# CROSS-VALIDATION OF MULTI-INPUT DETERIORATION PREDICTION MODEL (MID-PM) FOR NETWORK LEVEL PAVEMENT MANAGEMENT

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# CROSS-VALIDATION OF MULTI-INPUT DETERIORATION PREDICTION MODEL (MID-PM) FOR NETWORK LEVEL PAVEMENT MANAGEMENT

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## ABSTRACT

The development of an accurate deterioration prediction model for pavements is vital for effective pavement management in order to create a timely and accurate treatment intervention programme and thus reduce maintenance costs. A novel network level deterministic pavement deterioration model for flexible pavements, named Multi Input Deterioration Prediction Model (MID-PM), has been developed by evaluating the changes in pavement condition index (PCI). The proposed model utilises multiple input data such as distress (area and length of cracks), pavement age, traffic loading, maintenance effects, climatic effects and construction and material properties deposited in the Long-term Pavement Performance Database (LTTP) of the USA. This paper presents a validation study of the MID-PM model by comparing the results against other pavement deterioration models that have been developed in the past. In addition, the paper describes the process involved in the development of the model. The results show that the accuracy of empirical models for arterial roads is better than for collector roads in all climatic zones.

**Keywords**: Pavement deterioration prediction, pavement condition index (PCI), pavement management system, model validation.

### INTRODUCTION

An accurate pavement performance prediction model is necessary for pavement management at both project level and network level. Prediction of pavement performance at the network level is significant for adequate activity programming, plan prioritization and resource allocation. At the project level, it is necessary for finding the particular conservation actions that need to be taken, such as maintenance and rehabilitation (Prozzi and Madanat, 2004; Lytton, 1987). Therefore, numerous highway authorities have established a different pavement performance models for use in their pavement management systems. These performance models are essential and useful in forecasting at least one type of performance. Some of these models are simple and limited in their application while, others are comprehensive and suitable for a wide range of applications (Lytton, 1987 and Haas *et al*., 1994).

The pavement performance prediction models can be classified into two main groups: deterministic and probabilistic. The deterministic models forecast a particular number for a pavement life or its level of distress or other indicators of its condition; whereas, the probabilistic models expect a distribution of such events (Lytton, 1987, Haas *et al*., 1994).

The majority of deterministic prediction models were established based on linear or nonlinear statistical analysis. AI-Mansour et al. (1994) developed linear maintenance-effect models to estimate the changes in pavement roughness with different maintenance treatments. In addition, linear distress models were developed by Obaidat and Al-kheder (2005) to forecast pavement distress variables taking into account the effect of traffic, distance from maintenance unit, section area and pavement age. In addition, Kerali et al. (1996) developed a nonlinear regression model to predict rut depth by considering traffic loading, base materials and thickness. One of common deterministic models is the HDM-4 pavement deterioration model. Jain et al. (2005) calibrated this model to be used in local conditions in the India National Highway Network. Khraibani et al. (2012) developed a nonlinear model for explaining cracking behaviour with time and also to study the effects of several factors on this behaviour.

Fwa and Sinha (1986) found a linear relationship between present serviceability index-equivalent single axle-loads (PSI-ESAL) losses and unit maintenance expenditure. Ahmed et al. (2008) established a linear deterioration model to forecast pavement condition index (PCI) in Baghdad city by considering various distress variables. Ningyuan et al. (2001) presented a dynamic prediction model considering specific treatment effects to predict condition index for each treatment. Prozzi and Madanat (2004) developed a nonlinear deterioration model to estimate pavement serviceability by using experimental and field data of the American Association of State Highways Officials (AASHO) Road Test.

To deal with limited availability of historical data, the majority of probabilistic deterioration models were developed using the Markov chain technique for predicting distress quantity or overall performance index. Park et. al. (2008) developed a distress prediction model based on the Bayesian method for predicting the future pavement condition of discrete sections distresses such as longitudinal cracking. Amador-Jiménez and Mrawira (2012) introduced a more reliable framework for rut depth progression prediction by using the Bayesian method.

