RESILIENCE-BASED OPTIMIZATION MODEL FOR MAINTENANCE AND REHABILITATION OF PAVEMENT NETWORKS IN A FREEZE-THAW ENVIRONMENT

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ABSTRACT

According to Canada Infrastructure Report 2016, 62.6% of roads in Canada are in a good condition, nevertheless, with current investment rates, significant road networks will suffer a decline in its condition and will be vulnerable to sudden failure. Accordingly, this paper tackles the pavement resilience from an asset management perspective and aims at developing a resilience-based asset management framework for pavement networks. This was carried out through the development of five components; 1) a central database of asset inventory, 2) a pavement condition and level of service (LOS) assessment models, 3) a regression of the effect of Freeze-Thaw on pavement network, 4) a financial and temporal models, and 5) an optimization model to formulate the mathematical denotation for the proposed resilience assessment approach and integrate the above components. The model results were promising in terms of maintaining pavement resiliency by selecting a near optimal intervention plan that meets the municipality limitations.

Keywords: Asset management, Resilience, Freeze-Thaw, Optimization, Pavement, Resilience indicators, Maintenance and Rehabilitation.

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INTRODUCTION

An infrastructure is exposed to various multi-level disruptive events, from aging's effects to disasters, that impede its function and subsequently cause disruption in the interdependent infrastructure networks. Accordingly, maintaining the existing infrastructure networks is essential to meet the required Level of Service (LOS) and keep them operational in a satisfactory state (Turnquist and Vugrin 2013). Moreover, maintaining these assets is a necessity intended for increasing both; their resistance to both extreme disruptive event and regular events (i.e. repetitive events with significant impact on an asset) and their recovery capability to restore their performance within the desired time frame and meet the required LOS. Infrastructure networks are aging and there is not enough investment made to salvage what is being lost due to loading and severe environmental conditions. As per Canada's Infrastructure 2016 report, the current physical condition rating of roads is "Acceptable". Nevertheless, the current investment rate will diminish this condition unless prompt corrective measures were taken to increase the investment rate (FCM 2016). Moreover, there is a growing need to introduce new assets to the existing infrastructure networks to satisfy the growing population which has double during the period from 1960 to 2013 (Statistics Canada 2015). It is important to mention that the average age of the core infrastructure in Canada (i.e. bridges, roads, water, wastewater, etc.) was about 14.7 years in year 2013, according to Canada infrastructure report 2016. Still, those infrastructures resiliency is inferior due to the backlog in investment needs, aging, deterioration, severe weather conditions and previous disruptive events effects (FCM 2016). Consequently, there has been a growing interest towards resilience, and thus it has been a dominant aspect in the recent conferences and research trends.

In that context, there is a need to integrate resilience into asset management concept. This need arises from the fact of the growing burden on municipalities to maintain their assets in a satisfactory condition. Integration between the two concepts shall reduce the overall costs of maintenance and intervention plans in an efficient way to achieve the best budget allocation for infrastructure investments. Scholars also drew the attention towards the growing need to direct investments in a strategic way to enhance a system's resilience in the face of the anticipated disruptions. Such investments should involve a prioritization approach to satisfy limited budget and time constraints and achieve the overall effective resilience enhancement for the road network. Hence, it is essential to investigate the connection between resilience and other asset management concepts (i.e. Condition, reliability, and vulnerability). Resilience assessment models were limited about considering the effect of previous non-extreme disruptive events on resiliency. There is an inadequate research that integrates the effect of aging, deterioration, extreme and non-extreme events towards assessing pavement resiliency. Nevertheless, there are multiple optimization models for selecting near optimal intervention plans for pavement networks, limited research has been undertaken in the development of optimization models that aim at maximizing pavement resilience within the existing budgetary constraints

This paper is directed toward two key features that reflect an infrastructure's resilience integrity: (1) infrastructure condition under the regular events and their consequences, and (2) maintenance and recovery strategies taken to reduce the deterioration impact. This is well-aligned with the asset management perception as a base for resilience assessment (Levenberg et al. 2016). In that context, the goal of this paper is to establish a resilience-based asset management framework that integrates different intervention plans to pursue the pre-defined municipal resilience constraints based on the resilience definition of the authors. The objectives of this paper could be summarized as follows: (1) identify the key indicators that affect the resilience of the pavement sections, (2) design a resilience-based asset management framework for pavement maintenance and rehabilitation, and (3) build resilience optimization model that selects a near-optimal network intervention plan throughout the study time horizon under freeze-thaw effect. Towards the formulation of the predefined objectives, this work is set to be divided into four sections as follows: (1) the first section examines the prior work related to infrastructure network resilience assessment, especially the ones focusing on pavement networks, presents the resilience definition from perspective of the authors, (2) the second section presents the research methodology, details the developed models that formulate the resilience assessment framework based on the resilience definition proposed by the authors, (3) the third section demonstrates the implementation of the proposed framework on a case study of 20 pavement sections, including the optimization model to come up with a near optimal intervention plan, and (4) the fourth section discusses the results of applying this framework along with the framework's added value and insights. The main goal behind this research is integrating the asset management approach into resilience through a generic framework, in terms of the pre-defined indicators, and providing the asset managers with a decision-making tool for selecting an intervention plan throughout the life cycle.

LITERATURE REVIEW

Resilience is being investigated in different fields of study and thus distinguished according to that field, leading to draw the attention towards resilience concept and its definition (Vugrin et al. 2010). Numerous descriptions emerged defining resilience for infrastructure systems, nevertheless most of those definitions were associated with disaster management concept and resilience was assessed as an extreme hazard-based network feature (Baroud et al. 2015; Bocchini et al. 2013; Cimellaro et al. 2010; Gay and Sinha 2012; MacKenzie and Barker 2012; Ouyang et al. 2012; Vugrin et al. 2010). So, it is essential to address resilience from a life-cycle perspective and incorporate asset management notion into it. Under the asset management, authors defined an asset's resilience as "The ability of an asset or a system to maintain a minimum LOS after average (regular and periodic) and extreme disruptive events during its life-cycle within time and cost limitations". What is mainly introduced in this definition is linking resilience to asset management criteria and incorporating the regular periodic events that affect an asset's resilience, condition and LOS.

