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Empirical Markovian-based models for rehabilitated pavement performance used in a life cycle analysis approach

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ABSTRACT

Two empirical Markovian-based models are presented in this paper to predict the transition probabilities associated with rehabilitated pavement. The first model predicts the staged-homogenous transition probabilities as required by the staged-homogenous Markov model. The second model predicts the nonhomogenous transition probabilities as applicable to the non-homogenous Markov model. In both the models, the deterioration transition probabilities are predicted as a function of the corresponding values associated with original pavement and two adjustment factors reflecting the impacts of increased traffic load applications and decreased pavement strength. The predicted transition probabilities are used to estimate the future distress ratings required for developing the corresponding life cycle performance curve. The life cycle performance/cost ratio is used to evaluate the cost-effectiveness of potential longterm M&R plans. The life cycle performance is defined as the area falling under the life cycle curve. The life cycle cost is estimated to include initial construction cost, routine maintenance cost, major rehabilitation cost, and added user cost due to work zone. Two proposed cost models are used in the case study for estimating routine maintenance and added user costs. The case study indicates that the proposed empirical Markovian-based models have provided reasonable estimates of the transition probabilities as reflected by the corresponding life cycle performance curves.

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Markovian processes; pavement performance; performance prediction; life cycle analysis: pavement maintenance: pavement rehabilitation; pavement management

1. Introduction

Pavement management remains to be a focal point for many researchers seeking to find improved solutions to problems related to pavement maintenance and rehabilitation (M&R). Several models have recently been developed which typically deal with the pavement management problem at the network level using optimisation techniques to yield the best M&R plan (Bryce, Katicha, Flintsch, Sivaneswaran, & Santos, 2014; Cirilovic, Mladenovic, & Queiroz, 2015; Jorge & Ferreira, 2012; Mathew & Isaac, 2014; Saliminejad & Perrone, 2015). An effective pavement management model is required to incorporate a reliable performance model that can provide good estimates of the future pavement conditions, which is a key requirement for yielding a reliable long-term optimum M&R plan (Bektas, Smadi, & Al-Zoubi, 2014; Hong & Prozzi, 2015; Kargah-Ostadi & Stoffels, 2015). The optimum M&R plan at the network level generally results in identifying a number of projects to be implemented during a specified period of time. However, the detailed rehabilitation strategies and their optimal timings are typically dealt with at the project level using a different perspective, namely the life cycle analysis approach. Life cycle analysis is also part of pavement design analysis since the initial cost of pavement construction is a significant part of the life cycle cost.

Nevertheless, pavement performance prediction remains vital for yielding reliable pavement management solutions at both the project and network levels.

Pavement performance is essentially concerned with predicting the future pavement conditions using an appropriate condition indicator typically related to pavement service time. Several performance prediction models have been used in pavement management but the most commonly used ones are the stochastic-based models deploying different forms of the Markov model (Hong & Wang, 2003; Mandiartha, Duffield, Thompson, & Wigan, 2012; Meidani & Ghanem, 2015). This is because pavement performance has long been recognised to be probabilistic in nature implying that pavement future conditions cannot be determined with certainty. Recent applications of the Markov model have focused on estimating the pavement transition probabilities (i.e. deterioration rates) which are crucial for providing reliable estimates of the future pavement conditions (Abaza, 2016b; Kobayashi, Do, & Han, 2010; Lethanh & Adey, 2013; Ortiz-Garcia, Costello, & Snaith, 2006). Abaza (2015) proposed an empirical model to predict the deterioration transition probabilities associated with non-homogenous Markov chains using the present transition probabilities and two adjustment factors related to traffic loading and pavement strength. In another

study, Abaza (2016a) proposed a simplified linear approach to predict the deterioration transition probabilities associated with staged-homogenous Markov chains.

However, performance prediction of rehabilitated pavement was not adequately addressed in the literature but the focus was mainly on the performance prediction of original pavement. The performance of rehabilitated pavement is required if a long-term life cycle analysis is to be effectively performed for the purpose of yielding the best M&R plan. Recently, several life cycle analysis models have been developed focusing mainly on the life cycle cost analysis but not dealing with the long-term performance of rehabilitated pavement (Heravi & Esmaeeli, 2013; Pittenger, Gransberg, Zaman, & Riemer, 2012; Santos & Ferreira, 2013; Santos, Ferreira, & Flintsch, 2015). Therefore, the main contribution of this paper is the development of two empirical Markovian-based models to be used for predicting the deterioration transition probabilities associated with rehabilitated pavement. Another contribution of this paper is related to life cycle cost wherein potential cost models are proposed for estimating routine maintenance cost and added user cost due to work zone. In addition, a cost-effective life cycle analysis approach is proposed that takes into consideration both the pavement long-term life cycle performance and life cycle cost.

The predicted deterioration transition probabilities for rehabilitated pavement are then used to estimate the future pavement distress ratings required for developing the corresponding long-term life cycle performance curve at the project level. The area falling under the curve is typically used as a reliable measure of pavement performance (Abaza & Murad, 2009; Huang, 2004). Therefore, it is proposed to evaluate the cost-effectiveness of potential long-term M&R plans using the performance/cost (P/C) ratio with the life cycle performance (P) defined as the area falling under the life cycle performance curve. The life cycle cost (C) can include cost items such as initial construction cost, routine maintenance cost, major rehabilitation cost, and added user cost due to work zone. The most cost-effective M&R plan is the one associated with the highest (P/C) ratio.

2. Markovian-based performance prediction models: an overview

The discrete-time Markov model has been widely used in predicting the future performance of pavements. The discrete-time is typically represented by the number of transitions (i.e. time intervals) wherein each transition has a typical time length of 1 or 2 years. There are three typical forms of the discrete-time Markov model, namely the homogenous, staged-homogenous and non-homogenous models. The homogenous model is typically inaccurate as it assumes constant transition probabilities (i.e. pavement deterioration rates) over time. The other two models have been reported to provide similar results and are reviewed in this section (Abaza, 2015, 2016a).

2.1. Non-homogenous discrete-time Markov model

The main elements of the discrete-time Markov model are number of deployed pavement condition states (m), number of transitions (*n*) used in the analysis period, and transition probability matrix (P) comprised of the transition probabilities ($P_{i,j}$). The main objective of applying the discrete-time Markov model is to predict the state probabilities after a specified number of transitions as indicated by Equation (1). The state probabilities represent the pavement proportions that exist in the various deployed condition states at a specified future time. The transition probabilities denote the probabilities of pavements transiting from current state (i) to future state (j) in one transition (i.e. time interval). The discrete-time non-homogenous Markov model defined in Equation (1) can incorporate a distinct transition matrix, P(k), for each deployed transition.

