Performance based Evaluation of overall Pavement Condition Indices for Ontario Highway Systems

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ABSTRACT
An effective PMS requires selection of efficient pavement key performance indices (KPIs) and precise prediction of actual pavement condition. A cost-effective PMS is possible only when maintenance requirements are identified at right time with the realistic prediction of overall pavement condition. Generally, KPI models are developed as the dependent variable are expressed as a function of independent variables. For Ontario highways, several KPIs are used in order for management decisions, such as such as Pavement Condition index (PCI), Distress Manifestation Index (DMI), International Roughness Index (IRI), Riding Comfort Index (RCI) etc. The prediction models are estimated by using ordinary least square (OLS) approach. Since these KPI models are highly correlated, estimation of these correlated models by using OLS approach might not be adequate. An approach is required which presents a joint method of estimating coefficients in generally encountered sets of regression equations. This study estimates these KPI models considering all available variables effecting pavement performance by using ‘Seemingly unrelated regression (SUR)’ method. Historical pavement performance data recorded by the Ministry of Transportation of Ontario (MTO) are used in this study. A total of sixty one road segments from Ontario’s major highway networks consisting of one hundred fifty one pavement treatment cycles are selected for empirical investigations. The KPI models are estimated and significance of the parameters are also tested statistically. After comparing these models, it is found that PCI model is highly correlated with DMI and RCI model. However, IRI model is not found highly correlated to other models.

Key Words: Key Performance Index (KPI), DMI, PCI, IRI, and RCI

1. INTRODUCTION

Transportation agencies obstinately grappling difficulties with prediction of overall pavement condition in a realistic way. They are spending billions of dollars on pavement infrastructure management every year. Sketching the realistic distress prediction are becoming progressively more complex. An effective PMS is possible only when maintenance requirements are identified at right time with the realistic evaluation of overall pavement condition. Although performance evaluation is an important part of PMS but they must be translated into precise KPIs that align with the overall mission and goals of agency (*1*). KPIs are used for predicting future needs and in analyzing the cost effectiveness of maintenance and rehabilitation (M&R) activities. Thus, precise evaluation of performance by using appropriate KPI will improve current practice of PMS. Appropriate KPI model ensures maximized pavement performance through the application of the right pavement treatment that is applied at the most appropriate time.

Since PMS analysis results and corresponding maintenance strategy vary greatly depending on the selected KPIs, these models are to be developed by analysing the significance of specific variables which affect performance of pavement. Development of comprehensive accurate models of KPIs to predict overall pavement condition from the specific distresses and crakings is a constant challenge in pavement engineering (*2*). So far transportation agencies and researchers conducted extensive work concerning modeling of pavement performance to facilitate system management. Generally, KPI models are developed as the dependent variable are expressed as a function of explanatory variables (*3*).

For highway systems in Ontario, several KPIs have been used over the past 30 years in order to obtain rational M&R decisions, such as such as PCI, DMI, IRI, RCI etc. (*4*, *5*). The MTO has a long history of using PMS and is currently using a second generation Pavement Management System which is known as PMS-2. For highway systems in Ontario, PCI is used generally as an overall index that incorporates density and severity of fifteen types of distresses, and the roughness. In Ontario, the PCI and DMI models are developed by using ordinary least squares (OLS) approach from the rating and weightage of selected fifteen categories of distresses that are classified by the MTO (*6*).

However, different performance measures are developed or effectiveness of practicing KPIs are investigated by using regression models in different ways. Since Ontario's prediction models of PCI, DMI, RCI and IRI are highly correlated, development of these correlated models by using OLS approach might not be adequate. An approach is required which presents a method of estimating coefficients in generally encountered sets of regression equations and more efficient than an equation-by-equation application of least-squares. For this reason, in this study 'Seemingly unrelated regression (SUR)' method is used to develop these models as function of explanatory variables.

2. BACKGROUND

In Ontario highway systems, KPI models are developed from the condition survey of road for selected specific distresses. These models are developed based on the weightage of these distresses which are mostly evaluated or rated in a subjective manner. The weightage are assigned to specific fifteen categories of distresses for different types highways by MTO (*6*). A number of recent researches are conducted to evaluate pavement performance models or performance management practices.

DMI model was evaluated by using automated distress evaluation data in Southern Ontario, Canada (*7*). The randomized block design (RBD) approach was used for hypothesis test in this study. Hypothesis test was performed to determine the differences in DMI model on the basis of automated evaluation data.

