Pavement Management with dynamic traffic and ANN: a case study of Montreal

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|                     | Amador-Jiménez, Luis; Concordia University, Building, Civil and Environmental Engineering |
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Pavement Management with dynamic traffic and ANN: a case study of

Montreal

Md. Shohel Reza Amin
Research Assistant, Dept. of Building, Civil and Environmental Engineering,
Concordia University, 1515 St. Catherine Ouest
Montreal, QC H3G1M8, Canada
Tel: +14389364119. Fax: +1-514-848-7965.
Email: md_amin@encs.concordia.ca
(Corresponding Author)

Luis E. Amador-Jiménez
Associate Professor, Dept. of Building, Civil and Environmental Engineering,
Concordia University, 1515 St. Catherine Ouest
Montreal, QC H3G1M8, Canada
Tel: +1-514-848-2424 (ext. 5783). Fax: +1-514-848-7965.
Email: luis.amador@concordia.ca

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Pavement Management with dynamic traffic and ANN: a case study of Montreal

Abstract
This study improves pavement management system developing a linear programming optimization for the road network of the city of Montreal with simulated traffic for a period of 50 years and deals with the uncertainty of pavement performance modeling. Travel demand models are applied to simulate annual average daily traffic (AADT) every 5 years. A Backpropagation Neural Network (BPN) with a Generalized Delta Rule (GDR) learning algorithm is applied to develop pavement performance models without uncertainties. Linear programming of lifecycle optimization is applied to develop maintenance and rehabilitation strategies to ensure the achievement of good levels of pavement condition subject to a given maintenance budget. The BPN network estimated that PCI values were predominantly determined by the differences in PCI, AADT and ESALs. Dynamic linear programming optimization estimated that CAD 150 million is the minimum annual budget to achieve most of the arterial and local roads in good condition in Montreal.

Keywords: Pavement management; traffic simulation; backpropagation neural network; performance modeling; uncertainties; linear programming; lifecycle optimization.

Introduction
The aging road network in Montreal City is at an advanced state of deterioration. Inappropriate maintenance, low priority on infrastructure maintenance, and inadequate funding are the main factors for this state of deterioration. Lack of comprehensive pavement management system
(PMS) and a long-term plan are responsible for observing an increase in the budget for the City of Montreal of more than 560% since 2001 (Amin and Amador-Jiménez 2014). The City needs a holistic model of PMS to predict the response and performance of its pavements under predicted dynamic traffic loads that optimizes the allocation of treatment operations.

Life-cycle cost analysis (LCCA) for PMS has been applied in a number of studies (Chan et al. 2008; Salem et al. 2003; Li and Madanu 2009). Chan et al. (2008) assessed LCCA practices in the Michigan Department of Transportation and analyzed its accuracy in projecting the actual costs and choosing the best alternatives for the treatments operations during the lifespan of the pavement. Salem et al. (2003) applied risk-based life-cycle cost model that reflects the time to failure of each treatment alternative and informs about the uncertainty levels that accompany the estimated life-cycle costs. Li and Madanu (2009) developed an uncertainty-based method for highway project-level LCCA to deal with computational uncertainty that inherited with input factors. Zhang et al. (2013) applied life-cycle optimization model to develop a new network-level pavement asset management system (PAMS) from historical values of pavement distress.

Traditional PMS tools such as PAVER and HDM3 are based on cost-benefit analysis that are incapable of trading-off decisions between asset types and modes of transportation (Moazami et al. 2011; Jain et al. 2005; Amin and Amador- Jiménez 2014; Humphries 2012). The linear programming and other optimization techniques for PMS are capable of finding the optimal solution of cost-effectiveness of maintenance and rehabilitation (M&R) operations and the benefits of advancing or deferring a certain treatment (Hudson et al. 1997).
The Arizona Department of Transportation (ADOT) has applied Markovian chain–based pavement management systems (PMS) to support its pavement design, construction, and preservation activities (Li et al. 2006). Several other researchers also applied Markov decision process (MDP) as a PMS tool (Abaza et al. 2004; Golabi and Pereira 2003; Gao and Zhang 2008). The MDP models optimize the M&R strategies based on the steady-state probabilities. In reality, the pavements under a given maintenance policy usually takes many years to reach the steady state and the proportion of the pavements are deteriorating or upgrading year-by-year (Amin and Amador-Jiménez 2014).