The transition matrix is a squared matrix $(m \times m)$, where entries above main diagonal $(P_{i,j}; i < j)$ represent pavement deterioration rates, entries below main diagonal $(P_i; i > j)$ indicate pavement improvement rates, and entries along the main diagonal $(P_i; i = j)$ denote the probabilities of pavements remaining in the same condition state after one transition. Equation (1) yields the state probabilities after (n) transitions, $S^{(n)}$, provided that the initial state probabilities, $S^{(0)}$, and all transition probability matrices [P(k); k = 1,2, ..., n] are available over the analysis period. The state probabilities are represented by a row vector of size (*m*) with their sum adding to one. The initial state probabilities for new pavement (original or rehabilitated) can be assumed to take on the values of (1, 0, 0, ..., 0), which is a reasonable assumption provided the number of deployed condition states is sufficiently small.

$$S^{(n)} = S^{(0)} \left(\prod_{k=1}^{n} P(k) \right)$$
 (1)

 $S^{(n)} = (S_1^{(n)}, S_2^{(n)}, S_3^{(n)}, \dots, S_m^{(n)})$

$$S^{(0)} = \left(S_1^{(0)}, S_2^{(0)}, S_3^{(0)}, \dots, S_m^{(0)}\right)$$

$$\sum_{i=1}^{m} S_i^{(k)} = 1.0$$

Equation (2) provides a simplified form of the transition probability matrix in the absence of pavement M&R meaning that all entries below the main diagonal are assigned zero values. In addition, pavement deterioration is assumed to take place only in one step implying that pavements can either transit from condition state (i) to state (i + 1) or remain in the same current state (i) after the elapse of one transition. The validity of this assumption depends on the size of the transition matrix (m) and transition length. The larger the matrix size, the more valid becomes the assumption. However, the assumption is more valid if the transition length gets smaller. Abaza (2015, 2016a) reported that a transition matrix with 10 condition states and 1-year transition length were adequate to be used in predicting the future pavement performance. It is to be noted that the entry sum of any row in the transition matrix must add up to one:

$$P(k) = \begin{pmatrix} P(k)_{1,1} & P(k)_{1,2} & 0 & 0 & 0 & \dots & 0 \\ 0 & P(k)_{2,2} & P(k)_{2,3} & 0 & 0 & \dots & 0 \\ 0 & 0 & P(k)_{3,3} & P(k)_{3,4} & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \dots & P(k)_{m-1,m-1} & P(k)_{m-1,m} \\ 0 & 0 & 0 & 0 & \dots & P(k)_{m,m} \end{pmatrix}$$

$$(2)$$

$$P(k)_{i,i} + P(k)_{i,i+1} = 1.0, \quad P(k)_{m,m} = 1.0$$

$$0 \le P(k)_{i,i} \le 1.0, \quad 0 \le P(k)_{i,i+1} \le 1.0$$

The main disadvantage of the non-homogenous Markov model is that it requires the estimation of the transition probabilities for every transition in the analysis period. This in turns needs the availability of extensive historical records of pavement distress collected annually over the entire analysis period. Abaza (2015) proposed an empirical approach to predict the future non-homogenous transition probabilities for original pavement using mainly the present deterioration transition probabilities (k = 1), traffic load factor and pavement strength factor. Estimation of the present deterioration transition probabilities, $P(1)_{i,j,1}$, can be obtained from the state probabilities associated with two consecutive cycles of pavement distress assessment. Abaza (2016b) derived based on the transition matrix presented in Equation (2) the direct equations to back calculate the deterioration transition probabilities using mainly two consecutive sets of state probabilities.

2.2. Staged-homogenous discrete-time Markov model

The staged-homogenous Markov model applies a distinct transition probability matrix $(P_i^{(n_e)})$ for each staged-time period comprised of (n_s) transitions as presented in Equation (3). This requires dividing the analysis period (n) into a number of staged-time periods (s) each with equal length of (n) transitions. Therefore, the staged-homogenous Markov model requires a much reduced number of transition matrices compared to the non-homogenous Markov model. For example, only 4 staged-homogenous transition matrices are required compared to 20 non-homogenous transition matrices considering an analysis period of 20 transitions and 5-year staged-time period. The future deterioration transition probabilities, $P(j)_{i,i+1}$, can be linearly estimated from the present deterioration transition probabilities, $P(1)_{i,i+1}$, using the calibration constants (C_i) as indicated by Equation (3) (Abaza, 2016a). The calibration constants can be obtained from minimising the sum of squared errors (SSE) or based on experience and engineering judgement. Abaza (2016a) reported that five-year staged-time periods would be sufficient to provide reliable estimates of the future pavement performance:

$$S^{(n)} = S^{(0)} \left(\prod_{j=1}^{s} P_j^{(n_e)} \right)$$
 (3)

where $n = s \times n$

$$P(j)_{i,i+1} = C_i P(1)_{i,i+1} \le 1.0 \quad (i = 1, 2, ..., m - 1; j = 2, 3, ..., s)$$

$$P(j)_{i,i} = 1 - P(j)_{i,i+1}$$

$$C_1 \leq C_2 \leq C_3 \leq \ldots \leq C_s$$

 $C_1 = 1.0$, associated with the first staged-time period.

The future deterioration transition probabilities are expected to increase over time due to the increasingly higher traffic loading and decreasingly lower pavement structural capacity. Therefore, the calibration constants (C_i) are associated with increasingly higher values over time to reflect the impact of both increased traffic loading and reduced structural capacity. Abaza (2016a) provided estimates of the (C_i) constants which will be used in the sample presentation provided in this paper.

2.3. Prediction of pavement performance

The future performance of pavements can be predicted in terms of an appropriate pavement condition indicator such as the pavement condition index or pavement distress rating (DR) used in Equation (4). The distress rating associated with the kth transition, DR(k), at the project level can be estimated as the product sum of the state mean distress ratings (B_i) and the corresponding state probabilities, $S_i^{(k)}$. The state mean distress ratings are defined in Equation (4) using a Markov chain with 10 condition states and state DR ranges of 10 points based on a scale of 100 points. The higher the DR value, the better the pavement condition. Abaza (2016b) presented simplified models for estimating the observed DR(k) from distress assessment, and Equation (4) provides the corresponding predicted DR(k). Both observed and predicted DR(k) are needed for minimising the SSE as the error is defined to be the difference between the two DR(k) types:

$$DR(k) = \sum_{i=1}^{m} B_i S_i^{(k)} \quad (k = 0, 1, 2, ..., n)$$
(4)

where
$$S^{(k)} = \begin{cases} S_1^{(k)}, & 90 < DR \le 100, & B_1 = 95 \\ S_2^{(k)}, & 80 < DR \le 90, & B_2 = 85 \\ S_3^{(k)}, & 70 < DR \le 80, & B_3 = 75 \\ \vdots & & \vdots & \vdots \\ S_{10}^{(k)}, & 0 \le DR \le 10, & B_{10} = 5 \end{cases}$$

The future state probabilities, $S_i^{(k)}$, are the main parameters needed to predict the project distress ratings, DR(k), using Equation (4). The future state probabilities can be estimated from either the outlined non-homogenous or staged-homogenous Markov model. Both models will be used in the sample presentation provided in this paper for generating the life cycle performance curves associated with rehabilitated pavement.