Alsherri and George (1988) established a simulation model for predicting the reliability-performance with age, and also the expected pavement life. Hong and Wang (2003) developed a deterioration model based on a nonhomogeneous continuous Markov chain to estimate pavement performance degradation. Moreover, Hong and Prozzi (2006) improved the AASHO deterioration model by using the Bayesian approach with Markov chain Monte Carlo simulation to determine serviceability loss. Amador-Jiménez and Mrawira (2009) suggested a methodology based on the Markov chain dealing with 2 years of historical data to estimate pavement conditions.

To address uncertainty and nonlinearity, various computational intelligence techniques have been employed to predict pavement deterioration. Kaur and Tekkedil (2000) created a rut depth prediction model based on fuzzy logic while Bandara and Gunaratne (2001) used a fuzzy Markov model to estimate future deterioration rates associated with each distress type. Furthermore, a fuzzy regression model was developed to predict pavement serviceability index (PSI) whereas, Bianchini and Bandini proposed a hybrid prediction model based on a Neuro-fuzzy technique to forecast the change in present serviceability index (ΔPSI)) (Chang et al., 2003; Pan et al., 2011; Bianchini and Bandini, 2010). Kargah-Ostadi et al. (2010) developed international roughness index (IRI) progression based on artificial neural networks

(ANN) while, Shahnazari et al. (2012) developed prediction models to forecast pavement condition index (PCI) based on artificial neural networks (ANN) and genetic programming (GP).

The majority of deterministic and probabilistic deterioration models at the network level were developed to forecast distress progression or to predict overall pavement condition but not considering all contributory factors to performance. Although, the computational intelligence techniques have the ability to deal with uncertainty and nonlinearity, there are limitations with using them in pavement deterioration models because of the need for huge data quantities. Therefore, deterministic performance prediction models at the network level were developed to estimate the pavement condition index (PCI) by considering distress quantity, age, traffic and maintenance. These models were created for four climatic zones and two functional road classes. The paper presents a comprehensive review of deterioration models based on analysis techniques and its objective is to validate these developed models by using statistical methods.

## LTTP DATABASE

The Long Term Pavement Performance (LTPP) database is the comprehensive pavement database which is developed as part of the Strategic Highway Research Programme (SHRP) in North America (USDoT, 2012). The LTPP database contains condition information collected from visual and/or automated pavement surveys for each pavement section. This information consists of the performance requirements e.g. ride quality, roughness, skidding resistance and texture; distress such as cracking, rutting, patching and edge deterioration; and structural conditions such as pavement life (USDoT, 2012).

In addition, the LTPP database is a study of the in-service pavement sections' behaviour under actual traffic loading. These pavement sections are classified into General Pavement Studies (GPS) and Specific Pavement Studies (SPS). GPS includes a study series of roughly 800 in-service pavement test sections in all regions of United States and Canada, whereas SPS are studies of specific pavement parameters involving new construction, repair and rehabilitation actions. The LTPP database is divided into different modules which are Inventory, Maintenance, Monitoring, Rehabilitation, Materials Testing, Traffic, and Climatic (USDoT, 2012). for developing the empirical models, the data of asphalt concrete pavement on a granular base (GPS-1) were employed.

## INPUT PARAMETERS

The main challenge facing the development of deterioration prediction models is the existence of different factors affecting pavement condition, which should be considered in model development. These factors are pavement age, traffic loading, climate effect, initial design and construction, and maintenance effect (Fwa, 2006, Al-Mansour et. al., 1994). The following input parameters are considered in developing the models.

## Pavement Age

After a period of time, the influence of asphalt pavement hardening increases the asphalt stiffness. This makes asphalt pavement more brittle and subject to cracking. The pavement deterioration resulting from adverse environmental effects and its interaction with traffic loads accelerates because of “ageing”. The pavement age is measured from the construction date or from the date of last rehabilitation (Fwa, 2006, Al-Mansour et. al., 1994).