Prediction of pavement deterioration, a crucial part of PMS, is explicitly complicated since the pavement performance depends on a large number of dynamic and static attributes. Deterministic and stochastic models are applied to predict the pavement deterioration. Deterministic models are mechanistic, mechanistic-empirical and regression models (Archilla 2006; Yu et al. 2007; Santos and Ferreira 2013; Sathaye et al. 2010). Stochastic models apply Markov transition matrices that predict the ‘after’ condition of pavement knowing the ‘before’ condition (Ferreira et al. 2011; Ortiz-García et al. 2006; Kobayashi et al. 2010). Deterministic and stochastic models cannot properly address the uncertainties associated with data collection and computation. In addition, MDP models suffer from somewhat unrealistic assumptions of discrete transition time intervals and dependence of the future facility condition only on the current condition (Morcous 2002; Li et al. 2006). The MDP models lack the flexibility to consider the distinct conditions associated with individual pavement projects or sections (Li et al. 2006).
Ben-Akiva et al. (1993) developed the latent performance approach dealing with forecasting uncertainties during condition data collection. This latent model had computational limitations because number of outcomes, probabilities and computational effort to obtain M&R policies increase exponentially with the number of distresses being measured. Attoh-Okine (1999) proposed the Artificial Neural Network (ANN) for predicting the roughness progression in flexible pavements. However, some built-in functions of ANN such as learning rate and momentum term of ANN algorithm were not investigated properly. Several researchers also applied ANN as a tool of PMS (Shekharan 1999; Yang et al. 2006). These models have not yet overcome the functional limitations of neural network algorithms. This study accommodates the simulated traffic and addresses the model uncertainties of pavement performance function.

This study develops the linear programming of PMS for the road network of Montreal City that accommodates the simulated traffic during 50 years design period and deals with the uncertainty of the pavement performance modeling.

**Methodology**

This study has been executed in three main steps: first the simulation of traffic (volumes and truck loads), second the development of pavement performance models and third the optimization of long term budget allocation and scheduling of interventions (Figure 1).

![Flow chart of methodology](https://mc06.manuscriptcentral.com/cjce-pubs)

**Simulation of traffic**

Traffic volume, on each segment of the road network, has been simulated every five years for a period of 50 years (between 2009 and 2058) through a travel demand model. A discrete choice
model estimates the trip generations from different Traffic Analysis Zones (TAZs) using disaggregate household or individual level data. Trip generation is the function of gender, age, personal and household income, occupation, family size, auto ownership, number of children in the household, land use, and residential density. The model aggregates individual probabilities (of individual trip making decisions) to predict the total number of trips produced in the TAZs (Caliper 2005). The predicted trips are spatially distributed among TAZs by applying a doubly-constrained gravity model (Equation 1) (Mozalin et al. 2000).

A multinomial Logit (MNL) model is applied to estimate the choice of modes by commuters, assuming that the utility of an alternative is a function of the choice determinants, unknown parameters and an i.i.d Gumbel-distribution error term. Choice determinants are travel time and cost. Finally, a deterministic User Equilibrium (UE) model is applied to simulate the annual average daily traffic (AADT) on each road segment of the network. The deterministic UE method applies an iterative process to achieve a convergent solution so that no travelers can improve their travel times (or cost) by shifting routes (Prashker and Bekhor 2004).

**Pavement performance modeling**

This study applies a Backpropagation Neural Network (BPN) method with a Generalized Delta Rule (GDR) as a learning algorithm that minimizes uncertainty of pavements performance modeling. The GDR learning algorithm is applied to the neural network because the relationship is nonlinear and multidimensional (Freeman and Skapura 1991). The BPN network has two forms of activation functions chosen from either the hyperbolic tangent or the logistic function. This research uses the logistic function given that the output of the model (e.g. pavement condition) is
a positive value (Freeman and Skapura 1991) and the logistic function results in positive outputs in the unitary range (0, 1). Rather the hyperbolic tangent function in the range of (-1, 1). The errors, estimated from the difference between calculated and observed outputs, are transferred backward from the output layer in the ANN to each unit in the intermediate layer. Each unit in the intermediate layer receives only a portion of the total error based roughly on the relative contribution the unit made to the estimated output (Freeman and Skapura 1991). This process is repeated layer-by-layer until each node in the network has received a proportion of error that represents its relative contribution to the total error. The connection weights are updated based on the error received by each unit (Freeman and Skapura 1991).