3. Empirical models for rehabilitated pavement performance

The transition probabilities needed to predict the performance of rehabilitated pavement can be estimated using two distinct empirical Markov-based models. The first model predicts the staged-homogenous transition probabilities based on the corresponding values associated with original pavement. The staged-homogenous transition probabilities are assumed to remain constant over the corresponding staged-time period as indicated earlier. Similarly, the second model predicts the nonhomogenous transition probabilities wherein a distinct set of transition probabilities is estimated for each transition. Abaza (2015) used a similar empirical approach to predict the nonhomogenous transition probabilities for original pavement relying mainly on two major factors affecting pavement deterioration over time, namely the progressive increases in traffic load applications and progressive weakening of the pavement structure.

3.1. Empirical model for staged-homogenous transition probabilities

An empirical Markov-based model is proposed to predict the staged-homogenous deterioration transition probabilities, $PR(j)_{i,j+1}$, as presented in Equations (5a) and (5b). This model mainly applies the staged-homogenous deterioration transition probabilities of original pavements, $P(j)_{i,i+1}$, which are adjusted by two multiplication factors representing the impacts of increasing traffic loading and decreasing pavement structural capacity. The traffic factor is estimated as the ratio of the traffic load applications expected to travel on the rehabilitated pavement during the jth staged-time period (ΔWR_i) over the corresponding value of original pavement (ΔW). The traffic factor will typically be greater than one as traffic load applications are expected to increase over time, thus, resulting in higher deterioration transition probabilities. Similarly, the structural capacity factor is estimated as the ratio of the structural capacity of original pavement (*S*_i) at the start of the *j*th staged-time period over the corresponding value of rehabilitated pavement (SR₂). The structural capacity factor will be smaller than one if the structural capacity of rehabilitated pavement is larger than the corresponding value of original pavement, thus, resulting in lower deterioration transition probabilities. In essence, if it is required to maintain the same deterioration rates for both original and rehabilitated pavements, then it is required to provide rehabilitated pavement with higher structural capacity:

$$PR(j)_{i,i+1} = P(j)_{i,i+1} \left(\frac{\Delta WR_{j}}{\Delta W_{j}}\right)^{A} \left(\frac{S_{j}}{SR_{j}}\right)^{B} \quad (j = 1, 2, ..., N_{s}; N_{s} > 1)$$
(5a)

$$PR(j)_{i,i+1} = P(1)_{i,i+1} \left(\frac{\Delta WR_j}{\Delta W_1}\right)^A \left(\frac{S_1}{SR_j}\right)^B \quad (j = 1, 2, ..., N; \ N_s = 1)$$
(5b)

where
$$N_s = \Delta n/n_e$$

$$\Delta n = n_{j+1} - n_j$$

 N_s = number of staged-time periods within each rehabilitation cycle; Δn = service time period of each rehabilitation cycle in transitions; $n_{\rm s}$ = time length of each staged-time period in transitions; n_i = rehabilitation time of the jth rehabilitation cycle in transitions; N = number of rehabilitation cycles over an analysis period comprised of (n) transitions; $PR(j)_{i,j+1} = deteriora$ tion transition probabilities associated with the *j*th staged-time period for rehabilitated pavement; $P(j)_{i,j+1}$ = deterioration transition probabilities associated with the *j*th staged-time period for original pavement; S_i = structural capacity of original pavement at the beginning of the *j*th staged-time period; SR_i = structural capacity of rehabilitated pavement at the beginning of the jth staged-time period; $\Delta W_i = 18k$ (80kN) equivalent single load applications expected to take place over the original pavement during the jth staged-time period; $\Delta WR_i = 18k$ (80kN) equivalent single load applications expected to take place over the rehabilitated pavement during the jth staged-time period, and $P(1)_{i,i+1}$, ΔW_1 , S_1 = original pavement parameters associated with the 1st staged-time period.

Equation (5a) is to be used to predict the staged-homogenous deterioration transition probabilities for rehabilitated pavements when the number of staged-time periods (N_i) within each rehabilitation cycle is greater than one. The main assumption here is that the performance of rehabilitated pavement will be similar to that of original pavement considering the same staged-time period and provided that traffic loading and structural capacity are also similar. Equation (5b) is applied when each rehabilitation cycle consists of only one staged-time period ($N_c = 1$). In this special case, the corresponding transition probabilities are mainly dependent on the original pavement parameters associated with the first staged-time period. Figure 1 shows a typical pavement life cycle performance curve comprised of (N) rehabilitation cycles spanned over an analysis period of (n) transitions with (Δn) is the length of each rehabilitation cycle in transitions.

3.2. Empirical model for non-homogenous transition probabilities

The non-homogenous deterioration transition probabilities associated with the jth rehabilitation cycle can be estimated from the empirical model presented in Equation (6) using similar parameters as used in the empirical model defined in Equation (5). However, it is assumed that the original and rehabilitated pavements will have similar performances when considering the transitions (k) and $(n_i + k)$, respectively, as shown in Figure 1. Therefore, the deterioration transition probabilities associated with rehabilitated pavement for the $(n_i + k)$ th transition are estimated from the corresponding values associated with original pavement for the kth transition. The empirical model presented in Equation (6) will predict the non-homogenous transition probabilities for each rehabilitation cycle as a function of the non-homogenous transition probabilities associated with the original pavement in addition to the traffic load and structural capacity factors. The main difference compared to the model presented in Equation (5) is that the deterioration transition probabilities are individually estimated for each transition. The load factor is computed from the traffic load applications expected to take place during the transition under consideration. The pavement strength factor as represented by the structural capacity,

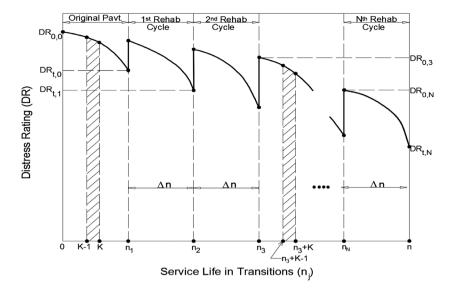


Figure 1. Typical pavement life cycle performance curve with (N) rehabilitation cycles.

