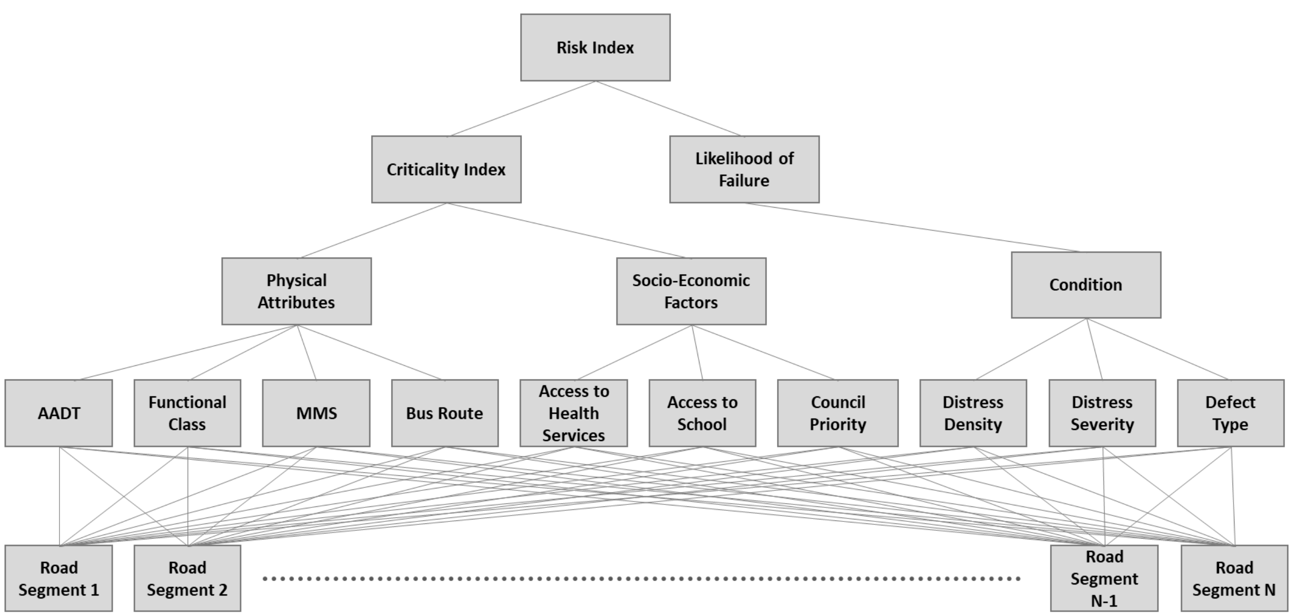


Figure 1: AHP structure for risk index calculation

After the AHP structure is developed, the next step is to create the pair-wise comparison matrix (PCM) at each level for different subset criteria under consideration to determine appropriate weighting. The weighting is determined by solving the eigenvalue problem in Eq. 3, where A is the pair-wise comparison matrix of n different criteria (Eg. 4), λ_{max} is the maximum eigenvalue, and w is the weight vector (w1, w2,…,wn).

$$Aw = \lambda_{max} w \qquad (3)$$

$$A = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ 1/a_{12} & 1 & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/a_{1n} & 1/a_{2n} & \cdots & 1 \end{bmatrix} \qquad (4)$$

Rigorous mathematical calculations and matrix algebra can be employed to calculate the weights as the elements in the eigenvector associated with the maximum eigenvalue of the matrix. A simpler alternative approximation can be used by first calculating the geometric mean (GM) of A and then estimating relative weights by normalizing the values. λ_{max} can then be calculated using Eq. 5, where *n* is the total number of criteria. A consistency ratio (CR) value is then calculated to identify if there are any inconsistencies in the pair-wise comparisons. A 10% tolerance is used for human judgment errors, therefore, if CR is greater than 0.1, matrix *A* needs to be revisited. CR is calculated using Eq. 7, where RI is the Random Index determined based on the number of criteria being compared (Saaty 2008) and CI is the consistency index (Eq. 6).

$$\lambda_{max} = \sum (Aw/w)/\, n \qquad (5)$$

$$CI = \frac{\lambda_{max} - n}{n - 1} \qquad (6)$$

$$CR = \frac{CI}{RI} \qquad (7)$$

Although AHP is designed to capture decision-maker knowledge, the conventional AHP has been criticized for its inability to adequately capture human uncertainty associated with judgment when performing the pair-wise comparison and expressing opinion in imprecise linguistic patterns (Buyukozkan, 2004). Fuzzy set theory was introduced in 1965 by Zadeh to deal with the vagueness associated with human perceptions (Zadeh 1965). Incorporating fuzzy set theory with AHP enables a more accurate description of the multi-criteria analysis process (Buckley, 1985; Cheng, 1999; Buckley et al. 2001; Bozbura, Beskese, & Kahraman, 2007). A triangular membership function using Eq. 8 is used for fuzzification of pair-wise comparison preference weightings as shown in Figure 2.

$$\mu_{\tilde{T}}(x) = \begin{cases} \frac{x-1}{m-1}, & l \le x \le m \\ \frac{u-x}{u-m}, & l \le x \le u \\ 0, & otherwise \end{cases} \quad (8)$$