Scholars were divided into two categories when it came to resilience assessment interpretation with respect to its interaction with other infrastructure networks, where some assessed resilience for an asset as a single isolated asset, while others incorporated the interdependency with other correlated networks. Even though, few scholars applied resilience concept as a single isolated asset where; regaining a network's resilient state is going to be a beneficial return on the interconnected infrastructure network (Gay and Sinha 2012). Nonetheless, other scholars accounted for the interdependent effect between the interconnected infrastructure networks while interpreting the asset resilience where; the interconnected network may be disrupted upon the failure of one asset (Baroud et al. 2015; MacKenzie and Barker 2012; Reed et al. 2009; Shah and Babiceanu 2015). Few scholars emphasized that while assessing resilience for infrastructure networks, it is essential to consider resilience as a disruptive event specific where; resilience shall vary according to the anticipated hazards (Gay and Sinha 2012; Ouyang and Dueñas-Osorio 2012). Several approaches were integrated to assess resilience for infrastructure networks. Risk analysis-based frameworks were used and integrated with mathematical models where; data from different domains were extracted to build a model that captures the resilience features along with the consequences of a certain disruptive event and the required recovery actions (Cimellaro et al. 2014; Ikpong and Bagchi 2014; Ouyang et al. 2012; Ouyang and Wang 2015; Shah and Babiceanu 2015). Other scholars developed an Integrated Input-output Model

(IIM) with resilience assessment mathematical models to capture interdependency effect between the interconnected infrastructure networks and systems and investigate its effect on both the disruption and recovery process (Baroud et al. 2015; MacKenzie and Barker 2012; Reed et al. 2009; Shah and Babiceanu 2015). Other approaches and tools were developed to forecast asset's capability and resilience capacity on a network level (Gay and Sinha 2012). Table 1 presents the different analysis methods used in each publication along with the targeted field of each method. The most commonly adopted methods for resilience assessment were based on mathematical modeling and simulation-based models. Those methods were mainly applied on power transmission grid, water distribution networks, and gas/oil pipelines cases, which are of the main fields of study in infrastructure resilience investigation. In parallel to the previously mentioned methods, interdependency analysis took place especially with power transmission grid cases. In Addition, decision making analysis was one of the mostly used methods reflecting the goal/objective of resilience assessment, which opts at aiding the decision-making entities in taking verdicts towards more resilient infrastructure systems.

Transportation networks had their share in both resilience definition and assessment based on different approaches. Scholars defined resilience as "the potential number of vehicles affected by natural threats in any given 10 year" (Herrera et al. 2017). The definition is obviously originated from disaster management approach, neglecting other factors like aging. Nevertheless, the definition integrates resilience and risk basis and was used to assess resilience for transportation networks (Herrera et al. 2017). Others considered resilience as structural design feature only emphasizing on the necessity of investment to increase an infrastructure's capacity, endure any extreme event, and recover with the least possible damage. In that context, scholars focused on pavement material and the possible techniques to enhance their resilience (Lu et al. 2017). Furthermore, vulnerability was incorporated with the physical condition to build frameworks that can enhance the resilience of the transportation systems through defining a resilience indicator distinguished as the number of independent pathways between two nodes in the transportation network (Wang and Zhang 2016). The pre-existing pavement condition due to the natural deterioration process was also incorporated in previous research along with multi-hazards scenarios effect to model pavement network performance and assess its resilience (Levenberg et al. 2016; Dehghani et al. 2014). The pre-existing conditions for an asset along with the anticipated intervention actions to be taken have a significant effect on an asset's resilience. Another methodology that adapts a proactive approach for intervention actions is forecasting the rest period for pavement under traffic loads and the climatic condition. Rest period is an essential measure that indicates when the first major intervention action should take place to avoid sudden failures in pavement network under sudden or severe disruptive events (Ahmed et al. 2016).

Transportation networks, especially pavement sector, received high attention in terms of developing optimization models for selecting the optimal maintenance and rehabilitation scenarios throughout their life cycle time. Several researchers developed network-level prioritization models that selects the most appropriate sections that need to be maintained to minimize the life cycle costs and maintain the network condition (Farashah 2012, Jayed 2011, and Mubaraki 2010). Other researchers utilized linear programming, and Genetic Algorithms (GA) to maximize the network performance and minimize the life cycle costs (Liu and Wang 1996, Tack and Chou 2002). Furthermore, scholars developed multi-layer intervention plan that accounts for uncertainties in the deterioration model. The model utilized a simulation-based GA approach that selects the near optimal intervention plan for the pavement sections throughout their life cycle (Chootinan et al. 2006). Even though, there exists multiple optimization models for selecting near optimal intervention plans for pavement networks, resilience-based decision making has not been thoroughly studied. Limited research has been undertaken in the development of optimization models that aim at maximizing resiliency within the limited budgetary constraints. Swei 2016 introduced several optimization models capable of estimating the early maintenance costs for transportation networks, Two sequential optimization models were applied to achieve the optimal allocation policy for PMS based on minimizing IRI for pavement segments for the network under study using a divide and conquer optimization algorithm.

In conclusion, resilience has been being investigated in different research practices and thus distinguished accordingly, leading towards the emerge of numerous infrastructure system resilience definitions. Nevertheless, most of those definitions were associated with disaster management concept and resilience was assessed as an extreme hazard-based network feature and none interpreted resilience into asset management, which is essential to have optimized intervention plans that accounts for both concepts. Moreover, indicators that reflect an infrastructure resilience were not thoroughly investigated in the previous examined literature and need further consideration. Accordingly, this research is directed to study resilience from the perspective of asset management, examining the cost tradeoff between preparedness measures, failures effect, and the infrastructure’s resilience indicators. Scholars drew the attention towards the growing need for direct investments in a strategic way to enhance a system’s resilience in the face of the anticipated disruption. Such investment should involve a prioritization approach to satisfy limited budget and time constraints and achieve the overall effective resilience enhancement for the road network. Hence, it is essential to investigate the connection between resilience and other asset management concepts (i.e. Condition, reliability, and vulnerability).

Resilience assessment models, like the IIM model, need an intensive database to be available for usage, which is not the case for most countries. Accordingly, other models should be used to mitigate the absence of such database and reliable historical data. Also, the effect of previous non-extreme disruptive events on the resilience was not widely considered, though different scholars mentioned it. Hence, it is essential to develop an asset management framework that reflects pavement resilience based on the predefined resilience indicators taking into consideration aging effects, deterioration, extreme and non-extreme disruptive events. Even though, the existence of multiple optimization models for selecting near optimal intervention plans for pavement networks, resilience-based decision making has not been thoroughly studied. Limited research has been undertaken in the development of optimization models that aim at maximizing pavement resilience within the existing budgetary constraints.

METHODOLOGY

This work was carried out through three phases. Resilience indicators identification was carried out in the first phase where; various indicators were identified from the previous literature and clustered, based on their effect on resilience features, to reflect the municipal infrastructure resilience definition of the authors. It was important to categorize the indicators to mitigate any replication between them. Then, the second phase was developing the resilience assessment model where; the pre-defined indicators were modelled against the typical aging and freeze-thaw effect. Then building the optimization model where; GA engine was utilized to select a near-optimal intervention plan throughout the asset's life cycle. Finally, a pilot case study was introduced for model implementation. The main objective of this study aims to reduce maintenance and rehabilitation works cost for pavement networks. The author believes that integrating resilience into asset management concept will combine and reduce the overall costs of M&R activities for pavement networks through maintaining appropriate network resilient state, while keeping pavement networks well maintained through their lifecycle. Two sequential phases were proposed to achieve research objectives; starting from models contributing to build the main resilience-based asset management framework, then going through post-disruption model which optimize M&R actions which can be translated to asset recovery plan. Details of each model will be presented and discussed in the following sub-sections.