S(k), can be estimated either based on experience and engineering judgement or from the outcome of non-destructive testing of the pavement structure. Abaza (2015) suggested using the structural number (SN) as a reliable indicator of the pavement structural capacity:

$$PR(n_{j} + k)_{i,i+1} = P(k)_{i,i+1} \left(\frac{\Delta WR(n_{j} + k)}{\Delta W(k)}\right)^{A} \left(\frac{S(k)}{SR(n_{j} + k)}\right)^{B}$$

$$(k = 1, 2, ..., \Delta n; j = 1, 2, ..., N)$$
(6)

where

$$\Delta WR(n_j + k) = WR(n_j + k) - WR(n_j + k - 1)$$

$$\Delta W(k) = W(k) - W(k-1)$$

 $PR(n_j + k)_{,i,i+1} =$ deterioration transition probabilities associated with the jth rehabilitation cycle for the $(n_j + k)$ th transition; $P(k)_{,i,i+1} =$ deterioration transition probabilities associated with the original pavement for the kth transition; $WR(n_j + k) =$ accumulated 18k (80kN) equivalent single axle load applications at the end of the $(n_j + k)$ th transition associated with the jth rehabilitation cycle; W(k) = accumulated 18k (80kN) equivalent single axle load applications at the end of the kth transition associated with original pavement; $SR(n_j + k) =$ structural capacity at the beginning of the $(n_j + k)$ th transition associated with the jth rehabilitation cycle, and S(k) = structural capacity of the original pavement at the beginning of the kth transition.

The accumulated traffic load applications, W(k), at the kth transition can be estimated from multiplying the first-year load applications (W_f) by the traffic growth factor, GF(k), as indicated by Equation (7) with (r) being the uniform annual traffic growth rate in decimal form. The deployed traffic growth factor is the one proposed by the Asphalt Institute (AI, 1999):

$$W(k) = W_f \times GF(k) = W_f \left[\frac{(1+r)^k - 1}{r} \right]$$
 (7)

The ratio associated with the traffic load factor can then be derived as presented in Equation (8). It is to be concluded that

this ratio is only dependent on the annual uniform traffic growth rate (r) and the rehabilitation time (n_j) associated with the jth rehabilitation cycle:

$$\frac{\Delta \mathrm{WR}(n_j+k)}{\Delta W(k)} = \frac{W_f \times \mathrm{GF}(n_j+k) - W_f \times \mathrm{GF}(n_j+k-1)}{W_f \times \mathrm{GF}(k) - W_f \times \mathrm{GF}(k-1)} = (1+r)^{n_j} \tag{8}$$

The model exponents (A & B) deployed in Equation (6) are not necessarily associated with the same values as of those exponents appearing in the empirical model defined in Equation (5). In both the models, reliable estimates of the exponents can be obtained from the calibration procedure provided that historical distress records are available for rehabilitated pavements. The calibration procedure can be performed by minimising the SSE wherein the error is defined as the difference between the predicted and observed distress ratings (Abaza, 2015). The predicted distress ratings are computed using Equation (4) which requires the future state probabilities to be estimated from the relevant Markov model. The models recommended in this paper for estimating the future state probabilities are the non-homogenous and stagedhomogenous Markov models as indicated by Equations (1) and (3), respectively. The deterioration transition probabilities associated with rehabilitated pavements as required by the stagedhomogenous and non-homogenous Markov models are to be predicted using Equations (5) and (6), respectively.

The two exponents (A & B) associated with the empirical models for rehabilitated pavement performance need to be estimated from calibration. The main calibration requirement is the availability of historical distress records for rehabilitated pavement. Abaza (2015) calibrated a similar model wherein the first-year transition probabilities were used to predict the non-homogenous transition probabilities for an original pavement project to be used in the case study presented later. The estimated values of the model exponents (A & B) were reported to be (1.4 & 1.2) for pavement performance with increasingly higher deterioration rates and (.7 & .4) for performance with decreasingly lower deterioration rates, respectively. These exponents were mainly developed for an original pavement structure

using distress records collected over a period of 17 years. The minimisation of SSE as outlined earlier was used to estimate the two exponents. This minimisation procedure was applied to calibrate the predictive empirical model for the original pavement project and led to the estimation of the model exponents. The calibrated model was then used to predict the distress ratings for the same pavement project and provided very close agreement between the observed and predicted distress ratings. The estimated two exponents can be used in the proposed empirical models to predict the transition probabilities for rehabilitated pavements provided they are related to the same pavement project and exhibit similar performance trends.

4. Life cycle cost

The life cycle costs associated with any pavement project typically include the initial construction cost (P_{IC}) , routine maintenance cost ($P_{\rm MC}$), major rehabilitation cost ($\tilde{P}_{\rm RC}$), and added vehicle operating cost due to work zone (P_{VOC}). Equation (9) indicates that the net present value of the life cycle cost (P_{1C}) is the sum of all these four costs in their present values. The initial construction cost is typically estimated based on local market prices for similar construction works. However, the other three cost items can be estimated as explained in the subsequent subsections:

$$P_{\rm LC} = P_{\rm IC} + P_{\rm MC} + P_{\rm RC} + P_{\rm VOC} \tag{9}$$

4.1. Routine maintenance cost

Routine maintenance is frequently applied to pavements to maintain safe operating conditions and provide good pavement appearance; however it doesn't add much to the pavement service life. It typically consists of crack sealing, pothole patching and localised surface treatments. The cost of routine maintenance greatly depends on the extent and severity of pavement distresses. Figure 2 provides an exponential model that relates annual routine maintenance cost to pavement distress rating with the corresponding exponential model presented in Equation (10). The data points used in developing this model are estimated to reflect local market prices. This model can be used to estimate the annual routine maintenance cost, $A_{MC}(k)$, as a function of the pavement distress rating at the kth transition, DR(k), to be obtained from the corresponding life cycle performance curve:

$$A_{\rm MC}(k) = 8.264e^{-0.034{\rm DR}(k)} \tag{10}$$

According to Equation (10), the routine maintenance cost is estimated as an annual amount using the unit of U.S. dollars per square metre of pavement surface (\$/m²). However, Equation (10) has been developed based on current local market prices; therefore the net present value of routine maintenance cost, P_{MC} is simply the algebraic sum of all relevant annual routine maintenance costs considering an analysis period of (n) transitions as indicated by Equation (11):

$$P_{\rm MC} = \sum_{k=1}^{n} A_{\rm MC}(k)$$
 (11)

4.2. Major rehabilitation cost

Major rehabilitation cost is estimated similar to the initial construction cost according to local market prices. It appears in

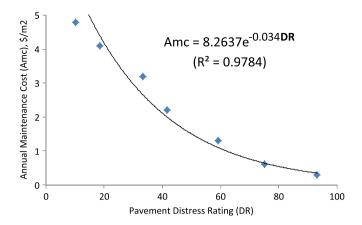


Figure 2. Annual routine maintenance cost as a function of pavement distress rating

Equation (12) as a future value (F_{RCi}) converted to a present one using the rehabilitation time (n_i) associated with the jth rehabilitation cycle and uniform annual discount rate (i) in decimal form. Equation (12) is simply used to convert the future money values associated with (N) rehabilitation cycles to a net present value. Rehabilitation work strategies typically involve either plain overlay, or cold milling and overlay, or removal and replacement of existing asphalt concrete layer. The pavement engineer is required to identify the appropriate future rehabilitation plans and estimate their corresponding future costs:

$$P_{\rm RC} = \sum_{j=1}^{N} \frac{F_{\rm RC}_j}{(1+i)^{n_j}} \tag{12}$$

A simplified model is presented in the sample presentation section to assist in estimating the overlay thickness required to provide the rehabilitated pavement with structural capacity similar to the one associated with original pavement. The model can be used in cases of either plain overlay or cold milling and overlay.