Use of joint estimation approach for the development of pavement performance models was found as in PMS (8). In this study, riding quality model was developed by joint estimation in terms of IRI from Minnesota Road Research Project (MnRoad) data. A nonlinear serviceability model was developed by using the same data set and the same variables as the equivalent existing linear model. The error of the new model was found as half of the existing model.

Effectiveness study of practicing performance indicators are found done by the New Zealand Transport Agency (NZTA) (*9*). In this study, a new measure 'rutting index (RI)' was developed with the goal that RI could effectively quantify the structural performance and behavior of a pavement. This RI was calculated for both network data and long term pavement performance (LTPP) data. However, this RI was developed based on OLS approach. Probabilistic duration modeling techniques were also found in investigating of performance measure during road design and construction (*10*). Weibull model by linear regression was also found in use in California's pavement management systems (*11*). In this study, the coefficients for the Weibull model were estimated from cracking versus age.

Zellner formulated the 'SUR' estimator that accounts for contemporaneous correlations and allows the dependent variables to have different sets of explanatory variables (*12,13*). This method uses a set of equations which are contemporaneously correlated and share a common error structure with non-zero covariance. The SUR method estimates the parameters of all equations simultaneously. In this process, the parameters of each single equation take the information provided by the other equations into account. On the other hand, calculating separate standard OLS solutions ignores any correlation among the errors across equations. However, because the dependent variables are correlated and the design matrices may contain some of the same variables there may be "contemporaneous" correlation among the errors across the equations. Thus, SUR models are often applied when there may be several equations, which appear to be unrelated. In SUR models, the results contribute in higher efficiency for estimating of parameters than estimates in OLS. These efficiency becomes higher with higher correlation among the error terms of the different equations, as well as with larger sample size and higher multi-collinearity between the regressors (*14*). Moreover, this approach is used with the motivation to impose and/or test restrictions that involve parameters in different equations (*15*, *16*, *17,18*).

Recently, 'SUR' approach is applied to capture deterioration process of pavement performance. This study applied SUR approach to the simultaneous estimation of pavement performance deterioration models (*3*). The deterioration of two major indicators, international roughness index and rut depth were analyzed in this model system. The results showed improved performance characterization and more accurate forecasting.

SUR approach is also found to be used to predict the pavement performance over time for Indiana roads. In this study, using the forecasts and historical thresholds, the service life of the pavement is determined and random parameter duration models are estimated to identify influential factors affecting pavement service life (*19*).

Most of the agencies developed these KPI models by considering individual performance indicator separately and independently. In PMS, for developing KPI models, empirical regression has proved to be an effective way to characterize the relationship between the explanatory variables and dependent variable. Since these KPI models are co-related to each other, only one type of indicator does not sufficiently capture the performance of a pavement. Thus, joint estimation of KPI models will be more effective methodology than estimation by OLS.

Although recent researches have contributed significantly for developing the KPI models based on the factors affecting the performance, however these are not estimated jointly. Moreover, recently, application of 'SUR' is found where pavement deterioration over time are estimated jointly (*3*, *19*). This study will focus on the jointly estimation of major KPI models considering all available performance variables for Ontario highways.

3. SCOPE AND OBJECTIVE OF STUDY

The objective of this study is to estimate the KPI prediction models by using SUR method which is a joint method of estimating coefficients. This study will considerer all performance variables available in MTO PMS-2 database which effect pavement performance in Ontario highways.

Empirical investigations will be conducted for a total of sixty one road segments which consist of one hundred fifty one pavement treatment cycles from Ontario's network of major highways.

4. PAVEMENT PERFROMANCE DATA

The MTO has record of all historical performance information in their PMS since 1980. The MTO-PMS-2 database contains all historical performance records of freeways, collectors, and arterial and local roads consisting of more than 1,800 pavement sections under the MTO's zone (Southern, Northern and Central Ontario). The section length in PMS-2 varies from 50 m to over 50,000 m. All inventory and geometric information are also recorded in PMS. The severity and extent of all distresses and cracking are updated from the condition survey of road for specific distresses in every year. This distresses are mostly evaluated and rated in a subjective manner (*20*). The KPI models are developed form the weightage that are assigned by MTO to specific categories of distresses for different types of highways (*6*). The road sections also contain all information of respective M&R that are undertaken.