Pavement performance curves are estimated for four categories of roads based on the road characteristics and the type of pavement: from now on arterial-flexible refers to an arterial road with asphalt concrete pavement, in a similar fashion a local-flexible, arterial-rigid and local-rigid refer to other combinations of either rigid or flexible pavements and road’s functional classification. A Pavement Condition Index (PCI) was used in this research, in practical applications it is advisable to replicate the work herein developed with independent indicators of damage such as cracking and rutting, that can be easily correlated to available interventions, such information was unfortunately not available.

For pavement deterioration, the input variables of the ANN for flexible pavements were: traffic volume in the form of AADT and equivalent single axle loads (ESALs), structural number (SN), pavement’s age (N) and difference of PCI between current and preceding year (ΔPCI = PCI2009 – PCI2010). The ΔPCI helps to track the application of treatment operations during the preceding...
year, and separate deterioration of intervened roads. Weather was constant across all road segments and hence ignored on the case study, however, climate must be included when dealing with roads traversing through various climate regions. The input variables for the rigid pavements were AADT, ESALs, slab thickness (T), N and ∆PCI. Since AADT and ESALs are log-linearly related to PCI, Log10 (AADT) and Log10 (ESALs) are taken as input variables of PCI.

Data on pavement condition, age, thickness and road characteristics was collected from the City of Montreal. From a total of 19826 segments in the network, the city counts with pavement condition for 6868 segments in the year 2009 and 10842 segment in 2010. The AADT was converted to 80-KN ESALs and only considers the total damage to the pavement caused by commercial vehicles. The ESALs were calculated based on simulated AADT and traffic mixture (number, type and distribution of commercial vehicles). Data on type and distribution of vehicles on the road network of Montreal City are adopted from the report prepared by the Cement Association of Canada (Cement Association of Canada 2012). The SN of the flexible pavements is calculated from the thickness of pavement layers and climate condition of Montreal City following the 1993 AASHTO Guide basic design equation.

**Linear programming of pavement management system (PMS)**

Lifecycle optimization to achieve and sustain acceptable mean network condition ($\bar{Q}$) at a minimum cost is used to find required levels of funding for Montreal road network (Equation 2 and 3). The maximization of total network condition under such a budget is then used to find optimal strategic results for pavement management (Equation 4 and 5). This formulation relied
on a decision tree containing all possible paths of pavement condition across time, after hypothetically receiving available treatments (Amin and Amador 2014). This tree is based upon a transfer function used to estimate condition ($Q_i$) as a convex combination based on the decision variable and the effectiveness or deterioration of the specific link on time $t$ (Equation 6).

The objective function is to minimize cost ($Z$) and maximize pavement condition of the road network $\left[ \sum_{t=1}^{T} \sum_{i=1}^{n} (L_i Q_{it}) \right]$. 

\[
\text{MINIMIZE} \quad Z = \sum_{t=1}^{T} \sum_{i=1}^{n} \sum_{j=1}^{a} C_{ij} X_{ij} L_i \quad (2)
\]

Subject to:
\[
\sum_{t=1}^{T} \sum_{i=1}^{n} L_i Q_{it} \geq \left( \overline{Q} \right) \sum_{i=1}^{n} L_i \quad (3)
\]

\[
\text{MAXIMIZE} \quad \sum_{t=1}^{T} \sum_{i=1}^{n} (L_i Q_{it}) \quad (4)
\]

Subject to:
\[
Z = \sum_{t=1}^{T} \sum_{i=1}^{n} \sum_{j=1}^{k} C_{ij} X_{ij} L_i \leq B_t \quad (5)
\]

$0 \leq Q_{t,i} \leq 100$ and $\sum_{j \in J_u} X_{ij} \leq 1$ \{for all times $t$ and for each asset $i$\}

\[
Q_{tij} = X_{tij} (Q_{(t-1)ij} + E_{ij}) + (1-X_{tij}) (Q_{(t-1)ij} + D_{ij}) \quad (6)
\]

Where $X_{tij}$ is 1 if treatment $j$ is applied on road segment $i$ at year $t$, zero otherwise; $Q_{it}$ is condition Index for road segment $i$ at year $t$; $Q_{tij}$ is condition Index of road segment $i$ at year $t$ for treatment $j$; $Q_{(t-1)ij}$ is condition Index of road segment $i$ at year $(t-1)$ for treatment $j$; $C_{ij}$ is cost ($\$$) of treatment $j$ at year $t$; $L_i$ is length of road (km) for road segment $i$; $E_{ij}$ is improvement (+) on road
segment \( i \) from treatment \( j \), \( D_{it} \) is deterioration (-) on road segment \( i \) at time \( t \), \( B_t \) is budget at year \( t \).