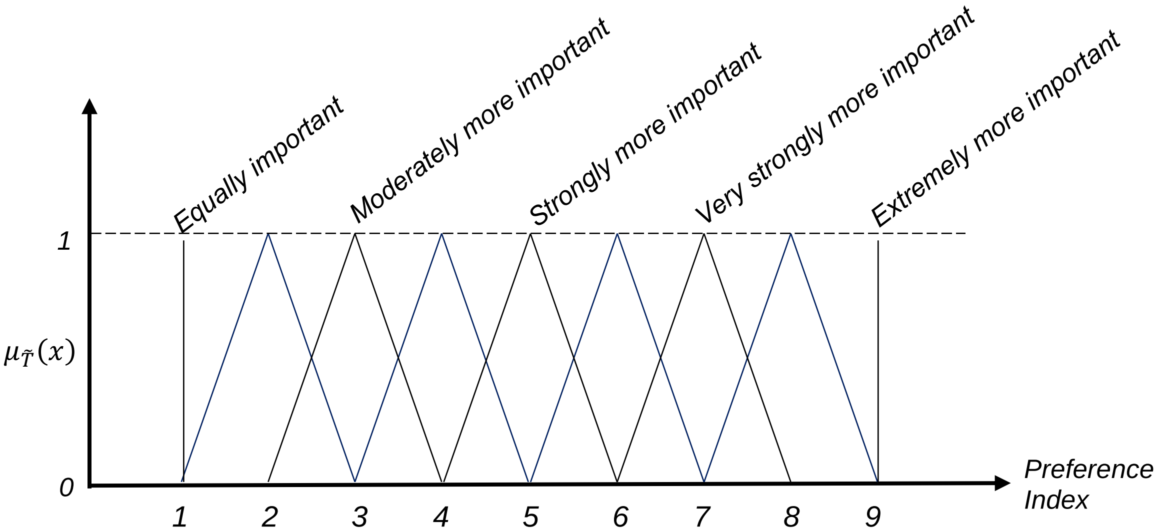


Figure 2: Fuzzy set membership function for AHP preference indices

As an example, a fuzzy pair-wise comparison matrix is developed for the physical influential factors including: AADT, Functional Class, Minimum Maintenance Standard (MMS), and Bus Route. Table 5 shows the fuzzy PCM using a triangular membership function.

Table 5: Fuzzy PCM matrix for physical attributes influential factors

	AADT	Functional Class	MMA	Bus Route
AADT	(1.00, 1.00, 1.00)	(2.00, 3.00, 4.00)	(2.00, 3.00, 4.00)	(6.00, 7.00, 8.00)
Functional Class	(0.25, 0.33, 0.50)	(1.00, 1.00, 1.00)	(1.00, 2.00, 3.00)	(2.00, 3.00, 4.00)
MMS	(0.25, 0.33, 0.50)	(0.33, 0.50, 1.00)	(1.00, 1.00, 1.00)	(2.00, 3.00, 4.00)
Bus Route	(0.13, 0.14, 0.17)	(0.25, 0.33, 0.50)	(0.25, 0.33, 0.50)	(1.00, 1.00, 1.00)

The fuzzy weight for each influential factor is determined using Eq. 9 based on the geometric mean $\tilde{r}_j$ of influential factor j. The fuzzy weights can be used to further continue the AHP process or use a defuzzification method to arrive at crisp numeric values. A Centre of Area (COA) approach with normalization is used for defuzzification using Eq. 10. Table 6 shows the fuzzy weight calculations for the four physical attribute influential factors. The suggested PCM results in a CR value of 0.027 which is less than 0.1 and is acceptable. Based on fuzzy AHP analysis, AADT has the highest relative importance with a value of 52.9% followed by Functional Class at 23.0%, MMS at 17.1%, and Bus Route at 7%. As discussed, the sum of all weights should always add up to 100%.

$$\widetilde{w_J} = \widetilde{r_j} \otimes \left(\sum_{j=1}^{n} \widetilde{r_j} \right)^{-1} \qquad (9)$$

$$w_j = \frac{\left(\frac{l+m+u}{3} \right)}{\sum w_j} \qquad (10)$$

Table 6: Fuzzy weight calculations for physical attributes influential factors

	Fuzzy Geometric Mean $\widetilde{r_J}$	Fuzzy Weight $\widetilde{w_J}$	Norm. Weights w_j
AADT	(2.21, 2.82, 3.36)	(0.337, 0.542, 0.843)	0.529
Functional Class	(0.84, 1.19, 1.57)	(0.128, 0.229, 0.392)	0.230
MMS	(0.64, 0.84, 1.19)	(0.097, 0.162, 0.298)	0.171
Bus Route	(0.30, 0.35, 0.45)	(0.045, 0.068, 0.113)	0.070

Using an MCA process, LoF is determined based on condition data, condition assessment protocols, and expert opinion on likelihood values. A Delphi process similar to previous sections can be used to capture expert input on condition data and LoF relationships. Condition data and components of a condition index, such as structural defects, in combination with expected service life and age of an asset can be a reasonable input to determine LoF. The PCI-LoF relationship can be translated into a mapping function as shown in Figure 3. Using the mapping function, deterioration curves associated with various road segments based on their physical characteristics can be converted into LoF projection curves to be used in the capital planning process (Figure 3). Th incorporation of quantitative deterioration models further improves the semi-qualitative nature of the proposed risk assessment process. It is important to note that in the pavement management context, LoF can be interpreted as representing the possibility of an unacceptable serviceability, increased accident rate, or other negative impacts on road users and network performance. This is slightly different in the case of other asset types such as watermains.