4.3. Added vehicle operating cost due to work zone

Vehicular traffic passing through work zone during a rehabilitation cycle typically incurs additional user cost. A main element of this added user cost is the additional vehicle operating cost which can be estimated using Equation (13). The future value of the added vehicle operating cost (F_{VOC}) is estimated in ($\$/m^2$) of pavement surface as a function of the affected average daily traffic (ADT_{aff}) in vehicles, added vehicle operating cost (VOC_{add}) in (\$/vehicle/lane closure), total number of lane closures (N_c), and project surface area (A_p) in m^2 . The project surface area is computed as the product of lane width (W_I) in m, number of lanes (N_I) in both directions and project length (L_p) in km. The total number of lane closures (N_c) is computed from dividing the project length in lane-km $(N_I \times L_P)$ by the average rehabilitation production rate $(L_{\mathbb{R}})$ in lane-km per lane closure per rehabilita-

$$F_{\text{VOC}} = \frac{\text{ADT}_{\text{aff}} * \text{VOC}_{\text{add}} * N_C}{A_p}$$
 (13)

where $A_p = 1000 * W_L * N_L * L_p$

$$N_C = \frac{N_L \times L_P}{L_R}$$

Equation (13) can yield a good estimate of the added vehicle operating cost provided that $\mathrm{ADT}_{\mathrm{aff}}$ and $\mathrm{VOC}_{\mathrm{add}}$ are both reasonably estimated from conducting relevant field assessments during similar performed lane closures. In particular, the observed average delay time per vehicle during a typical lane closure can be converted to an estimated equivalent monetary value. The added user cost due to delay time cost can also be added to the pavement life cycle cost. The future values of added vehicle operating cost (F_{VOC_j}) associated with (N) rehabilitation cycles can then be converted to an equivalent present value (P_{VOC}) as follows:

$$P_{\text{VOC}} = \sum_{j=1}^{N} \frac{F_{\text{VOC}j}}{(1+i)^{n_j}}$$
 (14)

5. Life cycle P/C ratio

The effectiveness of a long-term M&R plan for a particular pavement project can be evaluated using the P/C ratio as presented in Equation (15). The long-term performance (P) of a pavement project can be defined in terms of the area falling under the life cycle performance curve ($A_{\rm LC}$), which is the area falling under the typical curve shown in Figure 1 (Abaza & Murad, 2009; Huang, 2004). The life cycle cost (C) is the same net present value ($P_{\rm LC}$) defined in Equation (9). The major advantage of using the (P/C) ratio is to evaluate potential long-term M&R plans with the most effective M&R plan is the one associated with the highest (P/C) value. The life cycle cost can be determined in terms of the net present value provided that all M&R plans are associated with equal analysis periods; otherwise, the equivalent annual payment method has to be used:

$$\frac{\text{Performance}}{\text{Cost}} = \frac{P}{C} = \frac{A_{\text{LC}}}{P_{\text{LC}}}$$
 (15)

The area falling under the typical life cycle performance curve shown in Figure 1 can be calculated as indicated by Equation (16) using the curve ordinate values, DR(k). The partial curve area under either the original pavement (AUC_0) or the jth

rehabilitation cycle (AUC_j) can be determined using the trapezoidal method defined in terms of the initial and terminal DR values (DR_{a,i} and DR_{t,j}), and remaining DR values:

$$A_{\rm LC} = \sum_{j=0}^{N} AUC_j \tag{16}$$

where
$$\text{AUC}_j = \frac{1}{2} \Big(\text{DR}_{o,j} + \text{DR}_{t,j} + 2 \big(\sum \text{Remaining DR values} \big) \Big)$$

6. Sample presentation

In this section, a case study is presented to demonstrate the use of the proposed two empirical Markovian-based models for predicting the future performance of rehabilitated pavement. In particular, the life cycle performance curves are developed for 3 M&R plans with equal analysis periods comprised of 20 transitions and 1-year transition length. The presented *P/C* ratio is used to evaluate the effectiveness of the three M&R plans under consideration.

6.1. Basic data and background

The case study to be presented is related to four-lane urban arterial located in the city of Nablus, West Bank, Palestine. The arterial pavement consists of 13 cm (5 in.) asphalt concrete on top of 50 cm (20 in.) aggregate base designed to withstand 5-million 18k (80kN) ESAL applications. It currently carries about 25,000 vpd average daily traffic with about 4% average annual traffic growth rate. The distress ratings were annually collected for this arterial since its reconstruction in 1998. Abaza (2016a) applied the collected distress ratings to estimate the staged-homogenous deterioration transition probabilities, $P(k)_{i,i+1}$, associated with the original pavement structure as provided in Tables 1 and 2 deploying five-year equal staged-time periods. Abaza (2016a) mainly focused on estimating the initial and terminal deterioration transition probabilities, $P(k)_{1,2} & P(k)_{9,10}$, considering a Markov chain with 10 condition states (m).

In another study, Abaza (2015) used an empirical model and the same collected distress ratings to predict the initial and terminal non-homogenous deterioration transition probabilities with results provided in Table 3 for the first 10 transitions. Based on the estimated transition probabilities from the two studies, two distinct types of pavement performance were identified for the

Table 1. Sample initial and terminal staged-homogenous transition probabilities for rehabilitated pavement with increasingly higher deterioration rates.

N	J Service time (years)		$\Delta W_{j \times 10}^{6}$	PR(<i>j</i>) _{1,2}	PR(j) _{9,10}	
0	1	1.00	0–5	.909	(.182) ^c	(.384) ^c
	2	1.65	5–10	1.106	(.300)	(.634)
	3	1.95	10–15	1.346	(.355)	(.749)
	4	2.45	15–20	1.638	(.446)	(1.000)
$1 (N_s = 2)$	1	1.00	0–5	.909	(.182)	(.384)
3	2	1.65	5–10	1.106	(.300)	(.634)
	1	_a	10–15	(1.346) ^b	.315	.665
	2	_	15–20	(1.638)	.520	1.000
$3(N_s = 1)$	1	1.00	0–5	.909	(.182)	(.384)
. 3	1	_	5–10	(1.106)	.240	.505
	2	_	10–15	(1.346)	.315	.665
	3	_	15–20	(1.638)	.415	.876

^aNot applicable.