## Traffic Load

The traffic volume has a great effect on pavement deterioration as well as the vehicle types having a harmful influence on deterioration especially heavy trucks. Furthermore, the number of repetitions of the same traffic load has the great effect on the pavement deterioration. Typically, the traffic effect on deterioration consists of volume, vehicle type, load repetition and axle load type. Therefore, the equivalent single axle load (ESAL), and then cumulative ESAL are traffic modules adopted to address vehicle and axle load type, all volume and numbers of repetition (Fwa, 2006, Al-Mansour et. al., 1994).

## Climatic Effect

The climate is a key contributor to pavement distress. The climatic effect is represented by precipitation quantities and freeze-thaw cycles. The behaviour of asphalt pavements in cold weather is different than in warmer weather. For example, during the spring, freeze-thaw can produce structural damage to the pavement. Structural damage decreases the carrying capacity of the pavement and subjects the pavement to more distress such as cracking (Fwa, 2006, Al-Mansour et. al., 1994).

## Pavement Design and Construction

A pavement section design and construction have significant influence on its performance. In general, pavement design consists of two main parts which are pavement type and asphalt layer thickness. In performance prediction analysis, all pavement sections should be the same pavement type, flexible pavement or rigid pavement. Road functional classification was employed to reflect the structural design variation (Al-Mansour et. al., 1994).

## Maintenance Effect

“Highway maintenance can broadly be defined as actions taken to retain all the highway elements in a safe and usable condition” (Fwa, 2006). The pavement performance is affected by treatment action type, level, and timing. Commonly, there are two types of maintenance which are preventive (periodic) maintenance to limit the deterioration rate and corrective maintenance to keep the pavement structure in serviceable state (Al-Mansour et. al., 1994, Haas, 1994). Occasionally, the maintenance actions are not sufficient to maintain the pavement especially when it has one or more distresses and maintenance cost is too high. Therefore, overlay or reconstruction of the pavement is the best way to restore or upgrade the pavement to an acceptable serviceability level (Fwa, 2006).

### Distress Quantity

"Distress is the physical deterioration of the pavement surface such as cracking, pothole and rutting, and it is generally but not necessarily visible" (Haas et. al., 1994). At the project level, pavement performance is expressed in terms of assessing individually the pavement distresses, whereas at the network level, it is essential to find a composite index of performance considering all distresses (Litzka, 2006).

## DEVELOPMENT MULTI INPUT DETERIORATION PREDICTION MODEL (MID-PM)

The deterministic models are commonly used to find the empirical (regression) relationship between the dependent variable which is distress progression or condition index and one or more explanatory variables such as cracking area, age and ESAL. Subjective indices such as ride quality, condition index, serviceability, etc. and objective indices (rutting, roughness, cracking, etc.) are utilised as dependent variables. These performance indices are related to one or more independent variables such as structural strength, traffic loading and climatic effects (Prozzi and Madanat, 2004). The simplest empirical model is linear regression analysis which is described as:

$$Y_i = \alpha + \beta X_i + \varepsilon_i$$

Where
*Y*= dependent variable,
*X*= independent variable,
*ε*= prediction error,
α, β= regression parameters.

Occasionally, nonlinear regression analysis is necessary when the empirical relationship is not linear. In this case, a linear regression model may be underestimating or overestimating the condition during the pavement life (Shahin, 2005).

For developing empirical models, the collected condition data were separated into four groups representing climatic zones (wet freeze, wet non freeze, dry freeze and dry non freeze) to embed the climatic effect in prediction models. Then, each group was divided into two subgroups to consider road functional class (arterial and collector). The five independent variables: cracking area, length of crack, pavement age, ESAL, and maintenance effect (inlay or overlay thickness) were considered to create at network level empirical deterioration models for each subgroup. The following table 1 shows seven empirical deterioration models for each climatic zone and functional class. A detailed explanation of the development process can be found in an earlier paper associated with this research ( Mahmood et. al., 2014).