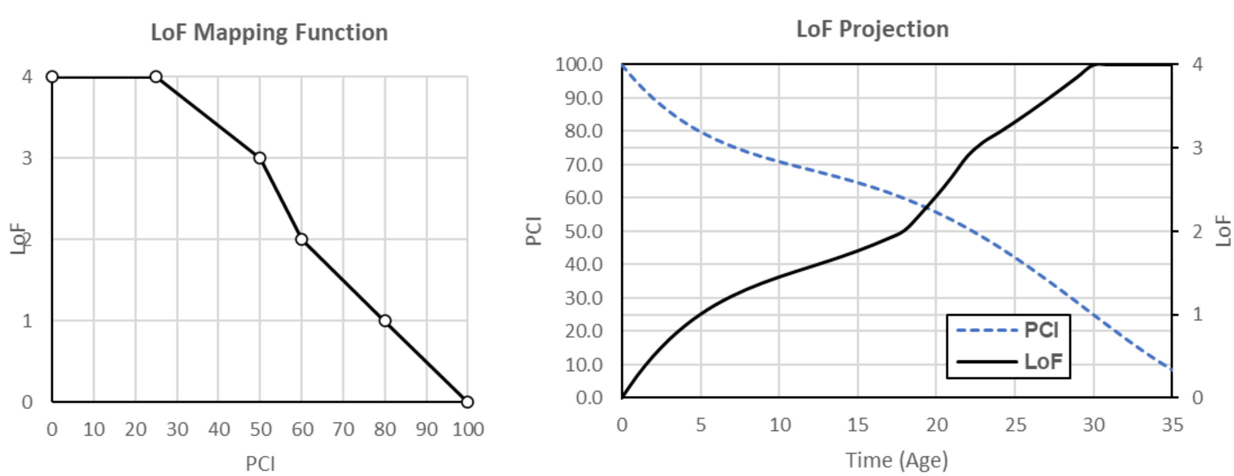


Figure 3: Use of LoF mapping function to transfer a deterioration curve into an LoF projection

CAPITAL RENEWAL PLANNING

To devise a capital plan, various methods of decision-making can be employed. Priority ranking, cost-benefit analysis, and mathematical optimization are among the most widely used methods for capital renewal decision-making. Priority ranking has been suggested and used in many pavement management applications (Zimmerman et al. 2011; Wolters et al. 2011). Using ranking, projects are typically selected in order based on a calculated Priority Index (PI). Prioritization is generally performed based on agency policies and can range from the subjective opinion of road managers, to age-based, or to condition-based ranking methods. Indicators such as pavement condition index (PCI) can be used to prioritize road segments. Other attributes such as functional class, traffic, or minimum service standards can also be used to determine a PI. After determining a PCI for each road segment, the entire network is sorted from the highest to the lowest priority segment. Next, the highest priority segment is selected and the required treatment type and its associated cost are determined. If the available budget is adequate to cover the cost, the segment and the associated treatment is selected. The cost of treatment is subtracted from the available budget and the process is repeated until all segments have been covered or the available budget has been used up.

Cost-benefit analysis (CBA) originated from the work of by two French engineers, Auguste Cournot and Jules Dupuit in the mid-19th century, who were known as the founding fathers of microeconomics (Arler 2006). CBA is a methodology to explicitly determine benefits and costs associated with a project in monetary terms (Thoft-Christensen 2012; Fraser and Jewkes 2013). CBA can be combined with MCA for a more comprehensive analysis where CBA assesses the monetary or financial aspects of the problem and MCA assesses those criteria that cannot be evaluated in monetary terms. Using the CBA method, an agency can prioritize projects based on the cost-effectiveness or the ratio of benefit over cost (B/C ratio) of a project. In general, an investment alternative is considered desirable when resulting benefit over cost ratio is greater than one, or in other words, the expected benefits exceed the expected costs. When a set of mutually exclusive alternatives exists, they can be ranked based on their B/C ratio and a ranking process can be employed to arrive at the final solution. A variation to the CBA method, called incremental CBA, looks at the incremental benefit gains and an alternative becomes more preferred than the current preferred one, if its incremental benefits are higher than its incremental costs (Fraser and Jewkes 2013). CBA is an effective method to determine the monetary implications of project alternatives in terms of costs and benefits. This is particularly useful at the project-level analysis when a limited number of projects are compared for the upcoming construction season. CBA, however, has a number of limitations when it comes to effective network-level preservation programing. Although, some variations of CBA try to take into account the time dimension of the analysis, it lacks the capability to analyze the impact of time delays or accelerations on the overall optimality of the results within a network of assets. Another key limitation of CBA, similar and priority ranking, is its inability to incorporate multiple constraints into the analysis.

Optimization is a branch of science in Operations Research (OR). OR provides a scientific approach to decision making that seeks to optimize the performance of a system, usually under conditions requiring the allocation of scarce resources. OR originated during World War II when the British government recruited scientists from different disciplines to solve the operational problems of the war, such as the deployment of radar and the management of convoy, bombing, anti-submarine, and mining operations, which coined the term Operations Research. In the context of optimization, a system can be a collection of interdependent entities that work together to accomplish the goal of the system. For example, a corporation can be thought of as a system whose goal is to maximize its profit, while subjected to resource constraints and regulations governing its business activities. The focus of optimization is, therefore, to understand the complex operations of any system so as to predict its behavior over time and to identify the best course of action that leads to an ideal level of performance, or in other words, an ‘optimal’ solution. This scientific approach to decision-making usually involves the use of mathematical models to represent the system’s behavior in terms of objective functions, decision variables, and constraints (Winston & Venkataramanan 2003).