^bLoad applications associated with rehabilitated pavement, ΔWR,

cStaged-homogenous transition probabilities, P(j), associated with original pavement as obtained from reference Abaza (2016a).

Table 2. Sample initial and terminal staged-homogenous transition probabilities for rehabilitated pavement with decreasingly lower deterioration rates.

N	j	C _i	Service time (years)	$\Delta W_{j\times 10}^{6}$	PR(<i>j</i>) _{1,2}	PR(j) _{9,10}
0	1	1 1.00 0–5		.909	(.650) ^c	(.180) ^c
	2	1.25	5–10	1.106	(.812)	(.225)
	3	1.50	10–15	1.346	(.975)	(.270)
	4	1.75	15–20	1.638	(1.000)	(.315)
$1 (N_s = 2)$	1	1.00	0–5	.909	(.650)	(.180)
3	2	1.25	5–10	1.106	(.812)	(.225)
	1	_a	10–15	(1.346) ^b	.856	.237
	2	_	15–20	(1.638)	1.000	.296
$3 (N_s = 1)$	1	1.00	0–5	.909	(.650)	(.180)
. 3	1	_	5–10	(1.106)	.746	.206
	2	_	10–15	(1.346)	.856	.237
	3	_	15–20	(1.638)	.982	.272

aNot applicable.

Table 3. Sample initial and terminal non-homogenous transition probabilities for pavement with one rehabilitation cycle $(N = 1, n_1 = 10, j = n_2 + k)$.

	Inc	Increasingly higher deterioration rates				Decreasingly lower deterioration rates			
Transition number (k)	P(k) _{1,2}	P(k) _{9,10}	PR(j) _{1,2}	PR(j) _{9,10}	$P(k)_{1,2}$	P(k) _{9,10}	PR(j) _{1,2}	PR(j) _{9,10}	
1	.182ª	.384ª	.315	.665	.650a	.180ª	.855	.237	
2	.197	.416	.341	.720	.674	.187	.887	.246	
3	.208	.439	.360	.760	.692	.192	.911	.253	
4	.220	.464	.381	.803	.712	.197	.937	.259	
5	.233	.491	.403	.850	.732	.203	.963	.267	
6	.246	.519	.426	.899	.752	.208	.990	.274	
7	.260	.548	.450	.949	.773	.214	1.000	.282	
8	.275	.580	.476	1.000	.795	.220	1.000	.290	
9	.290	.613	.502	1.000	.817	.226	1.000	.297	
10	.307	.648	.532	1.000	.840	.233	1.000	.307	

 $^{^{}a}$ Non-homogenous transition probabilities, P(k), associated with original pavement as obtained from reference Abaza (2015).

sample project under consideration, namely increasingly higher deterioration rates as depicted in Figure 3(a), and decreasingly lower deterioration rates as shown in Figure 4(a). In both the studies, Abaza (2015, 2016a) used a linear approach to estimate the remaining deterioration transition probabilities as presented in Equations (17) and (18) for performances with increasingly higher and decreasingly lower deterioration rates, respectively, making use of only the initial and terminal values:

$$P(k)_{i,i+1} = P(k)_{1,2} + (i-1) \left(\frac{P(k)_{m-1,m} - P(k)_{1,2}}{m-2} \right)$$

$$(i = 2, 3, \dots, m-2)$$
(17)

where
$$P(k)_{1,2} < P(k)_{2,3} < P(k)_{3,4} < \dots < P(k)_{m-1,m}$$

$$P(k)_{i,i+1} = P(k)_{1,2} - (i-1) \left(\frac{P(k)_{1,2} - P(k)_{m-1,m}}{m-2} \right)$$
 (18)

$$(i = 2, 3, ..., m-2)$$

where
$$P(k)_{1,2} > P(k)_{2,3} > P(k)_{3,4} > \dots > P(k)_{m-1,m}$$

6.2. Sample pavement life cycle performance curves

The initial and terminal deterioration transition probabilities for the rehabilitated pavement structure, $PR(j)_{1,2}$ and $PR(j)_{9,10}$, have been predicted using Equation (5) as applicable to the stagedhomogenous Markov model. The corresponding results are provided in Tables 1 and 2 for the cases of increasingly higher and decreasingly lower deterioration rates, respectively. Each table shows 3 distinct M&R plans with the first one representing the do-nothing alternative (N = 0) with 20-year service time, the second one involves one rehabilitation cycle (N = 1) with 10-year service time, and the third one includes three rehabilitation cycles (N = 3) spaced at equal 5-year service times (Δn). The service time (Δn) , associated with all deployed rehabilitation cycles, consists of an integer number of the staged-time periods (N_s) each comprised of 5 years.

The traffic load applications (ΔW_i) associated with each staged-time period as provided in Tables 1 and 2 are mainly used in the application of Equation (5) as the structural capacity associated with rehabilitated pavement is assumed to remain similar to that of the original pavement. The traffic load applications (ΔW_i) are computed based on 5-million design ESAL,



Figure 3a. Sample life cycle performance curve generated using stagedhomogenous Markov chain for increasingly higher deterioration rates without rehabilitation.

bLoad applications associated with rehabilitated pavement, ΔWR

 $[^]c$ Staged-homogenous transition probabilities, P(j), associated with original pavement as obtained from reference Abaza (2016a).



Figure 3b. Sample life cycle performance curve generated using staged-homogenous Markov chain for increasingly higher deterioration rates with one rehabilitation cycle (N = 1, $N_x = 2$, $\Delta n = 10$ years).

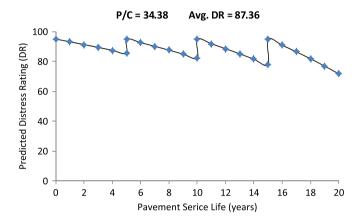


Figure 3c. Sample life cycle performance curve generated using staged-homogenous Markov chain for increasingly higher deterioration rates with three rehabilitation cycles (N = 3, $N_c = 1$, $\Delta n = 5$ years).

20-year analysis period (n) and 4% average annual traffic growth rate. The remaining staged-homogenous deterioration transition probabilities are linearly estimated as presented in Equations (17) and (18) using mainly the predicted initial and terminal values. The corresponding state probabilities, $S_i^{(k)}$, are predicted using the staged-homogenous Markov model indicated by Equation (3) with the corresponding distress ratings, DR(k), estimated using Equation (4). The estimated DR(k) are then used to develop the



Figure 4a. Sample life cycle performance curve generated using staged-homogenous Markov chain for decreasingly lower deterioration rates without rehabilitation.