**Data Analysis**

**Travel demand modeling and simulation of traffic volumes and loads**

Traffic volume (AADT) is simulated for each road segment of Montreal road network at 5-years interval during the fifty years analysis period by applying four-step travel demand model. Figure 2 shows the projected average AADT for four types of road categories during the analysis period. It is estimated that the average traffic volume on arterial-flexible roads will increase from 8955 to 17069 during the period of 2009-2058 (Figure 2). The AADT will be increase to 4808, 11812 and 7684 on arterial-rigid, local-flexible and local-rigid roads during the same period, respectively (Figure 2). Travel demand model at urban level is validated with original data of the year 2008. Comparative evaluation of original and calibrated AADT shows that the overall AADT on the road network of Montreal will be increased by only a 1.68% when applying the travel demand model. In particular the model overestimates AADT for arterial-rigid and arterial-flexible roads: 9.05% and 7.88% more, respectively. Conversely, the model underestimates AADT for local-rigid and local-flexible roads: 5.13% and 4.40% less, respectively. The DUE model assign traffic on a road segment based on the performance function (travel time) that is the function of free-flow travel time, volume and capacity of road segment and calibration parameters. This is why; increment of AADT is observed on the arterial roads applying the travel demand model.
The compounding effect from the traffic growth rate (1.01% annual growth) was removed from predicted traffic in order to measure the accuracy of the model. The comparative analyses shown that simulated traffic increases from 7.88% to 26.23% when compared to the AADT levels calculated by the compound traffic growth rate on arterial-flexible roads during the period of 2009-2058. Figure 2 illustrates the other cases.

Figure 2: Simulated 50-percentile AADT for different road categories during the period of 2009-2058

Accumulated traffic loads in the form of Equivalent Single Axles Loads (ESALs) were calculated from predicted AADT and locally observed truck distributions combined with truck factors (FHWA 2011). The model estimated 39.38, 11.56, 27.35 and 17.71 million ESALs for arterial-flexible, arterial-rigid, local-flexible and local-rigid roads, for the period between 2009 and 2058 (Figure 3). During this period of 50 years, the simulated traffic explains otherwise non-accounted increases of 26.80%, 18.32%, 13.59% and 6.80% of additional traffic loads (ESALs) for the arterial-flexible, arterial-rigid, local-flexible and local-rigid roads (Figure 3). These unaccounted differences could result in faster damage and inadequate timing of road interventions.

Figure 3: Simulated 50-percentile ESALs (million) for different road categories during the period of 2009-2058

Backpropagation Neural Network (BPN) for modeling of pavement performance
A Multi-Layer Perceptron (MLP) network was used to minimize the prediction error. The MLP procedure computes the minimum and maximum values of the range and find the best number of hidden layers to distribute the error term (IBM 2010). The MLP estimates the number of hidden layers based on the minimum error in the testing data and the smallest Bayesian information criterion (BIC) in the training data (IBM 2010). The logistic activation function is used for the hidden layers so that the activation of the hidden unit is a Gaussian ‘bump’ as a function of input units (IBM 2010).

The BPN network estimates that PCI values for arterial-flexible roads are predominantly determined by $\Delta PCI$ and pavement’s age (Table 1). Other input variable such as $\log_{10}(AADT)$, $\log_{10}(ESALs)$ and SN have 13.8 percent, 12 percent and 1.5 percent contributions in determining the PCI value (Table 1). The $\Delta PCI$ also significantly influence the PCI values of arterial-rigid, local-flexible and local-rigid roads by 33.1 percent, 33 percent and 32.9 percent respectively (Table 1). However, pavement’s age does not significantly influence the PCI values of arterial-rigid, local-flexible and local-rigid roads (Table 1).