In the context of pavement management, or more generally, asset management, the term optimization has been used rather loosely to describe methods such as incremental cost-benefit analysis, MCA, or even priority ranking. These methods, however, cannot be categorized as formal mathematical optimization and are far less effective as compared to true optimization methods. Performing a true optimization analysis for the purpose of allocation of capital funds, however, represents a complex problem (Abaza, 2007). One of the key challenges associated with optimization modeling of pavement preservation programs is the exponential increase in solution space size as the number of road sections and consequently decision variables increase (Al-Bazi & Dawood, 2010). Renewal fund allocation represents a type of optimization, called ‘combinatorial’ problems that deal with finding the best possible solution amongst a large number of possibilities based on the combination of decision variables. To handle complex combinatorial problems, the trend in recent literature has been to use evolutionary optimization techniques, such as genetic algorithms (GAs) (Liu et al., 1997). In addition to GA, more rigorous mathematical methods, such as mixed integer programming, can also be employed in this domain (Winston & Venkataramanan 2003). GA-based techniques are inspired by the process of natural selection and the principle of survival of the fittest in living species that result in an intelligent systematic search towards the optimum solution in the combinatorial space of all possible solutions (Goldberg, 1989). Many GA optimization models have been introduced for life cycle analysis and renewal planning in different asset domains, including pavements (de la Garza et al., 2011), bridges (Elbehairy et al., 2006), facilities (Rashedi & Hegazy 2014), and groundwater remediation (Zou et al., 2009). While the processes described in the literature provided useful models, their solution quality and speed greatly depended on problem size and model efficiency. Increasing problem size significantly affects the optimization results and degrades the performance, resulting in prohibitive processing time (Cook et al., 1997, Rashedi and Hegazy 2014).

Recent enhancements in advanced optimization technologies have led to the development of practical decision support tools that utilize true optimization capabilities. The improvements achieved through an optimized solution can be translated into substantial cost savings, added performance, and a higher level of service to the community. A capital planning tool with optimization capability can maximize the overall performance of a network over a multi-year analysis horizon while satisfying multiple constraints, such as budget limits, levels of service, operational considerations, etc., all at the same time. The resulting fund allocation plan represents the best possible course of action in terms of timing and selection of assets and treatment alternatives, while satisfying all the specified constraints. This optimum plan is, therefore, a defensible solution that results in the highest investment efficiency of taxpayer money. The optimization’s ability to effectively meet various criteria from all stakeholders can result in much higher degrees of satisfaction and support from the municipal councilors and the community at large during the funding approval and project justification process. To perform a true optimization analysis on our case study example network, a commercial optimization tool for capital planning called, DOT (Decision Optimization Technology)™, is used. DOT™ has the capability to optimize large-scale asset management problems to determine the best course of action in terms of timing and selection of a wide array of preservation treatments that results in the highest investment efficiency while satisfying a large number of constraints regarding serviceability criteria, socioeconomic policies, budgetary limits, co-located projects, and operational efficiency.

The City of Sarnia in the province of Ontario in Canada is used as a case study to demonstrate the implementation of the proposed risk-based capital planning process. The network under analysis has 450 centreline kilometers of roads that consist of over 2,400 road segments. The Risk Index (RI) for each road segment is calculated by looking at the physical and socio-economic attributes using the fuzzy AHP process as discussed previously. LoF is also determined based on a range of deterioration curves considering the mechanistic and traffic characteristics of the roads and current condition assessment data in the form of a pavement condition index (PCI). RI is scaled to a 0-100 range with four colour-coded levels of risk, including: Low (RI from 0 to 15), Moderate (RI from 15 to 30), High (RI from 30 to 50), and Extreme (RI from 50 to 100). It is important to note that a normalization factor is applied on numeric values such as AADT, using Eq. 11 to incorporate their criticality scores. Figure 4 shows the GIS visualization of Criticality, Condition, and Risk maps associated with this network.