Figure 4b. Sample life cycle performance curve generated using staged-homogenous Markov chain for decreasingly lower deterioration rates with one rehabilitation cycle (N = 1, $N_c = 2$, $\Delta n = 10$ years).

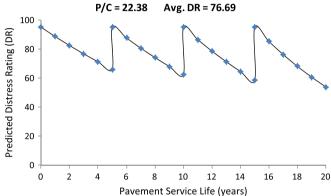


Figure 4c. Sample life cycle performance curve generated using staged-homogenous Markov chain for decreasingly lower deterioration rates with three rehabilitation cycles (N = 3, $N_c = 1$, $\Delta n = 5$ years).

life cycle performance curves presented in Figures (3) and (4) for the outlined two performance types and three M&R plans.

The empirical model defined in Equation (6) for predicting the non-homogenous transition probabilities has been also used to predict the relevant initial and terminal deterioration transition probabilities deploying one rehabilitation cycle with 10-year service time. Table 3 provides the corresponding results for the outlined two performance types with the traffic load factor computed using Equation (8) and structural capacity remains similar to that of original pavement. The relevant life cycle performance curves have been developed as shown in Figure 5 for both types of pavement performance applying mainly Equations (1) and (4). The model exponent (A) has been assigned the values of (1.4 and .7) for the empirical models presented in Equations (5) and (6) considering increasingly higher and decreasingly lower deterioration rates, respectively. These two values were primarily obtained from the calibration procedure performed for the same original pavement structure (Abaza, 2015), but couldn't be estimated for rehabilitated pavement due to the lack of relevant historical distress records.

6.3. Assessment of life cycle M&R plans using P/C ratio

The *P/C* ratio has been computed for the different M&R plans outlined in the previous subsection. The life cycle performance

Table 4. Sample life cycle performance/cost (P/C) ratios for rehabilitated pavement with increasingly higher deterioration rates for staged-homogenous Markov chain.

No. of rehab. cycles (<i>N</i>)	Routine maint. cost, P _{MC} (\$/m²)	Major rehab. cost, P _{RC} (\$/m²)	Add. veh. opt. cost, P _{VOC} (\$/m²)	Total cost, C (\$/ m ²)	Perf. (<i>P</i>)	Perf./cost ratio (P/C)	Average distress rating (DR _a)
0	35.01	0	0	35.01	1186	33.88	61.32
1	13.34	25	6.16	44.50	1654	37.17	78.31
3	8.60	33	9.24	50.84	1748	34.38	87.36

Note: $P = A_{LC'}$ and $C = P_{LC}$.

Table 5. Sample life cycle performance/cost (P/C) ratios for rehabilitated pavement with decreasingly lower deterioration rates for staged-homogenous Markov chain.

No. of rehab. cycles (N)	Routine maint. cost, P _{MC} (\$/m²)	Major rehab. cost, P _{RC} (\$/m²)	Add. veh. opt. cost, P _{VOC} (\$/m²)	Total cost, C (\$/ m ²)	Perf. (<i>P</i>)	Perf/cost ratio (P/C)	Average distress rating (DR _a)
0	56.74	0	0	56.74	875	15.42	44.15
1	25.62	30	6.16	61.78	1254	20.30	62.92
3	14.12	45	9.24	68.36	1530	22.38	76.69

Note: $P = A_{IC}$, and $C = P_{IC}$.

 (A_{1C}) has been computed using Equation (16) based on the ordinates, DR(k), of the presented life cycle performance curves. The life cycle cost (P_{1C}) is computed using only routine maintenance cost (P_{MC}) , major rehabilitation cost (P_{RC}) , and added vehicle operating cost (P_{VOC}) . The initial construction cost has been excluded because it is the same for all investigated M&R plans. The routine maintenance cost has been computed using Equations (10) and (11) depending mainly on the distress ratings, DR(k), associated with the life cycle performance curves shown in Figures 3-5. Tables 4 and 5 provide the estimated routine maintenance cost, P_{MC} , for the three M&R plans considering the case of staged-homogenous Markov model. It is to be reminded that routine maintenance is carried out annually but assumed not to add much to pavement performance or service life.

The presented life cycle performance curves have been developed under the assumption that the structural capacity associated with rehabilitated pavement is equal to the corresponding value for original pavement. This can be achieved by compensating the existing asphalt layer for the strength loss it has only endured over time; thus, maintaining the same structural capacity. The degradation of the aggregate base layer can be neglected as granular materials typically experience minor strength losses. Therefore, Equation (19) can be used to estimate the required overlay thickness, $h_a(n)$, as a function of the existing asphalt layer thickness, (h_1) , cold milling thickness, $h_{...}(n)$, original layer coefficient, (a_1) , and modified layer coefficient, $a_1(n)$, at rehabilitation time (n). Equation (19) simply compensates for asphalt strength loss by first subtracting the milling thickness from the existing asphalt thickness and then multiplying the outcome by a strength reduction factor, which is defined as the ratio of the modified layer coefficient to the original layer coefficient. The modified layer coefficients are typically estimated from destructive/non-destructive testing of pavement (AASHTO, 1993):

$$h_o(n) = h_1 - [h_1 - h_m(n)] \times \frac{a_1(n)}{a_1}$$
 (19)

$$h_o(n) = h_1 - \left[h_1 - h_m(n)\right] \times \frac{\mathrm{DR}(n)}{\mathrm{DR}_{max}} \tag{20}$$

Because the modified layer coefficients are not available for this sample project, it is proposed to use a strength reduction factor defined as the ratio of the distress rating, DR(n), at rehabilitation time (*n*) to the maximum distress rating ($DR_{max} = 95$). Therefore, Equation (20) has been used to estimate the overlay thickness associated with the rehabilitation plans shown in Figures 3-5. The overlay thicknesses associated with Figures 3(b) and 4(b) are estimated to be 7.5 and 10-cm considering 13-cm existing asphalt thickness (h_1) , 5-cm cold milling thickness (h_2) , and 66.94 and 40.18 distress ratings at 10-year rehabilitation

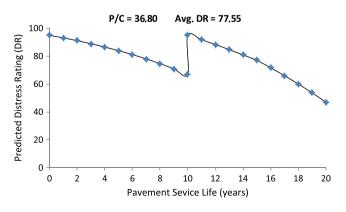


Figure 5a. Sample life cycle performance curve generated using non-homogenous Markov chain for increasingly higher deterioration rates with one rehabilitation cycle (N = 1, $\Delta n = 10$ years).