As discussed in previous section, several KPIs are used in Ontario highways with various purpose of pavement evaluation. Table 1 summarizes the description of condition indices used for Ontario highways. Although different KPIs are estimated, PCI is used generally as an overall index in pavement M&R decision trees. This M&R decision trees usually use a series of logical steps to apprehend the decision making process for selecting appropriate M&R treatments. Status of individual distresses and also other indices such as pavement roughness, and rut depth are also considered in these decision trees (*21*).

From the MTO-PMS-2 database, a total of sixty one road segments from Ontario's major highway networks are selected which have all yearly information on performance history including condition survey information. From these road segments, one hundred fifty one pavement treatment cycles are selected. The untreated pavement life starting just after one treatment to next treatment is considered as one pavement treatment cycle. These cycle length are found varying from three to fifteen years.

5. ESTIMATION OF KPI PREDICTION MODELS

Generally, PCI is used for M&R decision tree as an overall pavement condition index in Ontario highways. The DMI which is a component of the PCI, is also an important index. The PCI is composed of two sub-indices respectively representing RCI and DMI. In Ontario, the formula used to calculate PCI is defined as follows (*1*):

For Asphalt concrete (AC) Pavement,

$$PCI = Max(0, Min(100, 13.75 + 9 \times DMI - 7.5 \times IRI)) \quad \text{(1 a)}$$

For Composite Pavement,

$$PCI = Max(0, Min(100, 20.5 + 8.5 \times DMI - 11 \times IRI)) \quad \text{(1 b)}$$

The formula used to calculate DMI is pavement surface type related, as described in the following (*1*):

For AC Pavement,

$$DMI = 10 * (208 - \sum_{k}^{N} (S_k + D_k) \times W_k) / 208 \quad \text{(2 a)}$$

For Composite Pavement,

$$DMI = 10 * (196 - \sum_{k}^{N} (S_k + D_k) \times W_k) / 196 \quad \text{(2 b)}$$

Where, N is the number of distresses related to a given pavement type
Sk represents the severity rate of distress k

Dk represents the density rate of distress k
Wk is weighting factor of distress k

Since RCI is also a function of IRI, the PCI formula is also be expressed as:

For AC Pavement,

$$PCI = Max(0, Min(100, 13.75 + 9 \times DMI - 7.5 \times e^{(8.5 - RCI)/3.02})) \quad (3\text{ a})$$

For Composite Pavement,

$$PCI = Max(0, Min(100, 20.5 + 8.5 \times DMI - 11 \times e^{(8.49 - RCI)/2.44})) \quad (3\text{ b})$$

The formula used to calculate RCI is pavement surface type related, as described below:

For AC Pavement,

$$RCI = Max(0, Min(10, 8.5 - 3.02 \times \ln(IRI))) \quad (4\text{ a})$$

For Composite Pavement,

$$RCI = Max(0, Min(10, 8.49 - 2.44 \times \ln(IRI))) \quad (4\text{ b})$$

To compare these KPI models, all performance based variables are considered as independent variables. For OLS, standard multivariate regression requires that each of 'p' dependent variables has exactly the same design matrix such that (*12*,*22*):

$$y_{NXp} = \beta_{kxp}\, x_{NXk} + \varepsilon_{NXp} \quad (5)$$

Where, y is a matrix of p dependent variables, x is a k-dimensional design matrix, and ε is an error matrix, which is assumed to be distributed as N (Nxp) (0,Σ⊗IN). Multivariate regression theory using ordinary least squares (OLS) assumes that all of the coefficients in the model are unknown and to be estimated from the data as:

$$\hat{\beta} = (x'x)^{-1}\ (x'y) \quad (6)$$

The SUR model is a generalization of multivariate regression using a vectorized parameter model. The y matrix is vectorized by vertical concatenation, yv. The design matrix, D, is formed as a block diagonal with the jth design matrix, x_j, on the jth diagonal block of the matrix. The model is expressed as (*22*):

$$E[y_{\ (NXp)}] = \{x_{1\ (NXm1)}\ \beta_{1\ (m1X1)}\ , x_{2\ (NXm2)}\ \beta_{1\ (m2X1)}\ , x_{j\ (NXmj)}\ \beta_{1\ (mjX1)}\ \ , x_{p\ (NXmp)}\ \beta_{1\ (mpX1)}\};\quad (7)$$

where m_j is the number of parameters estimated (columns) by the j[th] design matrix, $x_{j..}$