$$\hat{x} = \frac{x_{max} - x}{x_{max} - x_{min}} \qquad (11)$$

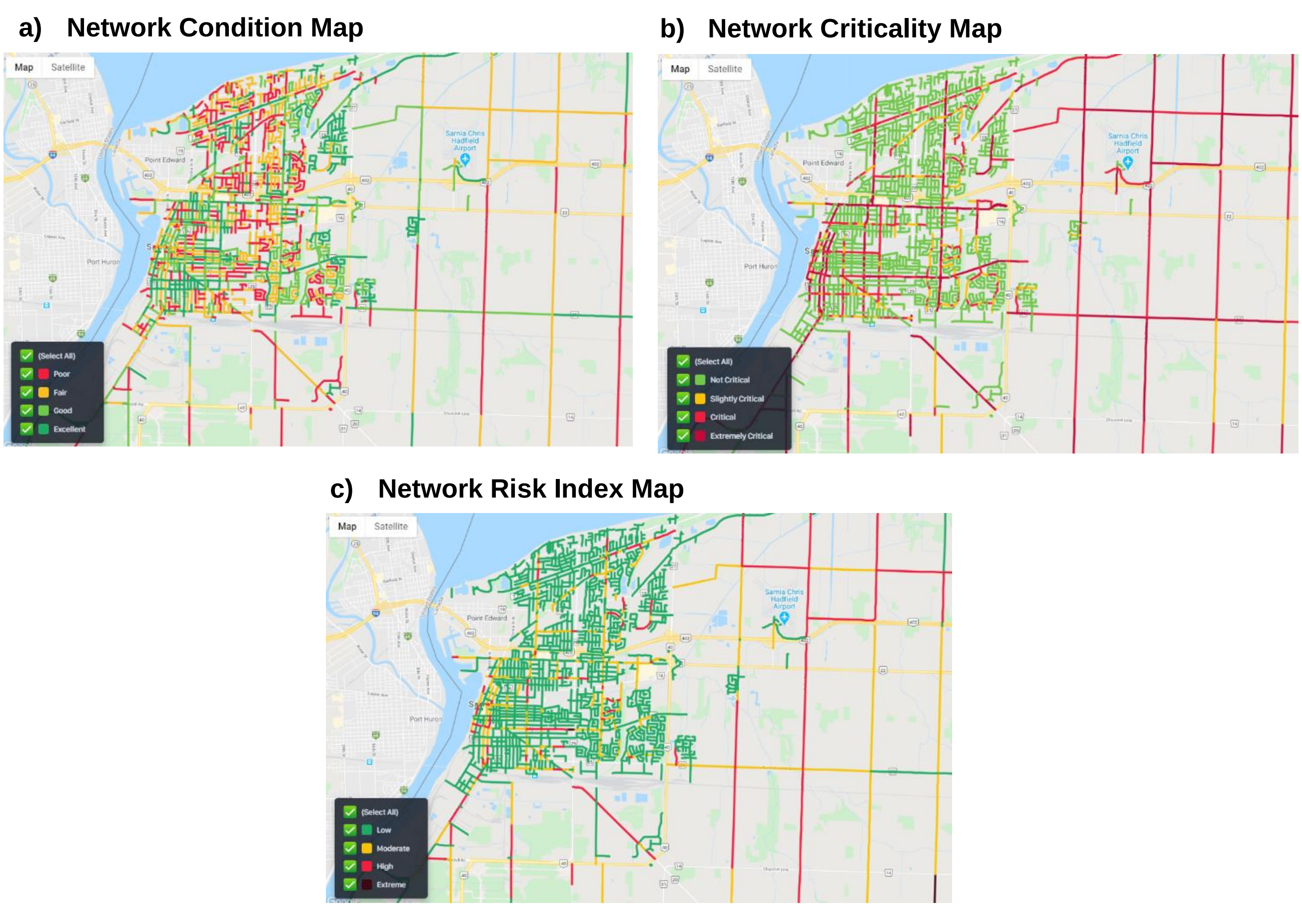
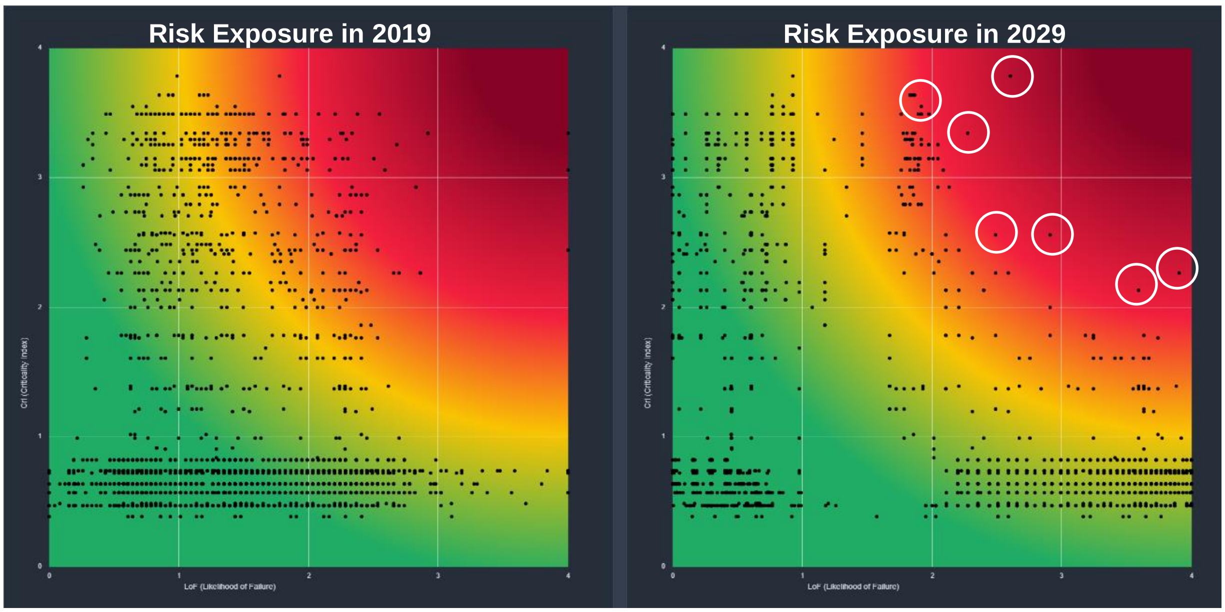


Figure 4: Network risk index calculation results

Two scenarios are compared to investigate the impact and using a risk tolerance as part of the capital planning process. The first scenario looks at a $2M annual investment without any risk tolerance constraint, while the second scenario applies a RI tolerance of 30 to collector and arterial segments (i.e., all collector and arterials are to be assigned Low and Moderate risk levels) and RI tolerance of 50 to local roads (i.e., local roads cannot achieve Extreme risk levels). Figure 5 shows the risk exposure matrix with various risk levels under both scenarios. Each point on the risk exposure chart represents a road segment at a risk level based on the CrI-LoF approach.

a) Scenario 1: $2M annual investment optimization with pure focus on physical performance