Resilience Assessment Indicators

Resilience associated parameters that were used to predict resilience for infrastructure systems from previous research are used as the base to formulate resilience related indicators. MacKaenzie and Barker used infrastructure performance measures and the interdependency between different assets to predict an infrastructure resilience (MacKenzie and Barker 2012). The MCEER framework interoperates technical, organizational, social, and economic aspects based on Asset's Robustness, Redundancy, Resourcefulness, and Rapidity (Cimellaro et al. 2010). Network and system condition were also used to predict an infrastructure's resilience taking into consideration many aspects like interdependency, time factor, network type, asset criticality and the disruption related criteria like its type, probability of failure due to each type (Gay and Sinha 2012; Ouyang and Dueñas-Osorio 2012; Bocchini et al. 2013). System recovery criteria such as resources availability, recovery time and cost constraints are significant indicators to an asset's resilient state as well (Gay and Sinha 2012). Integrating original system performance with the pre-active measures and rehabilitation process to predict system resilience, taking into consideration system interdependency and the recovery process required to maintain system's desired performance after disruption, defines various indicators that reflect an infrastructure's resilient state.

Indicators identification was carried-out through three steps. Intensive review for the previous work related to research objectives was undertaken as a first step to collect the indicators that affect an asset's resilience. Then, the second step aimed at filtering the collected indicators. Filtration was carried out based on the resilience perception and proposed definition of the authors. Those indicators were collected from literature then several brainstorming stages were conducted to reduce those indicators to match with the objective of this research and with author's definition. "Interdependency" was excluded and could be considered in latter research stage as an asset feature. "Asset criticality" was also excluded and assumed as an asset feature that would be included in the resilience enhancement model where it is expected to assign additional budget with criticality increase. Same conclusion was reached for "region" where it would be introduced as an asset feature in pre- and post-disruption optimization models. It is also important to point that LOS and asset condition should be separated when possible and as long LOS can be well-defined. This perception was used by other authors in their first stages of resilience assessment to have a better understanding about the unique behavior of each indicator (Gay and Sinha 2012). The last step was selecting and categorizing the indicators as shown Table 2. The indicators were split into three categories as follows: (1) asset-based, (2) disruption-based, and (3) recovery. Within each category, the relevant indicators were placed. For instance, asset condition, LOS, and redundancy fell under the asset-based indicators. Still, type of disruption, probability and consequences of failure fell under the disruption-based indicators. Finally, recovery cost and time fell under the recovery indicators.

Three asset-based indicators were identified; condition, LOS and redundancy. For pavement, several measures were used to represent pavement condition and LOS. International Roughness Index (IRI) was incorporated by several studies to measure pavement LOS. IRI involves using numerous instruments, (i.e. Laser mobile mounted devices) where; their main usage is quantifying the pavement roughness. Minimum acceptable IRI according to Federal Highway Administration is < 95 in/mile and < 171 in/mile for good and acceptable road riding quality respectively. On the other hand, Pavement Condition Index (PCI) was introduced in several studies as a measure for pavement condition where; it represents pavement distresses. Yet, many scholars correlated PCI to IRI where; quite few mathematical functions were derived between both indicators. Equation 1 presents a formula that predicts PCI based on the IRI value (Arhin et al. 2015). On a side note, the authors believe that Equation 1 needs to be further developed to account for other factors that affect PCI prediction accuracy through affecting IRI (i.e. snow removal contributes to LOS condition in heavy snow areas) (Arhin et al. 2015).

$$\log(PCI) = 2 - 0.436\log(IRI) \quad (1)$$

One important consideration is predicting pavement condition through PCI during its life cycle. Several deterioration models for PCI were introduced based on historical data analysis (Hamdi et al. 2012). After reviewing different models and based on the data available from the pavement network case study, Equation 2 was considered as the best fit for this study to model PCI deterioration (Hamdi et al. 2012).

$$PCI_i = 0.033i^2 - 2.688i + PCI_{in} \quad (2)$$

where;

$\boldsymbol{PCI_i}$ is the anticipated PCI at year i (%);

i is the year counter;

$\boldsymbol{PCI_{in}}$ is the initial PCI (%).

One of the leading factors in resilience concept is redundancy. In order to create a resilient infrastructure, redundancy design should be implemented. There is an extensive research on resilience but, a few studies spot the light on transportation network redundancy, and few researchers have developed quantitative network-based measures and computational methods to evaluate the multifaceted characteristics of transportation network redundancy. Two main criteria exist in transportation network redundancy; capacity and diversity. Network capacity represents the network-wide residual capacity taking into consideration travelers' behaviors and in case of disruptive events taking their choice during congestions, while network diversity evaluates the existence travel alternatives and travel modes in network and their effectiveness for travelers as well as the numbers of connections between two existing (Xu et al. 2015). For simplicity, network capacity criteria only will be used to estimate pavement corridors redundancy in later stage of this research and this matches with the author's scheme of processing the network as an isolated network, while different values for redundancy degree were assumed for the case study at this research stage.

As stated earlier from previous research, resilience is considered disruptive-event specific. Thus, Freeze-Thaw event was introduced as the main disruptive event in parallel with the PCI deterioration resulting from the aging. Equation 3 presents pavement reliability-based resilient modulus deterioration model under Freeze-Thaw cycles effect in cold regions. This formula presents the deterioration in resilient modulus for pavement, which denotes to the stiffness of the pavement layers to resist deformation from the applied stresses (Si et al. 2014). After intensive literature investigation, it was found that any degradation in the mechanical properties of the pavement layers, resulting from Freeze-Thaw effect, will directly cause additional distresses and accordingly drop the pavement condition (Doré et al. 2005; Ma et al. 2014; Si et al. 2014). Thus, it was assumed that the degradation in the resilience modulus, due to the Freeze-Thaw displayed in Equation 3, shall similarly occur to both the PCI and IRI. Equation 3 represents an exponential model for freeze-thaw cycles effect on the R.M of asphalt pavement. This model was verified and is believed to provide an excellent relationship between freeze-thaw effect and R.M (Ma et al. 2014).

$$RM = 625.33 + 151.92\, e^{-0.21X} \tag{3}$$

where;

$\boldsymbol{RM}$ is pavement resilience modulus after X Freeze-Thaw cycles;

X is the annual number of Freeze-Thaw cycles.

Two important indicators play great role in disruption aftermath reduction. Accurate deterioration forecast, and life-cycle prediction models would be of a great asset to obtain a better maintenance and rehabilitation intervention/recovery plan while combining both usual and extreme disruptive events. Pavement network damage pattern due to certain types of events would also be of a great use to develop the required intervention strategy (Lu et al. 2017). Accordingly, several questions arise; what are the available intervention actions available for post-disruption recovery? What is the effect of each action on pavement resilience and the corresponding costs for that action? And how long would it take to perform that action?