To illustrate in matrix notation, the SUR model is expressed as:

$$\underset{(Np\,X1)}{E(\boldsymbol{y_v}) = \begin{bmatrix} \hat{\boldsymbol{y}}_1 & (NX1) \\ \hat{\boldsymbol{y}}_2 & (NX1) \\ \cdots & \cdots\cdots \\ \hat{\boldsymbol{y}}_j & (NX1) \\ \cdots & \\ \hat{\boldsymbol{y}}_p & (NX1) \end{bmatrix}} = \underset{(Np\,XM)}{\overset{\mathbf{D}}{\begin{bmatrix} \boldsymbol{x_1} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ (NX\,m_1) & \boldsymbol{x_2} & \mathbf{0} & \mathbf{0} \\ & & \mathbf{0} & \mathbf{0} \\ & (NX\,m_2) & \boldsymbol{x_j} & \mathbf{0} \\ & (sym) & & \boldsymbol{x_p} \\ & & (NX\,m_j) & (NX\,m_j) \end{bmatrix}}} \underset{(M\,X1)}{\overset{\mathbf{B}}{\begin{bmatrix} \boldsymbol{\beta_1} & (m1X1) \\ \boldsymbol{\beta}_{\boldsymbol{2}} & (m2X1) \\ \cdots & \\ \boldsymbol{\beta}_{\boldsymbol{j}} & (mjX1) \\ \cdots & \\ \boldsymbol{\beta}_{\boldsymbol{p}} & (mpX1) \end{bmatrix}}} \tag{8}$$

Where, M is the total number of parameters estimated over the p models, $M = \sum_{j=1}^{p} m_j$

To solve the parameter estimates:

$$\hat{B} = [\underset{[M\,X\,N_p]}{D'} \quad \underset{[N_p\,X\,N_p]}{Q^{-1}} \quad \underset{[N_p\,xM]}{D}]^{-1} \quad [\underset{[M\,X\,N_p]}{D'} \quad \underset{[N_p\,X\,N_p]}{Q^{-1}} \quad \underset{[N_p\,x1]}{y_v}] \tag{9}$$

This 'SUR' approach is used with the application of the generalized least squares (GLS) approach and the unknown residual covariance matrix will be estimated, parameters will be estimated from the data. MTO has classified the distresses into fifteen categories which are shown in Table 2. For each distress, severity and extent is rated by five categories which are shown in Table 3 and Table 4 (*20*).

In this study, all fifteen distresses are considered as variables in the prediction model of KPI. In database, some rating of distresses are found as '0', those values are scaled up to 1 and all the ratings are scaled up accordingly. It is noted that, existing DMI model incorporates only fifteen categories of distresses. However, other factors which might have significant effect such as rut depth value in mm (absolute rut depth is more precise for PCI and IRI model than rating of wheel track rutting listed as distress 4 in Table 2), cycle length or service life of pavement before any treatment or between two treatments, Annual Average Daily Traffic (AADT), percent of truck, strength of subgrade soil, etc.. These variables are incorporated in to KPIs model along with all fifteen distresses. Log is taken into the models so that 'elasticity' or 'marginal effect' (how the dependent variable changes when the independent variable changes by an additional unit holding all other variables in the equation constant i.e. partial derivative) can be estimated directly.

Following KPI models (taking log-log in both sides) are considered for analysis:

$$DMI = e^{\beta_0}\, e^{\beta_1 \ln(x_1)}\, e^{\beta_2 ln\,(x_2)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots e^{\beta_{36}\, ln(x_{36})} \quad (10)$$

$$\text{Or, } DMI = e^{\beta_0}\, e^{(x_1^{\beta_1})} e^{(x_2^{\beta_2})} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots e^{(x_{36}^{\beta_{36}})}$$

$$\text{RCI} = e^{\beta_0}\, e^{(x_1^{\beta_1})}\, e^{(x_2^{\beta_2})} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots e^{(x_{36}^{\beta_{36}})} \quad (11)$$

$$PCI = e^{\beta_0}\, e^{(x_1^{\beta_1})}\, e^{(x_2^{\beta_2})} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots e^{(x_{37}^{\beta_{37}})} \quad (12)$$

$$IRI = e^{\beta_0}\, e^{(x_1^{\beta_1})}\, e^{(x_2^{\beta_2})} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots e^{(x_{37}^{\beta_{37}})} \quad (13)$$