b) Scenario 2: $2M annual investment optimization with risk tolerance constraint

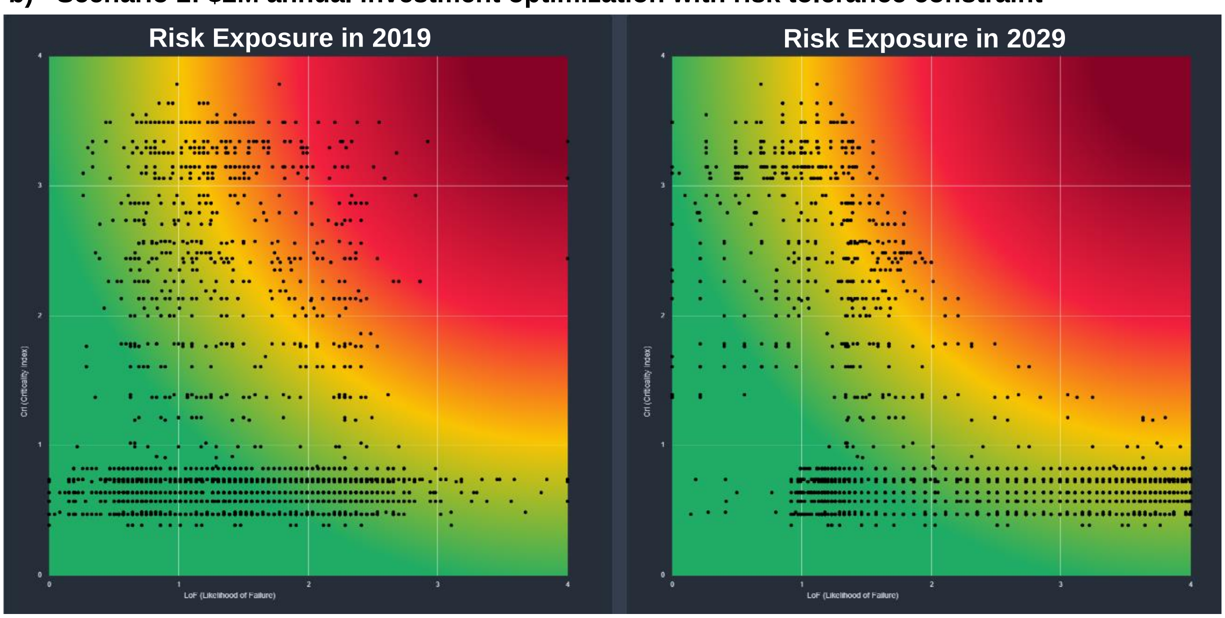
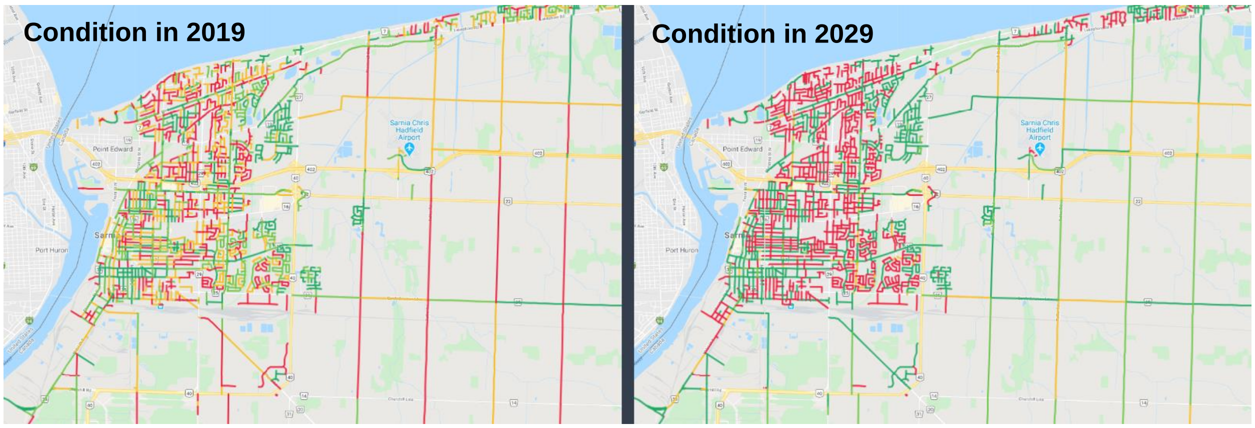


Figure 5: Risk exposure results of the two scenarios

Comparison of the results clearly indicates that without the risk tolerance constraint in Scenario 1, a number of segments will be in the high and extreme risk areas by the end of the plan. By introducing the risk tolerance constraint in the second scenario, all segments in high and extreme areas are eliminated by the end of the plan as part of the optimization process. Figure 6 also compares the network condition results under both cases. Overall, the result indicates that the $2M investment level is not adequate to improve condition and maintain a satisfactory risk tolerance at the same time.

a) Scenario 1: $2M annual investment optimization with pure focus on physical performance