| Climatic Zone | Road class | Prediction model | $R^2$ |
|---|---|---|---|
| Wet Freeze | Arterial | $PCI = 97.744 - 0.15\ cracking\ area - 0.064\ cracking\ length - 0.515\ Age + 3.748\ rehabilitation\ thinkness$ | 0.69 |
| | Collector | $PCI = 100.257 - 3.45\ Age - 0.168\ cracking\ Area - 0.04\ cracking\ length + 0.814\ rehabilitation\ thinkness + 0.062\ Cum.ESAL$ | 0.88 |
| Wet non freeze | Arterial | $PCI = 93.546 - 0.175\ Age - 0.083\ cracking\ Area - 0.038\ cracking\ length + 1.073\ rehabilitation\ thinkness$ | 0.52 |
| | Collector | $PCI = 104.336 - 0.15\ cracking\ Area - 1.122\ Age - 0.194\ cracking\ length$ | 0.95 |
| Dry Freeze | Arterial | $PCI = 97.252 - 0.245\ cracking\ Area - 0.074\ cracking\ Length - 0.359\ Age$ | 0.61 |
| | Collector | $PCI = 94 - 0.628\ Age + 0.072\ cracking\ Area - 0.055\ cracking\ Length + 23.603\ rehabilitation\ thinkness - 0.013\ Cum.ESAL$ | 0.7 |
| Dry non freeze | Arterial Collector | $PCI = 98.861 - 0.407\ Age - 0.235\ cracking\ Area - 0.065\ cracking\ length + 3.404\ rehabilitation\ thinkness - 0.003\ Cum.ESAL$ | 0.79 |

Table 1: Empirical pavement performance prediction models for each subgroup

## CROSS VALIDATION

To validate these empirical deterioration models, the cross-validation technique was employed. This technique was used to assess how well these models can predict PCI or to assess the model accuracy across various data samples [Field, 2009]. Eighty per-cent of data samples for each subgroup were randomly selected to create empirical deterioration models by performing multiple linear-regression analysis using statistical software (SPSS). The remaining 20% of data samples for each subgroup were used to evaluate the accuracy of empirical models. To check the accuracy, the determination coefficient $R^2$ and mean squared error MSE were calculated by using 20% of samples for each model as shown in table 2.

It can be seen that, the loss in $R^2$ value and MSE value for arterial roads for four climatic zones is not significant with less than 20% of $R^2$ value and 35% of MSE value. This means that the deterioration models for arterial roads have a good accuracy to predict PCI. However, the loss in $R^2$ value and MSE value for collector roads is significant especially in dry freeze zone and wet freeze zone but insignificant in wet non freeze. Figure 1 (in Appendix A) shows errors and linear relation in each subgroup. This means that empirical models for both dry freeze zones and wet freeze zones do not have good levels of accuracy for collector roads.

Table 2: Validation results of empirical deterioration models for each subgroup

| Climatic Zone | Road class | Linear regression | | Cross-Validation | |
|---|---|---|---|---|---|
| | | $R^2$ | MSE | $R^2$ | MSE |
| Wet Freeze | Arterial | 0.69 | 205.9 | 0.59 | 252.2 |
| | Collector | 0.88 | 85.1 | 0.31 | 258.7 |
| Wet non freeze | Arterial | 0.52 | 181.5 | 0.45 | 178.5 |
| | Collector | 0.95 | 38.2 | 0.82 | 71.2 |
| Dry Freeze | Arterial | 0.61 | 182.1 | 0.74 | 134. |
| | Collector | 0.7 | 133.7 | 0.35 | 617.4 |
| Dry non freeze | Arterial | 0.79 | 86.6 | 0.64 | 136.2 |

## CONCLUSION

The cross validation of the network level Multi Input Deterioration Prediction Model (MID-PM) for flexible pavements in different climatic zones and road classes are evaluated in this paper. It was found that the deterioration models for the arterial road class in all climatic zones have very good accuracy to estimate future PCI Pavement Condition Index (PCI). The accuracy level for collector road class was relatively poor due to a shortage of historical condition data. It is possible to improve the accuracy of these models if adequate historical data are available.