Where,

β_0, β_1, …β_{37} are regression coefficients;

x_1= Severity of Ravelling and Coarse Aggregate Loss; x_2= Extent of Ravelling and Coarse Aggregate Loss; x_3= Severity of Flushing; x_4= Extent of Flushing; x_5= Severity of Rippling and Shoving; x_6= Extent of Rippling and Shoving; x_7= Severity of Wheel Track Rutting; x_8= Extent of Wheel Track Rutting; x_9= Severity of Distortion; x_{10}= Extent of Distortion; x_{11}= Severity of Longitudinal Wheel Track: Single and Multiple; x_{12}= Extent of Longitudinal Wheel Track: Single and Multiple; x_{13}= Severity of Longitudinal Wheel Track: Alligator; ; x_{14}= Extent of Longitudinal Wheel Track: Alligator; x_{15}= Severity of Centreline: Single and Multiple Cracking; x_{16}= Extent of Centreline: Single and Multiple Cracking; x_{17}= Severity of Centreline: Alligator Cracking; x_{18}= Extent of Centreline: Alligator Cracking; x_{19}= Severity of Pavement Edge: Single and Multiple Cracking; x_{20}= Extent of Pavement Edge: Single and Multiple Cracking; x_{21}= Severity of Pavement Edge: Alligator Cracking; x_{22}= Extent of Pavement Edge: Alligator Cracking; x_{23}= Severity of Transverse: Half, Full and Multiple Cracking; x_{24}= Extent of Transverse: Half, Full and Multiple Cracking; x_{25}= Severity of Transverse: Alligator Cracking; x_{26}= Extent of Transverse: Alligator Cracking; x_{27}= Severity of Longitudinal Meandering and Midlane Cracking; x_{28}= Extent of Longitudinal Meandering and Midlane Cracking; x_{29}= Severity of Random Cracking; x_{30}= Extent of Random Cracking; x_{31}= Severity of shoulder cracking; x_{32}= Extent of shoulder Cracking; x_{33}=Pavement service life or cycle length between treatments; x_{34}=AADT, x_{35}= Percent Truck; x_{36}=Strength of Subgrade Soil in Mpa; x_{37}=Rut Depth in mm.

6. MODEL ESTIMATION AND RESULTS

In this study, the 'SUR' approach is used to estimate all parameters of all equation of KPIs simultaneously, whilst the correlations among all variables that affect pavement deterioration. Four multiple equations [equation no. 10,11, 12 and 13] are developed to simultaneously predict the pavement condition based on the pavement distress condition rating and other variables. Statistical analyses are carried out by using the software "SAS".

The significance of each multiple equations model is evaluated by the F value whether $\mathbf{F_{obs} > F_{critical\ for}}$ α =.025, p-1=35,36, n-p=122,123=1.48 . The fitting quality of single equations is evaluated by the coefficients of determination of estimation (R^2), standard errors of the estimate (SEE), and by the standard errors (SE) of the estimated parameters. The mean, standard deviations, minimum and maximum are shown in Table 5. ANOVA of KPI models are shown Table 6.

After estimating the "full" models by OLS and SUR, all explanatory variables that have a parameter with a marginal level of significance ($t_{obs} > t_{critical\ \mathbf{for\ 0.025,n\text{-}p=122,123}}$ =1.97) are considered as significant. Severity of shoulder cracking (x_{31}) and extent of shoulder cracking (x_{32})

are found insignificant for all models and revised estimate of parameters is shown in Table 7. Considering only significant variables, these models are further revised and SUR method is applied again. However, it is found with considering further significant variables, the model fitness is not improved and residual plots against variables show pattern, For these reason, 1^{st} revised models without shoulder cracking are selected as KPI models in this study. Covariance and correlation matrix of models is shown in Table 8 and Table 9 respectively.

It is found that all four models are significant since $F_{obs} > F_{critical.}$

From the correlation matrix, it is found that PCI model is highly correlated with DMI and RCI model. However, IRI model is not found highly correlated to other models.

Since the log model is providing the elasticity directly, it is found that for DMI model has high elasticity with severity of centreline alligator cracking, and severity of transverse of alligator cracking.

RCI model has high elasticity with severity of pavement edge alligator cracking, extent of pavement edge single and multiple cracking, extent of longitudinal wheel track alligator and severity of centreline single and multiple Cracking.

PCI model has high elasticity with severity of centreline alligator cracking, severity of pavement edge alligator cracking, extent of rippling and shoving, and extent of pavement edge single and multiple cracking.

IRI model has high elasticity with extent of flushing, severity of rippling and shoving, and extent of longitudinal wheel track alligator cracking.