c) Scenario 2: $2M annual investment optimization with risk tolerance constraint

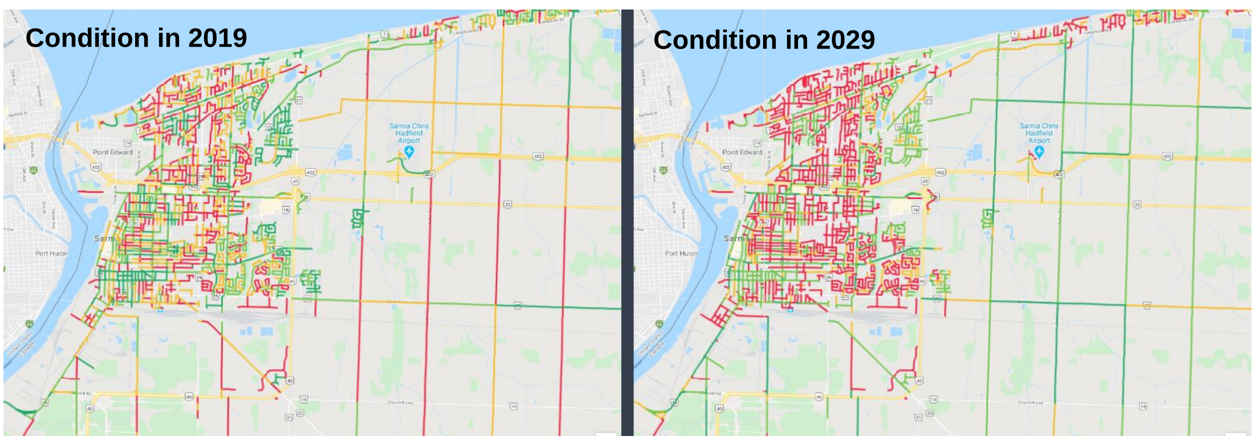


Figure 6: Network condition results for two scenarios

Scenario 1 with a pure focus on physical performance results in a better overall network condition as compared to Scenario 2. However, the consideration of risk makes the second scenario more practical. As an example, an ‘Extremely Critical’ road segment representing an arterial road with traffic of over 10000 vehicles per day at MMS level 2, did not receive any treatment in the first scenario. The road is currently in poor condition and requires a full depth reclamation treatment at a total cost of over $500K. In the first scenario, the money was saved from this segment and spent on other segments with a higher overall condition. The risk implications of this decision, however, contradicts the overall objectives of the decision-makers and can expose significant risk to road users and to the network performance as a whole. In the second scenario, this section received a full depth reclamation treatment followed by preventive maintenance in year 2026. The timing of the treatment was slightly later in the plan since the trade-off of maintaining good roads using preventive maintenance treatments was also taken into account as part of the optimization process. Therefore, the initial years of the plan were more focused on preventive maintenance activities and the full depth reclamation was applied mid-way through the plan to handle the risk implications of no intervention on an extremely critical road segment.

CONCLUSIONS

A practical and implementable pavement management plan should integrate risk analysis within the performance modeling process. Due to practical reasons and implementation difficulties, risk assessment is generally performed as a qualitative method. A multi-criteria analysis (MCA) approach is proposed to be used to improve the subjective nature of the qualitative risk assessment process. A Delphi and Fuzzy Analytical Hierarchy Process (FAHP) for risk assessment was discussed as part an optimized capital planning approach to devise effective capital renewal plans. The Delphi is used for a systematic communication and feedback process to arrive at a consensus among experts on an uncertain and often intangible issue related to criticality influential factors. The FAHP approach enabled a more accurate description of the multi-criteria analysis process by capturing decision-maker knowledge and the human uncertainty associated with judgment when performing the pair-wise comparison and expressing opinion in imprecise linguistic patterns. Results showed that without the risk tolerance constraint a considerable number of critical road segments achieved high and extreme risk levels by the end of the plan. By introducing a risk tolerance, all segments in high and extreme areas were eliminated. Although the effectiveness of preventive maintenance was considered as part of the optimization process, the risk implications of no intervention on critical road segments was better captured using the risk tolerance constraints as part of the analysis.

REFERENCES

Abaza, K.A. (2007). Expected performance of pavement repair works in a global network optimization model. ASCE Journal of Infrastructure Systems, 13, 124–134.

Al-Bazi, A., & Dawood, N. (2010). Developing crew allocation system for precast industry using genetic algorithms. Computer-Aided Civil and Infrastructure Engineering, 25, 581–595.

Alberti, Susanna & Fiori, Federico. (2019). Integrating Risk Assessment into Pavement Management Systems. Journal of Infrastructure Systems. 25. 10.1061/(ASCE).

AMO (Association of Municipalities of Ontario), (2015), What’s Next Ontario? Imagining a prosperous future for our communities. A Fiscal Overview, Association of Municipalities of Ontario, June 2, 2015.

Arler, F. (2006). Ethics and cost-benefit analysis. Research Report 4, Department of Development and Planning, Aalborg University, Aalborg, Denmark.

ASCE (American Society of Civil Engineers) (2017), Infrastructure Report Card: A Comprehensive Assessment of America’s Infrastructure, Washington D.C., 2017.

Babashamsi, P., Yusoff, N.I.M., Ceylan, H., Nor, N.G.M. and Salarzadeh, J.H. (2016), Evaluation of pavement life cycle cost analysis: Review and analysis, International Journal of Pavement Research and Technology, Vol. 9, pp. 241-254.

Bozbura, F. T., Beskese, A., & Kahraman, C. (2007). Prioritization of human capital measurement indicators using fuzzy AHP. Expert Systems with Applications, 32(4), 1100–1112.

Buckley, J. J. (1985). Fuzzy hierarchical analysis. Fuzzy Sets and Systems, 17(3), 233–247

Buckley, J. J., Thomas Feuring, Yoichi Hayashi (2001). Fuzzy hierarchical analysis revisited, European Journal of Operational Research,129(1), 48-64.

Buyukozkan, G. (2004). Multi-criteria decision making for e-marketplace selection. Internet Research, 14(2), 139–154.

Chan, Albert & Yung, Esther & Lam, Patrick & Tam, C. & Cheung, Sai. (2001). Application of Delphi Method in Selection of Procurement Systems for Construction Projects. Construction Management & Economics. 19. 699-718.

CIRC (Canadian Infrastructure Report Card) (2016), Infrastructure Report Cards: Informing the Future, can be accessed at: www.canadainfrastructure.ca.

CIRC (Canadian Infrastructure Report Card) (2019), Monitoring the State of Canada's Core Public Infrastructure, can be accessed at: www.canadainfrastructure.ca. Cook, W.J., Cunningham, W.H., Pulleyblank, W.R., & Schrijver, A. (1997). Combinatorial optimization. New York, NY: Wiley.

de la Garza, J., Akyildiz, S., Bish, D., & Krueger, D. (2011). Network-level optimization of pavement maintenance renewal strategies. Advanced Engineering Informatics, 25, 699–712.