Based on aforementioned questions, recovery indicators are used to represent the time and cost required for the recovery activities after undergoing a certain disruption. Based on the assumption of Freeze-Thaw cycles event, time and cost will be linked to the intervention actions. Thus, four interventions were considered in this model as follows: (1) do nothing, (2) routine maintenance, (3) minor rehabilitation, (4) major rehabilitation/reconstruction (Meneses and Ferreira 2015). Table 3 presents the unit cost and time for each intervention action, their application range, and their impacts on the PCI. Rehabilitation was divided into 2 categories to reflect the current practices in pavement rehabilitation while routine maintenance was assumed to occur regularly to maintain the same decay affecting pavement during its life cycle based on the used regression deterioration model for pavement condition. The mathematical formulation of maintenance actions impact on the condition index is displayed through equations 4 to 6.

$$PCI_{ik} = \begin{bmatrix} Do\ Nothing & 0.033i^2 - 2.688i + PCI_{in} \\ Overlay & (0.75)PCI_{in} \\ Deep\ Batching & (0.90)PCI_{in} \\ Reconstrcution & PCI_{in} \end{bmatrix} \tag{4}$$

$$NCI_i = \sum_{\mathrm{i=1}}^{\mathrm{n}} [\mathrm{W_k} * PCI_{ik}] \tag{5}$$

$$NCI = \overline{NCI_\iota} \tag{6}$$

where;

PCI_{ik} is the pavement condition index at year i for corridor k,

PCI_{in} is the initial pavement condition index,

NCI_i is network condition index at year i,

W_k is the weight for corridor k, and

NCI is network condition index at the end of the planning horizon.

For each intervention action scenario, cost and time are calculated based on Table 3 and the concept of time value of money. Thus, a financial model is developed to account for those costs and later link it into the optimization model. The same goes to intervention time. The mathematical formulation for the model is presented through equations 7 to 9.

$$RC_{ik} = [X_{ik} * RUC_x * L_k] \tag{7}$$

$$NRC_i = \sum_{k=1}^{s}[RC_{ik}] \tag{8}$$

$$NRC = \sum_{i=0}^{T}[NRC_i * (1 + in)^I] \tag{9}$$

where;

RC_{ik} is the rehabilitation/Recover cost of corridor k at year i,

X_{ik} is a binary decision variable with "0" representing the "Do nothing" option and "1" representing the "Rehabilitation/Recovery" action,

RUC_x is the recovery unit cost of decision variable X,

L_k is corridor length,

NRC_i is network recovery cost at year i,

NRC is the net present value of the cumulative network recovery costs over the study planning horizon T and in is the annual interest rate percentage.

Optimization Model

Optimization was used to mimic author's resilience definition. Where to satisfy definition's objective and constraints, optimization would work as a great tool to achieve that. Reaching the balance between recovery cost and asset resilience is a key asset management decision. The existence of numerous valid intervention scenarios increases the decision-making process complexity manifold. For instance, applying four decision variables for each link in each year then the possible combinations would be $4^{years*links}$ and problem space grows exponentially with increase in years and links. Furthermore, the need for placing additional constraint (i.e. annual budget limitation, minimal LOS and condition, etc.) escalates the problem's difficulty in terms of limiting the search space for valid solutions. Thus, there was a need for an optimization engine that undertakes trade-off analysis among various interventions scenarios and supports the decision-makers in selecting a near optimal intervention plan throughout the planning horizon. The optimization engine features through GA engine. GA is derived from biological systems, which simulate the natural survival of the fittest. Each string of chromosomes consists of genes, which represent a solution. Mutation and crossover operations are carried out through exchanging of genes where; new solutions are generated and evaluated to replace the weaker members in the population. The process continues until a satisfactory solution is met. Throughout this process, there are four key factors that impact the performance of the output: (1) number of generations; (2) population size; (3) mutation rate; and (4) crossover rate (Elbeltagi and Tantawy 2005 cited in Abu-Samra 2014).

Advanced spreadsheet modelling and Evolver™ Version 7.0 were utilized to develop the optimization model. It operates through a powerful optimization engine that is designed to meet the performance thresholds and limited monetary and temporal constraints. As highlighted earlier, the key motivation behind this study was developing an overall resilience index that incorporates the recovery cost, recovery time, redundancy, LOS, and condition. Thus, the objective of the optimization engine is mathematically formulated to minimize the International Roughness Index, IRI, (Maximize LOS) at the end of the planning horizon, as shown in Equation 10. With an aim to simplify the problem's complexity and minimize the search space, the decision variables are modelled in two-levels. The first level was formulated using binary coding rules; where "0" represents the "Do Nothing" option and "1" represents the existence of an intervention/recovery action. Given the fact that three intervention actions were considered in this study, to indicate the different maintenance actions that need to be undertaken in different condition states, a second level was formulated using a set of SMART rules that select the appropriate intervention action based on the condition and LOS application ranges defined earlier in Table 3. Thus, a "1" in the first level of decision variables might represent either "1" or "2" or "3" in the second level, which reflects the most appropriate intervention action, depending on the PCI application ranges. Finally, five constraints are set to ensure that the chosen intervention scenarios are valid. Alike the first level of decision variables, the constraints are modelled through binary coding rules; where "0" a represents meeting the constraint and "1" represents failing to meet not meeting the constraint. The five constraints are as follows: (1) annual recovery cost should not exceed the available annual budget, (2) annual recovery time should not exceed the total number of annual available resources, represented by working hours, (3) PCI of any section at any point of time throughout the planning horizon should meet the minimal condition threshold, (4) IRI of any section at any point of time throughout the planning horizon should meet the LOS threshold, and (5) number of annual interventions should not exceed 20% of the total number of sections in the network to avoid extreme service disruption. The mathematical formulations of the constraints are mathematically formulated as shown in Equations 10 through 15.

Minimize overall weighted average network IRI_i;

$$\frac{1}{s}\sum_{k=1}^{s}\sum_{i=1}^{T} \mathrm{W_k} * IRI_{ik} \tag{10}$$

Subject to the following constraints:

$$RC_i \leq \text{Annual budget} \tag{11}$$

$$RT_i \leq \text{Annual working hours} \tag{12}$$

$$PCI_i \geq PCI_{th} \tag{13}$$

$$IRI_i \leq IRI_{th} \tag{14}$$

$$\sum_{k=1}^{s} X_{i_k} \leq 20\% * \mathrm{s} \tag{15}$$

$$\textbf{Decision variables} = \begin{bmatrix} X_{i_k} & \cdots & X_{T_k} \\ \vdots & \ddots & \vdots \\ X_{i_s} & \cdots & X_{T_s} \end{bmatrix}$$

For I_{t_o} = 0, 1, … 10

t = 1, 2, … T

o = 1, 2, … O

where;

$\boldsymbol{RC_i}$ is the recovery cost at year i ($);

$\boldsymbol{RT_i}$ is the recovery time at year i (hrs);

$\boldsymbol{PCI_i}$ is the pavement condition index at year i (5);

$\boldsymbol{PCI_{th}}$ is the minimal acceptable pavement condition index (%);

$\boldsymbol{IRI_i}$ is the international roughness index at year i;

$\boldsymbol{IRI_{th}}$ is the international roughness index predefined threshold;

$\boldsymbol{X_{i_k}}$ is the intervention action for corridor k (i.e. "0" for "Do Nothing and "1" for "Intervention action").

k is the corridor counter

s is the total number of corridors

T is the planning horizon

CASE STUDY

The model was applied to a 3.75 KM residential road network located in Kelowna city, British Columbia province, Canada. The network data was collected from the open-source City of Kelowna GIS maps (City of Kelowna 2016). The network was divided into 20 corridors of flexible asphalt pavement for undertaking the study analysis. The condition rating and the IRI were estimated based on Canada infrastructure report 2016 to impersonate the same pavement conditions (FCM 2016). Table 4 displays the physical, spatial, and condition-related data of the 20 corridors under this study. As visualized in Table 4, the IRI fluctuated between good, acceptable and not acceptable according to FHWA values for measuring road quality; such that pavement LOS is considered good if its value is below 95 in/mile and considered acceptable if the its value falls between 95 to 171 in/mile (Arhin et al. 2015).