[Table 1]

The $\log_{10}(AADT)$ and $\log_{10}(ESALs)$ have considerable importance to estimate the PCI values in BPN models for arterial-rigid, local-flexible and local-rigid roads. For example, the $\log_{10}(AADT)$ has 23 percent importance to estimate PCI values of arterial-rigid with similar values for the other categories (Table 1). The $\log_{10}(ESALs)$ variable contributes 24.8 percent of PCI values for local-rigid roads (Table 1). The structural characteristics of pavement such as SN and
slab thickness of flexible and rigid pavements do not have significant influence in determining the PCI values respectively (Table 1). The reason is that the categorical values of thickness of pavement’s layers for broader categories of AADT are applied in this study both for flexible and rigid pavements from the report prepared by the Cement Association of Canada (2012). There is a strong potential that the BPN models might estimate the significant or considerable influences of SN and slab thickness on the PCI for flexible and rigid pavements respectively, if the actual data on thickness of pavement’s layers for each road segment can be accommodated into the BPN network.

The PCI value of each road segment is estimated based on the estimated relationship between the PCI values and input variables applying BPN, and simulated traffic applying travel demand modelling. The estimated PCI values are averaged for each road category for each period to determine the average PCI value of arterial flexible, arterial rigid, local flexible and local rigid roads. The average PCI values of the four road categories are plotted and fitted in the different curves in the Figure 4 to show how the performance curves of the four road categories look like during the 50 years analysis period. This study finds out that the polynomial and exponential curves better represent the pattern of PCI curves for the selected four road categories.

Figure 4: Pavement performance curves for different road categories during the period of 2009-2058

The original and estimated PCI values of Montreal road network for the year 2009 were compared to validate the accuracy of the estimated PCI values using BPN model. The
comparison shows that the BPN models estimate on an average 3.26% less PCI values compared to the original values. The lower estimation of PCI values is associated with the higher estimation of AADT (1.68%) predicted by the travel demand model. The BPN models estimate 3.23% and 4.48% lower PCI values comparing to the original PCI values for arterial-rigid and arterial-flexible roads since these categories of roads observe 9.05% and 7.88% increases of AADT, respectively. On the other hand, the BPN models estimate 3.74% and 1.61% lower PCI values comparing to the original PCI values for local-rigid and local-flexible roads since these roads observe 5.13% and 4.40% decreases of AADT, respectively. Both the original and estimated PCI values show that the overall structural quality of rigid pavements is poor comparing to flexible pavements in Montreal Island.

**Pavement treatment operations**

Table 2 presents the criteria employed to identify the type of intervention that is applicable to every segment at different points of time and following several possible paths (deteriorated or improved). The criteria includes cost, effectiveness and range of applicability, these criteria came from the Cement Association of Canada (2012). The timing of the intervention is modeled as a binary decision variable (Equations 2 and 3) and the overall optimization algorithm takes care of identifying the optimal set of interventions for the whole network during the analysis term (50 years in this case) within a complex structure with time dependencies that link the repercussions of decisions through time. The aggregation of individual annual interventions found at the solution return the minimum maintenance budget to achieve and sustain good pavement condition. The computational time to find a global maximum was 48 seconds. It was found that CAD 150 million is the minimum annual budget that ensures having good average roads
condition (Figure 5). This research qualitatively defined pavement condition in four categories such as excellent (PCI ≥80), good (80 > PCI ≥ 70), fair (70 > PCI ≥ 50) and poor (PCI<50). Figure 6 shows that pavement condition will rapidly deteriorate after 31st year of the analysis period under annual maintenance budget of CAD 125 million. Additional investment in maintenance budget on the top of CAD 150 million will not significantly improve the pavement condition rather the proportion of roads in good condition will be upgraded to excellent condition. Figure 7 shows that the overall pavement condition of Montreal road network will not be improved under the annual maintenance budget of CAD 175 million.

[Table 2]

Figure 5: Predicted conditions of roads after treatment operations under annual maintenance budget of CAD 150 million

Figure 6: Predicted conditions of roads after treatment operations under annual maintenance budget of CAD 125 million

Figure 7: Predicted conditions of roads after treatment operations under annual maintenance budget of CAD 175 million

The predicted annual budget of CAD 150 million will almost equally be distributed for the treatment operations of flexible and rigid pavements during first 20 years, but flexible pavements will require more maintenance budget during the period of 2029 -2045 (Figure 8). Considerably higher maintenance budget will be invested for treating rigid pavements after 36th design period (Figure 8). The majority of the maintenance budget for flexible pavements will be invested in
reconstruction (RC), resurfacing (RS), repair and overlay during the first 6 years of the analysis period. For the remaining of the analysis period, annual budget for flexible pavements will be invested in rout and sealing (CS) treatment (Figure 9). Similar pattern of budget distribution is found in treatment operations for rigid pavements (Figure 10).