Figure 5b. Sample life cycle performance curve generated using non-homogenous Markov chain for decreasingly higher deterioration rates with one rehabilitation cycle (N = 1, $\Delta n = 10$ years).

time, respectively. Similarly, the overlay thicknesses for Figures 3(c) and 4(c) are estimated to be 3.5 and 5.5-cm assuming 2-cm cold milling thickness, and 82.18 and 66.10 distress ratings at 5-year rehabilitation time, respectively. The present values of the corresponding rehabilitation costs, $P_{\rm RC}$, as provided in Tables 4 and 5 are estimated based on \$2/m² per centimetre of the total milling and overlay thickness. For example, \$11/m² is the present cost of one cycle of 2-cm cold milling and 3.5-cm overlay with a total present cost of \$33/m² for three cycles.

At advanced service times, pavement reconstruction is typically a potential alternative which mainly includes removal of the existing asphalt layer, thickness adjustment of aggregate base, and placement of new asphalt layer. In this case, the SN associated with the new pavement structure can be estimated from summing the products of the new layer thicknesses and their corresponding layer coefficients (AASHTO 1993). The new SN can then be used in the presented predictive empirical models to represent the structural capacity of the rehabilitated pavement structure. Similarly, the original SN can denote the structural capacity of the original pavement structure.

The future added vehicle operating costs (F_{VOC}) are computed using Equation (13) assuming 6 km road length (L_p) , 4 lanes in both direction (N_t) , 18,000 veh affected average daily traffic (ADT_{aff}), $3.5 \,\mathrm{m}$ lane width (W), 1.2/veh/lane closure added vehicle operating cost (VOC_{add}), and 1 and 2 lane-km rehabilitation production rates per lane closure (L_R) for M&R plans with 1 and 3 rehabilitation cycles, respectively. The corresponding (F_{VOC}) values are computed to be 6.16 and \$3.08/m² per cycle with results provided in Tables 4 and 5. It is assumed that these values represent the present values (P_{VOC}) as they are estimated based on current local market prices. The \$1.2/veh/lane closure (VOC_{add}) is mainly estimated assuming 10 min average delay time which is converted to an equivalent average fuel consumption cost. Tables 4 and 5 also provide the life cycle cost (C), performance (P), (P/C) ratios and average DR values. Examination of Figures 3–5 reveals the following conclusions:

- It is clearly cost-effective to apply M&R works than to do nothing as better pavement can be achieved at lower overall cost.
- The 3 M&R plans associated with increasingly higher (2) deterioration rates are clearly more cost-effective than the corresponding ones for decreasingly lower deterioration rates as they have yielded higher P/C ratios and average DR values. This can be attributed to lower areas under the life cycle performance curves and higher M&R costs in the case of decreasingly lower deterioration rates as provided in Tables 4 and 5.
- The M&R plan associated with one rehabilitation cycle is the most cost-effective in the case of increasingly higher deterioration rates as indicated by its highest *P/C* ratio shown in Figure 3(b). However, the M&R plan associated with three rehabilitation cycles is the most cost-effective in the case of decreasingly lower deterioration rates as depicted in Figure 4(c).
- The M&R plan presented in Figure 5(a) has similar P/C ratio and average DR as for the one presented in Figure 3(a), which is an indication that both empirical models used to estimate

- the staged-homogenous and non-homogenous transition probabilities for rehabilitated pavement performance are compatible. The same conclusion applies to Figures 5(b) and 4(b).
- The terminal distress rating $(DR_{t,i})$ for the jth rehabilitation cycle is lower than the corresponding value associated with the preceding cycle. This is true for all presented sample life cycle performance curves because of increased traffic load applications but structural capacity kept similar to that of original pavement. Nevertheless, the initial distress ratings (DR_{a,i}) remained unchanged compared to the value associated with original pavement.

7. Conclusions and recommendations

The presented case study has provided reasonable estimates of the future deterioration transition probabilities associated with rehabilitated pavement as applicable to both the stagedhomogenous and non-homogenous Markov models. The presented sample life cycle performance curves have reflected the expected pavement performance as related to the two typical deterioration trends, namely the increasingly higher and decreasingly lower deterioration rates. The results have also indicated that the proposed two empirical models for predicting the deterioration transition probabilities are quite compatible. The future deterioration transition probabilities for rehabilitated pavement have been estimated based on the corresponding values associated with original pavement. The deterioration transition probabilities associated with original pavement have been assumed to be part of the input data deployed in the presented case study. Abaza (2015) can be consulted for details on the non-homogenous transition probabilities for original pavement and, similarly, Abaza (2016a) for the staged-homogenous transition probabilities.

In this case study, the two exponents (A and B) associated with the proposed predictive empirical models have been assumed to take on the values as of those estimated for the empirical model associated with the same original pavement structure (Abaza, 2015). This has proven to be a reasonable assumption since the predicted performances of rehabilitated pavement have exhibited trends similar to the ones associated with original pavement. However, the minimisation of SSE as outlined in Abaza (2015) can be used to obtain new estimates of the model exponents once adequate distress records become available for rehabilitated pavement. There are other simpler methods that can be used to estimate the model exponents with less distress data requirements and they are currently under investigation by the author. For example, one method mainly requires two consecutive cycles of distress assessment to be used in estimating one set of the transition probabilities for rehabilitated pavement. The predictive empirical models can then be searched for the best estimates of the two exponents provided all other relevant input data are available. The search will cover the expected exponent ranges and will terminate when both sides of the empirical model equations are very close in values. The two exponent ranges are typically (1-2) in the case of increasingly higher deterioration rate and (0-1) in the case of decreasingly lower deterioration rates. It is therefore recommended that the exponents be developed at the project level but can be used to predict the performance of similar pavement projects.

The presented sample results have also indicated the effectiveness of the P/C ratio in evaluating different potential M&R plans. The sample life cycle performance curves are used to provide the life cycle performance as represented by the area falling under the curve. The life cycle performance curves can also be used to provide the best rehabilitation timings needed to schedule future major rehabilitation works. For example, rehabilitation schedule timings of 5 and 10 years have been mainly used in developing the presented sample life cycle performance curves. Therefore, it is recommended that life cycle performance curves be developed for different rehabilitation schedule timings, generally 5-10 years, and the best timing schedule is the one associated with the highest *P/C* ratio, which is also an indication of the best M&R plan. In this regards, it is recommended to use the empirical model that predicts the non-homogenous transition probabilities as it can easily deal with more flexible rehabilitation timing schedules. It is also recommended that the structural capacity for rehabilitated pavement be greater than the corresponding value associated with original pavement, which is needed to counterbalance the impact of increased traffic load applications and maintain at least similar deterioration rates as those associated with original pavement.

Disclosure statement

No potential conflict of interest was reported by the author.

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