Optimization model was designed as indicated earlier to mimic author's resilience definition. Where to satisfy definition's objective and constraints, optimization would work as a great tool to achieve that. For ease of calculations at this stage of research, redundancy will be given different static values for each corridor. Nevertheless, redundancy value for each corridor is dynamic, where it varies according to the type of maintenance performed, the existence of new pavement corridors construction plans, and the severity of the predicted disruptive event on each corridor. The effect of the age and Freeze-Thaw on the asset deterioration was forecasted using the model presented earlier to predict the anticipated PCI and IRI of each corridor. The selection of the intervention actions was rule-based where; intervention actions rely on the corridor corresponding PCI as presented before in Table 3. Based on resilience definition proposed by the authors, LOS is the main threshold for undertaking an intervention, and accordingly, 50% and 171 in/mile values for PCI and IRI respectively were used as the unacceptable thresholds for each corridor. The interest rate was assumed at 2%. The optimization attributes could be summarized as follows: (1) crossover rate: 80%, mutation rate: 20%, stoppage criteria: time-based.

To combine network results for the condition, LOS, and redundancy, corridor length was used to compute the weight of each segment from the total network length. The corridor weight was determined based on the percentage of the length of the sections over the total network length. For instance, the length of corridor 1 is 143 m and the total network length is 3.75 KM. Thus, corridor 1 weight would be computed as the percentage of its length divided by the total network length, which results in a 3.82%, as illustrated in Equation 16. Accordingly, the annual condition, LOS, and redundancy state of the network could be computed as shown in the Equation 17. The condition, LOS, and redundancy of the network at the end of the planning horizon is equal to the condition, LOS, and redundancy of the last year. Yet, the recovery indicators (i.e. recovery cost and time) were summed up, as shown is Equation 18, to compute the annual costs and time to undertake the recovery actions, as they are represented in monetary and temporal terms respectively. The cumulative recovery cost and time is simply the summation of the recovery cost and time throughout the planning horizon.

$$W_k = \frac{L_k}{L_{net}} \tag{16}$$

$$\mathrm{Cond}_{Net_i} \text{ or } \mathrm{LOS}_{Net_i} \text{ or } \mathrm{Red.}_{Net_i} = \sum_{k=1}^{s} \frac{(L_k * Cond_{k_i} \text{ or } LOS_{k_i} \text{ or } Red._{k_i})}{L_{net}} \tag{17}$$

$$\mathrm{RC}_{Net_i} \text{ or } \mathrm{RT}_{Net_i} = \sum_{k=1}^{s} \mathrm{RC}_{k_i} \text{ or } \mathrm{RT}_{k_i} \tag{18}$$

where;

$\boldsymbol{W_k}$ is the weight of corridor k (%);

$\mathbf{L_k}$ represents the length of corridor k (m),

$\boldsymbol{L_{net}}$ is the total length of the sections within the network (m),

$\mathbf{Cond}_{\boldsymbol{Net_i}}$ is the condition of the network at year i (%);

$\mathbf{LOS}_{\boldsymbol{Net_i}}$ is the overall level of service of the network at year i;

$\mathbf{Red.}_{\boldsymbol{Net_i}}$ is the overall redundancy index of the network at year i (%);

k is the pavement sections counter;

s is the total number of sections;

$\mathbf{RC}_{\boldsymbol{Net_i}}$ is the recovery cost of the network at year i ($);

$\mathbf{RT}_{\boldsymbol{Net_i}}$ is the recovery time of the network at year i (hrs);

$\mathbf{RC}_{\boldsymbol{k_i}}$ is the recovery cost of corridor k at year i ($);

$\mathbf{RT}_{\boldsymbol{k_i}}$ is the recovery time of corridor k at year i (hrs).

RESULTS AND ANALYSIS

The proposed model was applied to the case study through two different scenarios; with and without taking intervention actions into consideration, to better understand the effect of the Freeze-Thaw on the pavement condition and performance. The indicators were assessed for each the corridor through the models explained earlier in the methodology section. A sample of a corridor, corridor 5, is demonstrated in Figure 1. As shown from Figure 1 LOS represented by the IRI is the main threshold that reflects the need of intervention to keep pavement corridors LOS within the acceptable range. In this corridor, four intervention actions were undertaken during the study planning horizon. All interventions were rehabilitation actions (Overlay and/or Deep-patching) where; one action was carried out after the first year from the starting point due to the deteriorated initial conditions of that corridor, and others action were planned on other different times from the starting point due to aging and Freeze-Thaw effect on the pavement deterioration. Nevertheless, assuming no intervention actions were undertaken to maintain the pavement corridor under the desired thresholds, the deterioration of the corridor in terms of LOS, and condition would be huge and various complications will arise accordingly. Moreover, the end users of that corridor will experience low service that will hinder not only residents of this area, but also other industries that might be using this corridor for transportation purposes. Furthermore, the failure likelihood of the corridor, in case of sudden collapse, would increase, leaving the asset managers with no intervention options but undertaking the costly corridor reconstruction option due to the severe state of both LOS and condition.

After applying the resilience assessment model on the network level, it was obvious that, without any intervention actions taken through the study planning horizon, the pavement network would suffer from severe deterioration in LOS and condition and would fall drastically below the acceptable thresholds. Nonetheless, the model demonstrated promising results in terms of maintaining the pavement's resilience state to avoid any major collapse due to any sudden event based on LOS and PCI thresholds. The overall weighted average IRI fell within the acceptable ranges, reaching 122.35 in/mile. Besides, the overall pavements condition was rated good with an overall weighted average PCI of 81.45%. Figure 2 displays the deterioration in PCI, and IRI under annual Freeze-Thaw cycles and aging taking intervention actions into consideration. Thus, the model is undertaking trade-off analysis between undertaking intervention actions to keep the network in an acceptable condition and LOS states, or saving money and time but deviating from the condition and LOS thresholds. In order to maintain an acceptable LOS for the corridors, NPV value of $306k was allocated to undertake the intervention actions throughout the 20 years life cycle. In addition, the intervention actions resulted in a total of 8.27k hours recovery time as highlighted in Figure 3.

The result of the optimized intervention plan of the resilience assessment model is shown in Table 5. It could be noticed that the reconstruction activities would be taking place early throughout the study planning horizon. This was anticipated due to the LOS and condition thresholds that were preset to satisfy the resilience definition conditions where; the PCI and IRI restrained the model from falling below their thresholds and thus forcing it to undertake early intervention actions. Moreover, as shown in Table 5, 57 minor rehabilitation actions and 9 major rehabilitation actions were planned throughout the planning horizon to maintain the pavement network resilience state. Nevertheless, incorporating more disruptive events on pavement network, would generate diverse intervention plans with different required budget to keep the network resilient enough against those disruptive events.