7. CONCLUSIONS

In this study KPI prediction models are developed and compared considering all performance based variables effecting pavement performance by using ‘SUR’ approach. Ontario’s prediction models of PCI, DMI, RCI and IRI are highly correlated. For this reason, ‘SUR’ approach is used which estimates coefficients in generally encountered sets of regression equations in an efficient way than an equation-by-equation application of least-squares. Statistical analyses are carried out by using the software “SAS”.

These model incorporated not only fifteen categories of distresses but also other variables such as cycle length or service life of pavement before any treatment or between two treatments, Annual Average Daily Traffic (AADT), percent of truck, strength of subgrade soil, and rut depth value in mm.

Comparing the F_{obs} value ($F_{obs} > F_{critical}$) , all four models are found significant. However, two variables (severity of shoulder cracking and extent of shoulder cracking) are found insignificant.

DMI model has high elasticity with severity of centreline alligator cracking, and severity of transverse of alligator cracking. RCI model has high elasticity with severity of pavement edge alligator cracking, extent of pavement edge single and multiple cracking, and extent of longitudinal wheel track alligator and severity of centreline single and multiple cracking. PCI model has high elasticity with severity of centreline alligator cracking, severity of pavement edge alligator cracking, extent of rippling and shoving, and extent of pavement edge single and multiple cracking. IRI model has high elasticity with extent of flushing, severity of rippling and shoving, and extent of longitudinal wheel track alligator cracking.

PCI model is highly correlated with DMI and RCI model. However, IRI model is not found highly correlated to other models.

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LIST OF TABLES

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TABLE 1 Performance Measures and Indicators Used in Pavement Management in Ontario

Performance Measure	Performance Index	Remark
	Technical Measures	
Assessment of overall pavement condition, structural strength and functional serviceability of both network and individual pavement sections	Pavement Condition Index (PCI)	PCI is currently used by regions to generate an annual pavement maintenance program and investment planning strategies
Overall pavement surface condition for individual pavement sections and network	Distress Manifestation Index (DMI)	DMI is used to support PCI and is favoured by regions that have lower class roads
Evaluation of pavement riding quality in terms of roughness or smoothness	International Roughness Index (IRI)	Pavement roughness data is collected by use of high-speed inertial profilers
Evaluation of pavement riding quality in terms of user comfortableness	Riding Comfort Rating (RCR)	RCR was collected prior to IRI data
Pavement surface skid resistance	Skid Number	Measured at project level on a request basis
Transverse profiles and rutting measurement	Rut depth in mm measured in both left and right wheel paths	Rutting is measured at network level using high-speed equipment
Assessment of pavement structural strength or service life	Structural Adequacy Index (SAI) or deflection value measured by FWD equipment	Currently used at project level
	Economic measures	
Maintenance costs and service life Traffic accidents and costs Travel time, travel cost and travel time reliability, etc.	Highway agency cost Social and economic Impacts Road user costs	For inclusion in the PMS2 analysis function

TABLE 2 Distress categories for Ontario Highways

Distress of Flexible Pavement
1. Ravelling and Coarse Aggregate Loss
2. Flushing
3. Rippling and Shoving
4. Wheel Track Rutting
5. Distortion
6. Longitudinal Wheel Track: Single and Multiple
7. Longitudinal Wheel Track: Alligator
8. Centreline: Single and Multiple Cracking
9. Centreline: Alligator Cracking
10. Pavement Edge: Single and Multiple Cracking
11. Pavement Edge: Alligator Cracking
12. Transverse: Half, Full and Multiple Cracking
13. Transverse: Alligator Cracking
14. Longitudinal Meandering and Midlane Cracking
15. Random Cracking

TABLE 3 Condition Rating of Distress Density

Density/Extent	Condition Rating
Few: less than 10% of pavement surface affected	1
Intermittent: 10-20% of pavement surface affected	2
Frequent: 20-50% of pavement surface affected	3
Extensive: 50-80% of pavement surface affected	4
Throughout: 80-100% of pavement surface affected	5

TABLE 4 Condition Rating of Distress Severity

Severity	Condition Rating
Very Slight	1
Slight	2
Moderate	3
Severe	4
Very Severe	5