DOT (Decision Optimization Technology) (2019), [online]: https://www.infrasolglobal.com/

Elbehairy, H., Elbeltagi, E., Hegazy, T., & Soudki, K. (2006). Comparison of two evolutionary algorithms for lcc optimization of bridge deck repairs. Journal of Computer Aided Civil and Infrastructure Systems, 21, 561–572.

FHWA (Federal Highway Administration), Preservation, 2017, [online] (June 2017) https://www.fhwa.dot.gov/preservation/

Fraser, N.M., and Jewkes, E.M. (2013). Engineering economics, financial decision making for engineers. 5th ed. Pearson Canada Inc., Toronto, Ont., Canada

Goldberg, D.E. (1989). Genetic algorithms for search, optimization, and machine learning. Reading, MA: Addison Wesley.

Haider S. W. and Dwaikat M. B. (2011), Estimating Optimum Timing for Preventive Maintenance Treatment to Mitigate Pavement Roughness, Transportation Research Record, (2235), 43-53.

Hicks R. G., Moulthrop J., and Daleiden J. (1981), Selecting a Preventive Maintenance Treatment for Flexible Pavements, Transportation Research Record, (1680), 99-1025.

Keeney, R., Raiffa, H., (1993). Decisions With Multiple Objectives: Preferences and Value Tradeoffs. Cambridge University Press, Cambridge, UK.

Labi S. and Sinha K. C. (2005), Life-Cycle Evaluation of Flexible Pavement Preventive Maintenance, ASCE, Journal of Transportation Engineering, 131(10), 744-751.

Lai, Y., Liu, T., Hwang, C., (1994). TOPSIS for multi objective decision making. Eur. J. Oper. Res. 76 (3), 486–500.

Lamptey G., Labi S., and Li Z. (2008), Decision support for optimal scheduling of highway pavement preventive maintenance within resurfacing cycle, Decision Support Systems, (46), 376–387.

Linstone, H. and Turoff, M. (1975) The Delphi Method: Techniques and Applications, Addison Wesley, Reading, MA, pp. 3–12.

NCPP (National Center for Pavement Preservation), 2019, [online]: https://www.pavementpreservation.org/about/background/

Pavement Management Guide, AASHTO, Washington, DC, 2011

Peshkin, D. G., T. E. Hoerner, and K. A. Zimmerman. (2004), NCHRP Report 523: Optimal Timing of Pavement Preventive Maintenance Treatment Applications. Transportation Research Board of the National Academies, Washington D.C., 2004.

Promothes Saha & Khaled Ksaibati (2016) A risk-based optimization methodology for pavement management system of county roads, International Journal of Pavement Engineering, 17:10, 913-923.

Rashedi R., Maher M., and Barakzai K., (2018), Defining Needs for Optimized Management of Gravel Road Networks, Transportation Association of Canada Annual (TAC) Conference, Innovations in Pavement Management, Engineering, and Technologies, Saskatoon, SK, Canada.

Rashedi R., Maher M., Roberts N., and Konarski K. (2017). Unleashing the Cost Savings of Optimized Road Asset Management to Municipalities, CSCE 2017 – Leadership in Sustainable Infrastructure, Vancouver, BC, Canada, May 31 – June 3.

Rashedi, R., & Hegazy, T. (2014), Capital renewal optimization for large-scale infrastructure networks: genetic algorithms versus advanced mathematical tools. Structure and Infrastructure Engineering, 11(3), 253-263.

Saaty T. L. (2008), Decision making with the analytic hierarchy process, International Journal of Services Sciences, Vol. 1, No. 1.

Saaty, T. L. (1990) How to Make a Decision: The Analytic Hierarchy Process. European Journal of Operational Research, Vol. 48, No. 1, 1990.

Shahtaheri, Maryam & Haas, Carl & Rashedi, Roozbeh. (2017). Applying Very Large Scale Integration Reliability Theory for Understanding the Impacts of Type II Risks on Megaprojects. Journal of Management in Engineering. 33. 04017001. 10.1061/(ASCE)ME.1943-5479.0000504.

Thoft-Christensen, P. (2012). Infrastructures and life-cycle cost-benefit analysis. Structure and Infrastructure Engineering, 8(5): 507–516. doi:10.1080/15732479.2010.539070.

Transportation Research Board (1989), NCHRP Synthesis of Highway Practice 153: Evolution and Benefits of Preventive Maintenance Strategies, Transportation Research Board, National Research Council, Washington, D.C., December, 1989.

van Laarhoven P.J.M., W. Pedrycz, (1983) A fuzzy extension of Saaty’s priority theory, Fuzzy Sets and Systems 11 (1983) 229–241.

Wang, Yamei & Li, Zhongwu & Tang, Zhenghong & Zeng, Guangming. (2011). A GIS-Based Spatial Multi-Criteria Approach for Flood Risk Assessment in the Dongting Lake Region, Hunan, Central China. Water Resources Management. 25. 3465-3484.

Winston, W.L., & Venkataramanan, M. (2003). Introduction to mathematical programming. Belmont, CA: Duxbury Press.

Wolters A., Zimmerman K, Schattler K., Rietgraf A. (2011), Implementing Pavement Management Systems for Local Agencies. ICT-11-094-1. Illinois Center for Transportation, Rantoul.

Zadeh LA (1965) Fuzzy sets. Inf Control 8:338–353

Zimmerman, K.A., O. Smadi, D. G. Peshkin, and A. S. Wolters, (2001) Update to AASHTO

Zou, Y., Huang, G.H., He, L., & Li, H. (2009). Multi-stage optimal design for groundwater remediation: A hybrid hi-level programming approach. Journal of Contaminant Hydrology, 108, 64–76.