CONCLUSIONS

This paper tackles resilience from asset management perspective. Main resilience indicators were identified based on previous literature targeting infrastructure resilience assessment. Each indicator was defined and demonstrated to contribute and develop a resilience-based asset management model for pavements maintenance and rehabilitation. Deterioration model, due to freeze-thaw, for pavement condition and level service is manipulated from previous structural deterioration model. Financial and life-cycle models for recovery/intervention actions were introduced through computational models that account for the intervention costs and time and link them to the later used optimization model. Single objective optimization model that relies on a combination of meta-heuristic rules and genetic algorithms was utilized to formulate the mathematical denotation for the proposed resilience definition. This model is an initial step towards providing more resilient municipal infrastructures where; recovery plans should follow pro-active measures and incorporate resilience enhancement to adapt with any sudden or unforeseen events to some extent rather than just adapting a reactive approach, which deals with the sudden events after their occurrence. Moreover, this paper incorporates the aging effect into the computation of the resiliency, especially for pavement networks, which has recently grasped the attention of numerous researchers and practitioners. It also highlights the fact that an infrastructure should maintain its resiliency during its life cycle while maintaining a minimum acceptable LOS. This study is beneficial for asset management experts, where it develops an effective resilience-based asset management framework for pavements maintenance and rehabilitation.

The case study investigated and demonstrated the consequences of aging and Freeze-Thaw on pavement deterioration. Furthermore, the model results were promising in terms of maintaining pavement resiliency and selecting a near optimal intervention plan that meets the municipality limitations in terms of condition, LOS, and cost. The proposed pavement resilience assessment framework is beneficial for asset management experts where; intervention plans would not only be targeting enhancing or restoring pavement condition or LOS, but also incorporating the implementation of proper recovery strategies for both regular and/or extreme events into the intervention plan, while taking the regular deterioration and aging effects into account. Moreover, integrating both asset management and resilience concept is vital as infrastructure networks are suffering from aging and are vulnerable to many disruptive events, with limited budget available for undertaking the necessary intervention actions. Thus, a growing need is required to optimize the investment allocated to those assets, deliver the required LOS and avoid the long service cuts after the occurrence of any disruption.

Although, the framework showed great potential, further development to include other extreme disruptive events, ex. Flooding, through the study planning horizon is required. In later stage of research, other limitations shall be addressed include such as; introduce detailed intervention actions for pavement maintenance, rehabilitation and retrofit if required and link their usage criteria to the optimization model, consider redundancy as indicator for the available alternative routes for both emergency and regular users, present both pavement surface condition and structural condition with two different parameters to serve as an additional asset condition related indicator, ex. PCI and Pavement deflection, and apply the model with different budget constraints to reflect the viability of the proposed concept.

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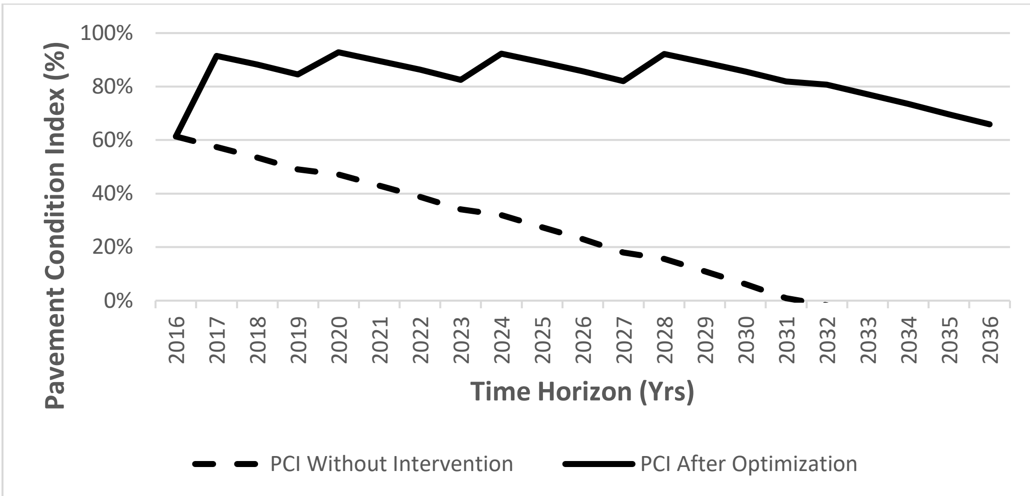

FIGURE 1 (a): *Optimized vs. without interventions for corridor 5 (Section-level)* - Pavement Condition Index

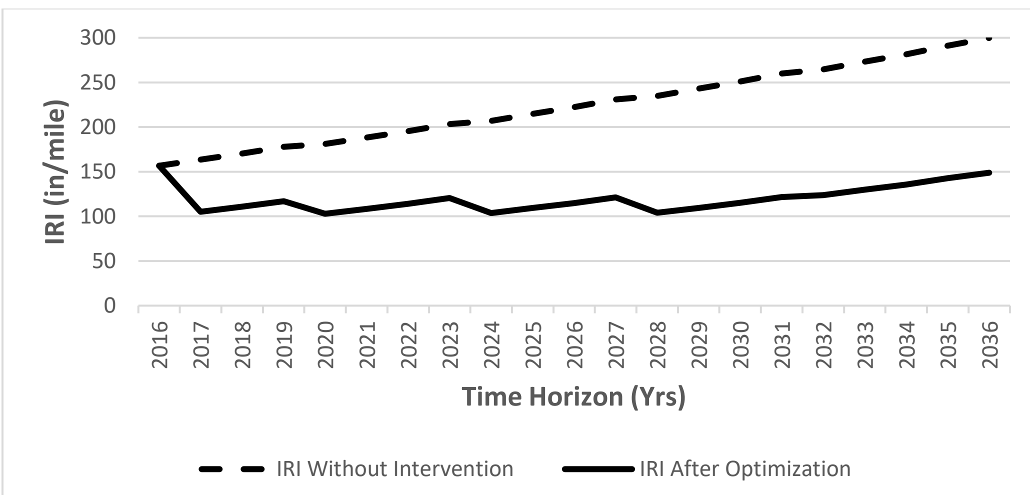

FIGURE 0 (b): *Optimized vs. without interventions for corridor 5 (Section-level)* - Level of Service