Figure 8: Distribution of annual maintenance budget (CAD $150 million) among rigid and flexible pavements

Figure 9: Distribution of annual maintenance budget for different treatment operations of flexible pavements

Figure 10: Distribution of annual maintenance budget for different treatment operations of rigid pavements

It is worthwhile mentioning that the herein proposed model improves over the conventional PMS. Firstly, it bases performance on dynamic traffic. Traditional methods use deterioration curves that are based on the historical traffic (volume and growth). But traffic volume and distribution is related to land use, economy, employment opportunities, and travel behavior. This study predicts dynamic traffic volume and loads by applying travel demand modeling. Secondly, this proposed model deals with the uncertainties of developing pavement performance curves. Traditional deterministic and stochastic methods for predicting pavement deterioration are not only unable to address dynamic traffic loads, but also have drawbacks of model uncertainty, subjective evaluations of pavement condition and steady-state probabilities for transition of pavement condition from one state to another. This model helps the transportation authorities to manage continuous aggregate behavior of the transportation system, estimate more accurate pavement
deterioration and solve lifecycle optimization problems of pavement management at any time interval during the lifespan of pavement.

Conclusion

Traditional PMS methods are limited to a static traffic prediction and inaccurate deterioration models, erroneously biasing investment decisions of pavement interventions. This study develops a linear programming approach for PMS that accommodates simulated traffic during a long term analysis period. Even if dynamic traffic is considered, PMS models still do not address the uncertainty of the predictions. This research proposes a method to address uncertainty on pavement deterioration predictions. A case study of Montreal road network is used to illustrate the proposed method. Arterial roads of Montreal City, mostly constructed in 1950’s, were found at an advanced state of deterioration. Linear programming was applied to develop M&R strategies ensuring the good pavement condition of roads at a minimum maintenance budget. Lifecycle optimization of PMS estimated that CAD 150 million is the minimum annual budget to achieve most of arterial and local roads are at least in good condition in Montreal City. The developed model of PMS has two-fold improvement on the conventional methods of PMS. Firstly, this study predicts dynamic traffic volumes and loads during the fifty-year analysis period by applying travel demand models. Secondly, this model deals with the computational errors of developing the pavement performance curves. This proposed model will help the transportation authorities to manage continuous aggregate behavior of transportation system, estimate more accurate pavement deterioration and solve lifecycle optimization problems of pavement management at any time interval during the lifespan of pavement.
The fast rate of deterioration of Montreal roads is confirmed by the estimations from the model: even though overall vehicle traffic is expected to double within 50 years, truck traffic is expected to suffer a much faster increase; doubling the number of ESALs every 15 years, this is a direct result from economic activity and some traffic could be regional. A backpropagation Neural Network (BPN) of the type multilayer perceptron combined with a Generalized Delta Rule (GDR) was able to improve the estimation of future deterioration of pavements. Both rigid and flexible pavements deteriorated at a similar rate, no big differences were observed. A budget of at least CAN$150 million is required to sustain arterial and local roads of Montreal in good condition.

Roads in the island of Montreal need to undergo through a stabilization period for about 25 years, a steady state seems to be reached after that and only preventive maintenance treatments are applied after that. Future research should study more complex maintenance rules regarding the limited back-to-back application of certain interventions, per instance limiting the number of consecutive crack sealing before enforcing an overlay. Future research can study alternate methods for traffic prediction. Future research should use individual distress indicators of pavement damage instead of PCI.

References


Simulated Annual Average Daily Traffic (AADT)

Traffic Loads

Equivalent Single Axle loads (ESALs)

Pavement Performance Modeling (Backpropagation Neural Network)

Pavement management system

Travel demand modelling
- Trip generation – Discrete choice model
- Trip distribution - Doubly-constrained gravity model
- Mode choice - Multinomial Logit (MNL) model
- Traffic assignment – Deterministic User

Data Input
- Disaggregate household data on demographic and socio-economic characteristics of commuter
- Auto ownership
- Land use and residential density
- Total number of travelers in different income groups
- Travel time and cost