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## Appendix A

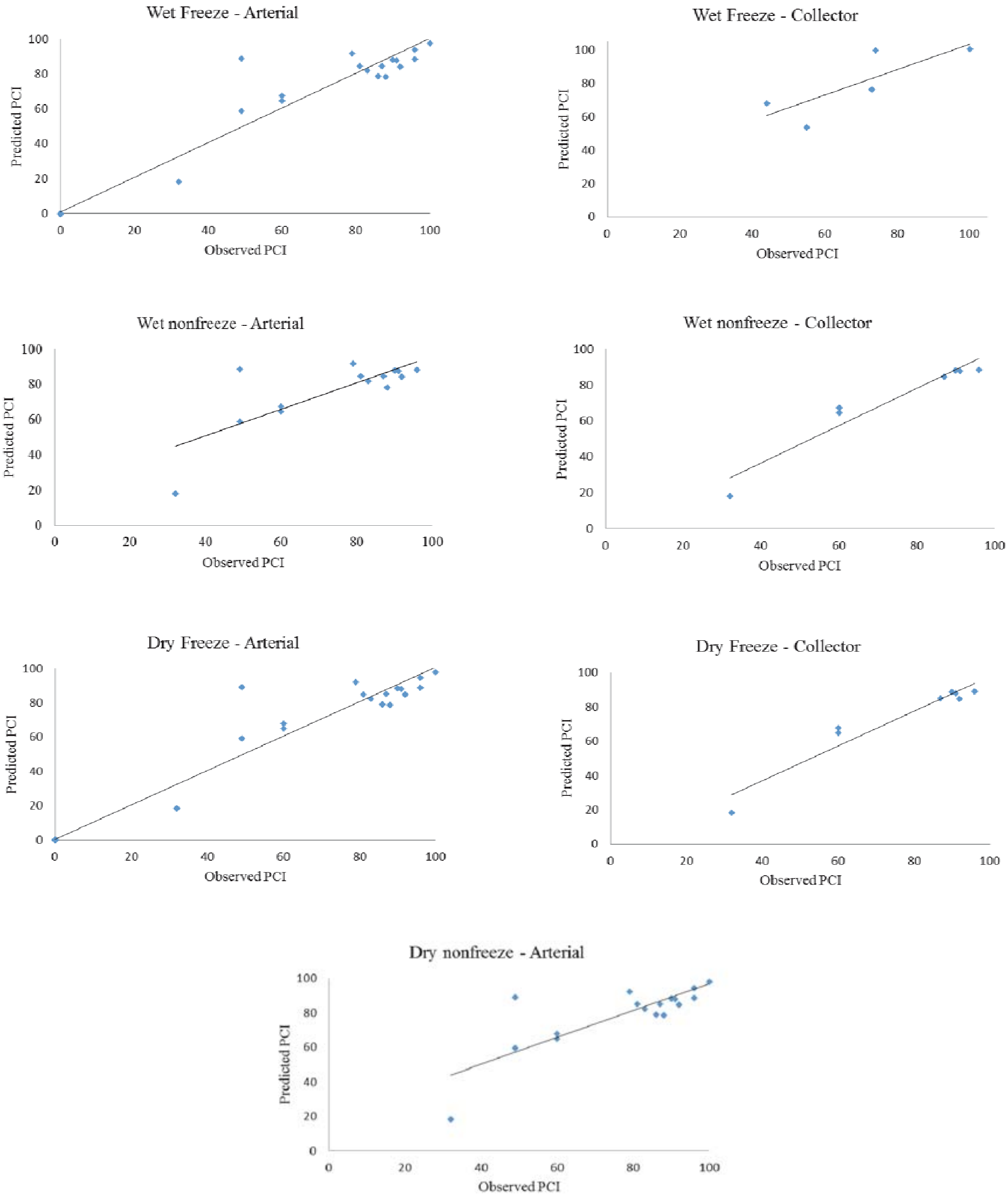


Figure 1: the accuracy of empirical deterioration model for each subgroup