TABLE 5 Descriptive statistics of KPIs Model Variables

Variable	N	Mean	Std Dev	Minimum	Maximum
LnDMI	158	2.076139	0.105176	1.75	2.3
LnRCI	158	1.993861	0.120205	1.5	2.26
LnPCI	158	4.304114	0.131368	3.91	4.56
LnIRI	158	0.196203	1.02978	-6.91	1.26
LnSubStr	158	3.546956	0.220293	2.70805	3.912023
Ln x1	158	1.054917	0.425343	0	1.79176
Ln x2	158	1.273588	0.525734	0	1.79176
Ln x3	158	0.189473	0.436859	0	1.386294
Ln x4	158	0.149911	0.354742	0	1.609438
Ln x5	158	0.097675	0.310338	0	1.386294
Ln x6	158	0.111016	0.359232	0	1.609438
Ln x7	158	0.763611	0.524295	0	1.79176
Ln x8	158	1.05413	0.732591	0	1.79176
Ln x9	158	0.998459	0.441734	0	1.609438
Ln x10	158	0.946003	0.525625	0	1.79176
Ln x11	158	0.921228	0.515573	0	1.609438
Ln x12	158	0.916878	0.552559	0	1.79176
Ln x13	158	0.291227	0.535617	0	1.609438
Ln x14	158	0.195265	0.364997	0	1.386294
Ln x15	158	1.150056	0.425515	0	1.79176
Ln x16	158	1.286093	0.5162	0	1.79176
Ln x17	158	0.121023	0.359292	0	1.609438
Ln x18	158	0.10455	0.317155	0	1.609438
Ln x19	158	0.594668	0.621906	0	1.79176
Ln x20	158	0.518951	0.576583	0	1.79176
Ln x21	158	0.098192	0.349779	0	1.609438
Ln x22	158	0.060343	0.216657	0	1.098612
Ln x23	158	1.100514	0.366734	0	1.79176
Ln x24	158	1.255841	0.522897	0	1.79176
Ln x25	158	0.202304	0.429467	0	1.386294
Ln x26	158	0.159839	0.35088	0	1.386294
Ln x27	158	0.834792	0.53555	0	1.386294
Ln x28	158	0.783418	0.54517	0	1.79176
Ln x29	158	0.448563	0.54885	0	1.386294
Ln x30	158	0.458536	0.60521	0	1.79176
Ln x33	158	1.60827	0.561968	0.693147	2.70805
Ln x34	158	10.41515	0.778109	8.740817	12.02187
Ln x35	158	2.539968	0.668356	0.693147	4.018183
Ln x36	158	-0.19386	3.60433	-6.91	2.48

TABLE 6 ANOVA of KPIs SUR Models

	DMI Model					RCI Model					PCI Model					IRI Model				
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	34	1.4802	0.0435	20.87	<.0001	34	1.0854	0.0319	3.32	<.0001	35	2.2729	0.0649	18.15	<.0001	35	70.513	2.0146	2.56	<.0001
Error	123	0.2565	0.0020			123	1.1832	0.0096			122	0.4364	0.0036			122	95.977	0.7867		
Corrected Total	157	1.7367				157	2.2685				157	2.7094				157	166.49			

Root MSE	0.045	**R-Square**	0.85	**Root MSE**	0.098	**R-Square**	0.47	**Root MSE**	0.06	**R-Square**	0.84	**Root MSE**	0.886	**R-Square**	0.423
Dependent Mean	2.07	**Adj R-Sq**	0.81	**Dependent Mean**	1.993	**Adj R-Sq**	0.334	**Dependent Mean**	4.30	**Adj R-Sq**	0.79	**Dependent Mean**	0.196	**Adj R-Sq**	0.25
Coeff Var	2.2			**Coeff Var**	4.919			**Coeff Var**	1.38			**Coeff Var**	452.0		