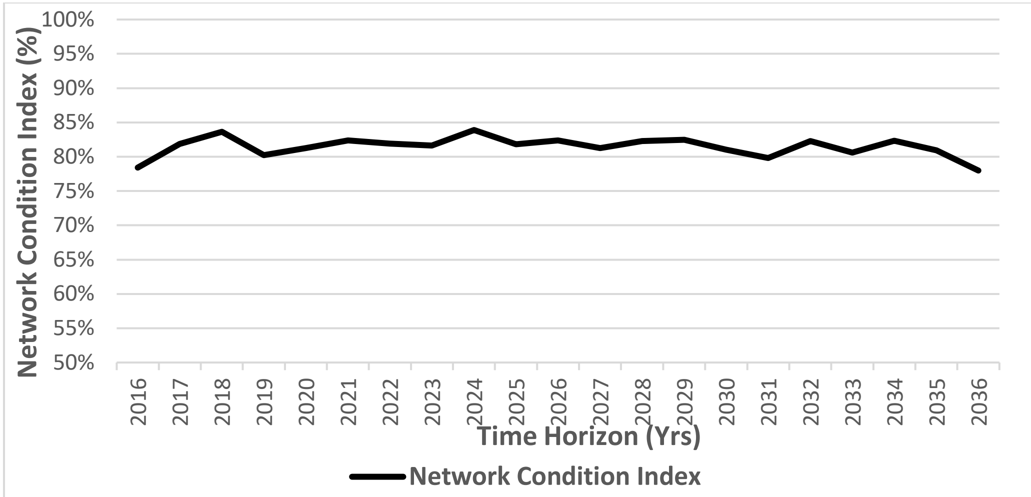

FIGURE 2 (a): *Pavement condition and LOS* under annual Freeze-Thaw cycles and aging *(Network Level-Optimized)* - Pavement Condition Index

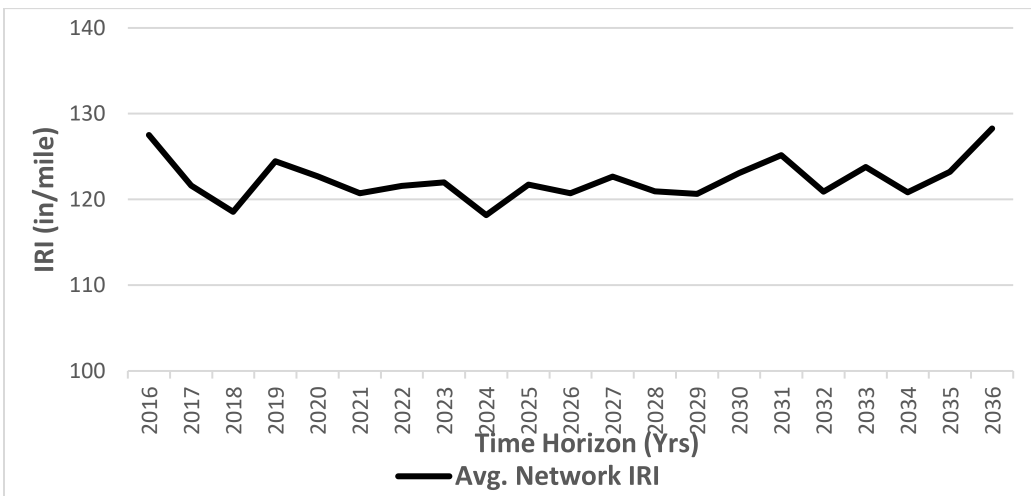

FIGURE 2 (b): *Pavement condition and LOS* under annual Freeze-Thaw cycles and aging *(Network Level-Optimized)* - Level of Service

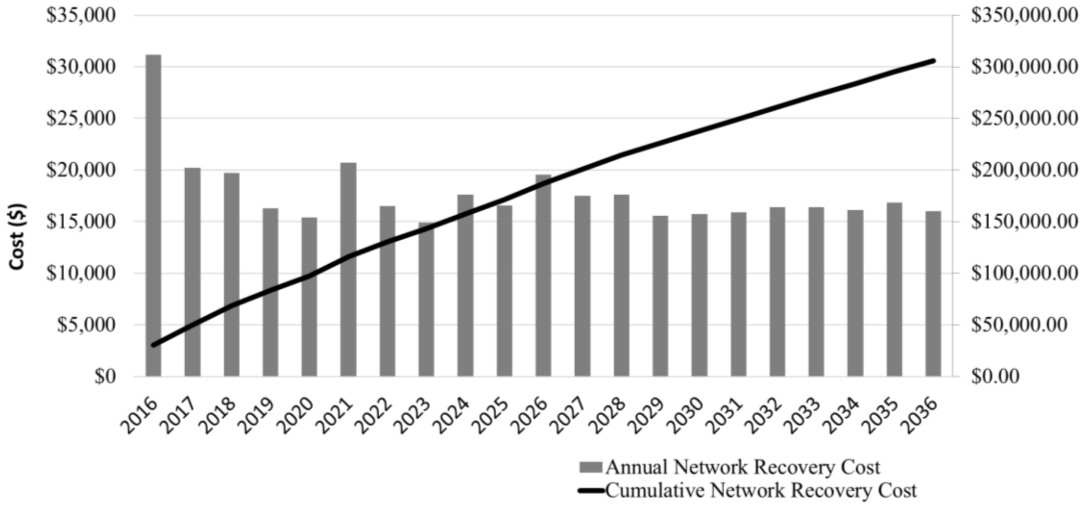

FIGURE 3 (a): *Network annual and cumulative recovery cost and time - Recovery cost*

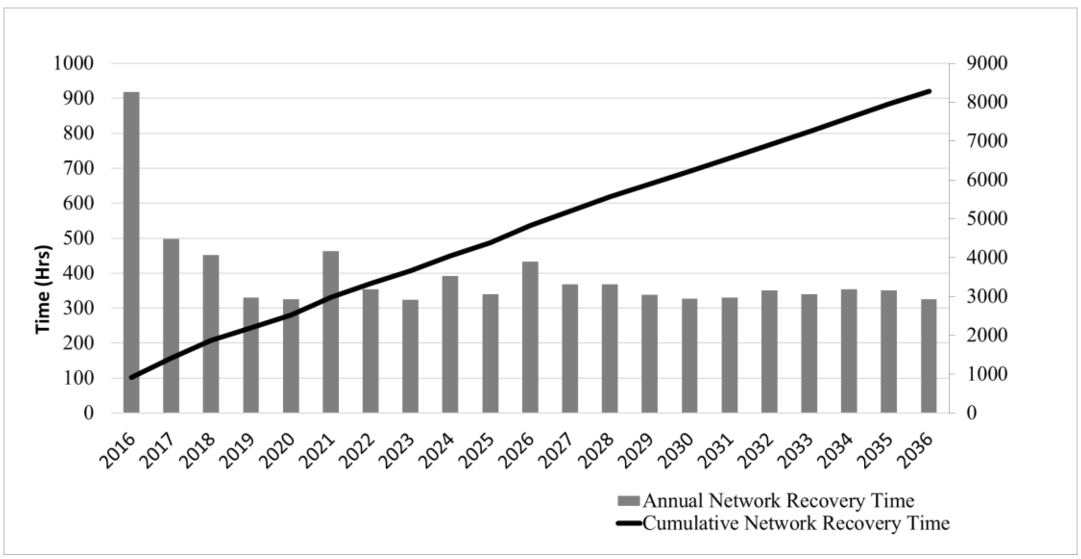

FIGURE 3 (b): *Network annual and cumulative recovery cost and time - Recovery time*

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Table 1: Modelling and analysis techniques for infrastructure resilience assessment