Data Input
- Predicted PCI
- Treatment operations
- Unit cost of treatment operations
- Length of road segments
- Annual maintenance budget

Linear programming of life-cycle optimization

Flexible pavement

Rigid pavement

Data Input
- Simulated AADT and ESALs
- Structural number (SN)
- Pavement’s age (N)
- Slab thickness (T)
- Difference of PCI between current and preceding year, ∆PCI

Data Input
- Simulated AADT
- Distribution of commercial vehicles
- Load Equivalency Factor (LEF)
- Directional split and lane distribution factor
- Number of Commercial Trucking Days per Year
- Design periods – 50 years

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<td></td>
<td>Flexible</td>
<td>Rigid</td>
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<td>ΔPCI</td>
<td>.364</td>
<td>.331</td>
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<td>Log₁₀(AADT)</td>
<td>.138</td>
<td>.230</td>
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<tr>
<td>Log₁₀(ESALs)</td>
<td>.120</td>
<td>.194</td>
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<tr>
<td>Pavement’s Age (N)</td>
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<tr>
<td>Structural Number (SN)</td>
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<td>.100</td>
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<tr>
<td>Slab Thickness (mm), T</td>
<td>.083</td>
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Table 2: Treatment and Operational Windows Used in Network-Level Trade-Off Analysis

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<thead>
<tr>
<th>Pavement Type</th>
<th>Treatments</th>
<th>Operational window</th>
<th>Unit cost (CAD$)</th>
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<tr>
<td></td>
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<td>AGE ≤ 5</td>
<td>Arterial</td>
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<tr>
<td>Rigid</td>
<td>Reseal joints, % length (m)</td>
<td>80 ≥ PCI (Arterial) ≥ 77; 80 ≥ PCI (Local) ≥ 73</td>
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<td>Partial depth PCC repair, % area, (sq. m.)</td>
<td>5 ≤ AGE ≤ 12; 76 ≥ PCI (Arterial) ≥ 68; 72 ≥ PCI (Local) ≥ 55</td>
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<td>Full depth PCC repair, % area, (sq. m.)</td>
<td>12 ≤ AGE ≤ 25; 67 ≥ PCI (Arterial) ≥ 56; 54 ≥ PCI (Local) ≥ 44</td>
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<td></td>
<td>Reconstruction - Arterial 200 mm PCC pavement, 25.4mm dowels (m²)</td>
<td>Base - MG 20, mm (t); Subbase - MG 112, mm (t)</td>
<td>AGE ≥ 26; PCI (Arterial) &lt; 55</td>
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<td></td>
<td>Reconstruction - Local 175 mm PCC pavement, no dowels (m²)</td>
<td>Base - MG 20, mm (t); Subbase - MG 112, mm (t)</td>
<td>AGE ≥ 26; PCI (Local) &lt; 43</td>
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<td>Rout and seal, m/km (m)</td>
<td>AGE ≤ 5; 80 ≥ PCI (Arterial) ≥ 76; 80 ≥ PCI (Local) ≥ 72</td>
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<td>Spot repairs, mill 40 mm/patch 40 mm, % area (sq. m.)</td>
<td>5 ≤ AGE ≤ 10; 74 ≥ PCI (Arterial) ≥ 69; 70 ≥ PCI (Local) ≥ 65</td>
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<td>Mill HMA, mm (t)</td>
<td>10 ≤ AGE ≤ 15; 68 ≥ PCI (Arterial) ≥ 64; 64 ≥ PCI (Local) ≥ 59</td>
<td>10.4</td>
</tr>
<tr>
<td></td>
<td>Resurface with ESG 10, mm (t)</td>
<td>15 ≤ AGE ≤ 25; 63 ≥ PCI (Arterial) ≥ 58; 58 ≥ PCI (Local) ≥ 46</td>
<td>135</td>
</tr>
<tr>
<td>Flexible</td>
<td>Reconstruction - Arterial HMA - ESG 10, mm (t) 70-28</td>
<td>Base - MG 20, mm (t); Subbase - MG 112, mm (t)</td>
<td>AGE ≥ 26; PCI (Arterial) &lt; 58</td>
</tr>
<tr>
<td></td>
<td>Reconstruction - Local HMA - ESG 10, mm (t) 64-28</td>
<td>Base - MG 20, mm (t); Subbase - MG 112, mm (t)</td>
<td>AGE ≥ 26; PCI (Local) &lt; 46</td>
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