TABLE 7 Parameter Estimates of SUR Models

	DMI SUR Model		RCI SUR Model		PCI SUR Model		IRI SUR Model	
Variable	**Parameter Estimate**	**Standard Error**	**Parameter Estimate**	**Standard Error**	**Parameter Estimate**	**Standard Error**	**Parameter Estimate**	**Standard Error**
βo	2.4701	0.114109	1.646431	0.245051	4.535518	0.149515	1.470538	2.247057
x1	-0.01217	0.014153	0.030985	0.030395	-0.00354	0.01854	-0.28116	0.276547
x2	-0.01786	0.010205	-0.02552	0.021915	-0.02586	0.013366	-0.0193	0.198849
x3	-0.01289	0.033492	-0.02319	0.071925	-0.00923	0.043864	-2.25963	0.651195
x4	-0.01848	0.042394	0.046437	0.091043	-0.01126	0.055522	2.420838	0.824006
x5	-0.0155	0.036938	0.018321	0.079325	-0.02016	0.048376	1.788376	0.717994
x6	0.025388	0.030436	0.016037	0.065363	0.040724	0.039863	-2.39868	0.592244
x7	-0.00392	0.012608	0.025008	0.027077	0.003584	0.016514	-0.10437	0.245447
x8	-0.04385	0.0094	0.00093	0.020187	-0.04237	0.012311	0.316994	0.18271
x9	0.008063	0.013956	-0.00659	0.029971	0.004829	0.0183	-0.09994	0.280302
x10	-0.05189	0.011854	-0.05453	0.025458	-0.07026	0.015532	0.288384	0.232956
x11	0.014766	0.017419	-0.04235	0.037407	-0.00617	0.022814	0.150141	0.338838
x12	-0.03424	0.01627	0.00236	0.03494	-0.02668	0.021307	-0.093	0.315974
x13	-0.04136	0.021196	-0.03079	0.04552	-0.05137	0.027767	-0.46708	0.414807
x14	0.003255	0.031552	0.054553	0.067759	0.023591	0.041337	0.792135	0.619087
x15	0.01119	0.01699	0.051359	0.036486	0.034321	0.022253	0.102133	0.331145
x16	-0.01223	0.012652	-0.00553	0.027171	-0.0178	0.016577	0.097972	0.249017
x17	0.05873	0.048923	-0.01705	0.105063	0.063269	0.06407	-0.64635	0.950134
x18	-0.10471	0.057733	-0.01682	0.123983	-0.13661	0.075609	0.727951	1.121247
x19	-0.0216	0.018649	-0.06743	0.04005	-0.04868	0.024426	0.608716	0.363408
x20	0.013055	0.018769	0.055606	0.040307	0.036243	0.024585	-0.1011	0.36647
x21	0.015266	0.055581	0.064067	0.119363	0.053282	0.0728	0.108837	1.083195
x22	-0.06161	0.091426	-0.11341	0.19634	-0.11697	0.11976	-1.09658	1.786478
x23	-0.00479	0.01732	-0.04202	0.037196	-0.0186	0.022689	-0.18006	0.338883
x24	-0.01333	0.011556	-0.0332	0.024818	-0.02337	0.015139	0.255992	0.226376
x25	0.026734	0.032203	-0.05646	0.069156	-0.00681	0.042181	0.610106	0.628599
x26	-0.07352	0.04292	-0.00054	0.092172	-0.06457	0.056212	-0.74823	0.834553
x27	-0.01378	0.019195	-0.03213	0.041221	-0.018	0.025138	-0.79039	0.372779
x28	-0.0089	0.018549	0.038659	0.039834	0.002544	0.024295	0.648841	0.361346
x29	-0.01002	0.020734	0.038128	0.044526	-0.01214	0.027154	-0.00311	0.40269
x30	-0.01421	0.018804	-0.0515	0.040383	-0.02206	0.024628	-0.20902	0.365613
x33	-0.00326	0.007693	-0.01216	0.016522	-0.00728	0.010075	-0.11527	0.149415
x34	-0.00469	0.007918	0.028895	0.017005	0.005083	0.010381	-0.11691	0.158231
x35	-0.00442	0.007292	0.032762	0.015661	0.008997	0.009558	0.04834	0.144831
x36	-0.0273	0.021142	0.032679	0.045403	-0.00612	0.027697	-0.1064	0.414164
x37					-0.00001	0.000304	0.060101	0.02376

TABLE 8 Covariance Matrix of KPI Models

Cross Model Covariance

	LnDMI	LnRCI	LnPCI	LnIRI
LnDMI	0.002086	0.000145	0.002026	-0.00338
LnRCI	0.000145	0.009619	0.00392	-0.01499
LnPCI	0.002026	0.00392	0.003577	-0.00974
LnIRI	-0.00338	-0.01499	-0.00974	0.786701

TABLE 9 Correlation Matrix of KPI Models

Cross Model Correlation

	LnDMI	LnRCI	LnPCI	LnIRI
LnDMI	1	0.03236	0.74154	-0.08335
LnRCI	0.03236	1	0.66825	-0.17235
LnPCI	0.74154	0.66825	1	-0.1836
LnIRI	-0.08335	-0.17235	-0.1836	1