Modelling/Analysis technique	Publication	Field/Domain
Quantitative approach	(Vugrin et al. 2010; Baroud et al. 2015; Ip and Wang 2009; Alderson et al. 2015)	Power transmission grid; Transportation network; Inland Waterway Network
Simulation	(Gay and Sinha 2012; Turnquist and Vugrin 2013; Shah, S. S. and Babiceanu 2015; Cuppens et al. 2012; Cimellaro et al. 2014; O'Rourke 2007)	Urban Waste water network; Water distribution networks; gas/oil pipelines;
Interdependency analysis	(MacKenzie and Barker 2012; Baroud et al. 2015; Shah, S. S. and Babiceanu 2015; Reed et al. 2009)	Power transmission grid; Inland Waterway Network; Telecommunications system
Mathematical model	(Ouyang et al. 2012; Ouyang and Dueñas-Osorio 2012; Shah, S. S. and Babiceanu 2015; Ikpong and Bagchi 2014; Cimellaro et al. 2014; Ouyang and Wang 2015)	Power transmission grid; Bridges; gas/oil pipelines;
Structural analysis	(Bocchini et al. 2013; Reed et al. 2009)	Design bridge layout options; Telecommunications system
Decision making analysis	(Bocchini et al. 2013; Shah, J. et al. 2014; McDaniels et al. 2008; Creese et al. 2011; Brownjohn and Aktan 2013; Agarwal 2015; Lundberg and Johansson 2015)	Design bridge layout options; Hospital; Oil storage and transfer depot; Bridges, Transportation network
Life-cycle cost analysis	(Bocchini et al. 2013)	Design bridge layout options;
Risk analysis	(Pedicini et al. 2014; Creese et al. 2011; Timashev 2011; Agarwal 2015)	Urban Waste water utility management program; Oil storage and transfer depot; gas/oil pipelines
Non-probabilistic judgmental characterization	(Chang et al. 2014)	City resilience
Comparative analysis	(Knudson and District, PE Tualatin Valley Water 2013)	Community resilience
Optimization	(Piratla and Ariaratnam 2013; Alderson et al. 2015)	Power transmission grid; Water distribution networks;
Hydraulic power concept analysis	(Saldarriaga et al. 2008)	Water distribution networks
Vulnerability analysis	(Francis and Bekera 2014; Creese et al. 2011; Ikpong and Bagchi 2014)	Oil storage and transfer depot; Bridges
Statistical Process Control (SPC) methods	(Jung et al. 2013)	Water distribution networks
Media information/reports analysis	(Westerdahl 2014)	Nuclear reactor
Network theory model	(Lam and Tai 2012)	Transportation network;
Belief functions	(Attoh-Okine et al. 2009);	Transportation network;
Disaster resilience of ‘‘Loss-Response’’ of location model	(Zhou et al. 2010)	Agricultural drought

Table 2: Asset Management based resilience indicators

Category	*Indicator*	*Description*
Asset Based Indicators	Asset Condition	The current asset condition relative to its original one.
	Level of Service	"The defined service quality for an activity or service area against which service performance may be measured" (InfraGuide 2003).
	Redundancy existence	The capability of the system to substitute degraded system elements and maintain system functionality after disruption or loss of function (Gay and Sinha 2012).
Disruption Based Indicators	Type of Disruption	The nature and cause of disruption.
	Probability of failure	The chances that a certain asset will fail under a risk event.
	Consequences of failure	The negative impacts for a risk event.
Recovery Indicators	Recovery time constraints	The defined acceptable time for an infrastructure to recover to its original state after disruption.
	Recovery costs constraints (Resourcefulness)	The defined budget, including resources available, to achieve the recovery work after disruption.

Table 3: Intervention actions (Meneses and Ferreira 2015)

Maintenance action	**Notation in 2nd level decision variables**	**PCI application range**	**Impact on PCI (%)**	**Recovery Time (hr/unit)**	**Recovery Cost ($/unit)**
Routine Maintenance (i.e. Crack filling, sealing, etc.)	-	-	-	0.30	10
Rehabilitation (Overlay)	1	65% - 100%	75%	0.45	15
Rehabilitation (Deep Patching)	2	40% - 65%	90%	0.60	20
Reconstruction	3	0% - 40%	100%	1	30

Table 4: Case study network criteria per corridor

Corridor ID#	PCI (%)	IRI (in/mile)	Length (m)	Number of lanes	Section Area (m^2)	Average Annual Daily Traffic (AADT)	Number of surrounding roads
1	96%	97.47	143	3	1,287	12,000	2
2	73%	137.01	146	4	1,752	8,000	2
3	79%	127.13	151	4	1,812	10,000	1
4	79%	127.13	275	2	1,650	11,000	3
5	66%	148.10	184	3	1,656	7,000	2
6	66%	148.10	278	4	3,336	9,500	3
7	94%	100.99	294	4	3,528	10,500	3
8	88%	111.42	158	2	948	8,500	4
9	94%	100.99	168	4	2,016	6,800	1
10	84%	118.59	187	4	2,244	7,500	3
11	44%	185.90	228	3	2,052	9,000	4
12	52%	172.90	134	4	1,608	6,000	4
13	73%	137.01	113	4	1,356	5,000	3
14	88%	111.42	154	4	1,848	11,000	4
15	44%	185.90	258	2	1,548	10,000	2
16	73%	137.01	124	3	1,116	6,000	2
17	59%	160.17	293	2	1,758	9,000	2
18	44%	185.90	103	2	618	12,000	4
19	73%	137.01	119	2	714	9,000	1
20	52%	172.90	231	4	2,772	8,000	4

* Truck Percentage is 10%

*Traffic Growth Rate is 5%

* Lane Width is 3.00 m

* Average speed is 25 km/hr.

* Pavement corridors are located in residential area.

Table 5*:* Optimal Intervention Plans

Year	**Overlay**	**Deep Patching**	**Reconstruction**	**Number of Sections**
2016	-	Corridors 12,20	Corridors 11, 15, 18	5
2017	Corridors 2, 7, 13	Corridors 5, 17	-	5
2018	Corridors 3, 4	Corridor 6	-	3
2019	Corridor 1	-	-	1
2020	Corridors 5. 8, 20	-	-	3
2021	Corridors 10, 14	Corridors 16, 19	-	4
2022	Corridors 2, 4, 11, 18	-	-	4
2023	Corridors 6, 7, 17	-	-	3
2024	Corridors 1, 5, 15	Corridor 12	-	4
2025	Corridors 8, 13	-	-	2
2026	Corridors 3, 10, 14	Corridor 9	-	4
2027	Corridors 4, 18, 20	-	-	3
2028	Corridors 5, 11,19	-	-	3
2029	Corridors 1, 7, 9, 17	-	-	4
2030	Corridors 10, 13, 16	-	-	3
2031	Corridors 2, 6	-	-	2
2032	Corridors 1, 12, 15, 20	-	-	4
2033	Corridors 8, 16, 19	-	-	3
2034	Corridors 3, 4, 9, 14, 17	-	-	5
2035	Corridors 2, 11, 18	-	-	3
2036	Corridor 8	-	-	1
Number of Sections	57	9	3	69