Pavement Deterioration Model Using Markov Chain and International Roughness Index

A S Sati, S Abu Dabous, and W Zeiada
Department of Civil and Environmental Eng., University of Sharjah, Sharjah, United Arab Emirates
Email: U17105765@sharjah.ac.ae, Sabudabous@sharjah.ac.ae, wzeiada@sharjah.ac.ae

Abstract. Pavement deterioration leads to drop in serviceability and possibly failure of pavement sections due to initiation and expansion of distresses such as cracks and rutting. This paper aimed at predicting the future condition of pavement sections based on Markov chain model and the international roughness index (IRI). Developing this model can facilitate life cycle analysis and selecting the correct treatment at the right time. The historical IRI data of Canadian pavement sections were collected from Long term pavement performance (LTPP) database. IRI values were used to assess condition of the pavement sections based on the recommended ranges by the Federal highway administration (FHWA). The transition probabilities were estimated using the percentage prediction method based on historical condition data extracted from the LTPP. These probabilities are assembled in a transition probability matrix essential for the Markov chain model. The developed matrix can be used to forecast pavement conditions after any number of transition periods. The developed method assists in predicting pavement performance and facilitates the decision-making process. The method is applied to a real case study to examine its validity. The model can be expanded further by considering additional data from additional pavement networks.

1. Introduction
Pavement deterioration is the process in which the distresses develop in pavement material under the impact of environmental and traffic loading conditions. Sometimes the deterioration of pavement can lead to significant risk of increasing accidents and fatalities. Estimating performance of existing pavements and predicting their future conditions are important requirements for pavement management systems [1]. In recent years, there is a rapid growth in the pavement evaluation technology which helps a lot but at the same time complicates the process. Pavement management is the process of assessing and forecasting the pavement conditions over the service life and identifying the appropriate maintenance and rehabilitation (M&R) of roads or any paved facility. In addition, it requires a periodical collection of data from the pavement sections. Several agencies around the world have developed a road performance database. The Long-Term Pavement Performance (LTPP) which was developed in the early 1980s. It is one of the most extensive research programs supported by the Federal Highway Administration (FHWA) to collect pavement data in Canada and United State.

There are many indicators that can be used to determine the pavement condition such as pavement condition index, international roughness index (IRI), and the present serviceability index. In this research, the determination of the pavement sections condition is based on the IRI data included in the LTPP for pavement sections in Canada. The aim of this study is to develop a model that can predict...
2. Literature review
Numerous studies aimed in developing a deterioration model for many infrastructure facilities. Deterioration models are developed mainly to predict the future condition of the facility. Regarding the infrastructure deterioration models proposed Case based reasoning (CBR) to generate deterioration model of infrastructure facility with no specific facility selected [2]. Later after describing the CBR architecture, an application example was presented from the highway bridges domain. Later in the same year, the same group of researchers established a new CBR system which was developed and used in building as a proof of concept then they used it in modeling the deterioration of concrete bridge decks [3]. One year later a new approach was proposed in bridge deterioration models by identifying some categories that best represent the environmental conditions surrounded the bridge deck [4]. The proposed approach provided transportation agencies with an excellent decision support tool for bridge structures. Ranjith et al. presented Markov chain model that predict the future condition of timber bridge elements [5]. They used different methods to derive the transition probabilities and compare them to find the optimum one. Madanat et al. used Poisson regression model followed by the Markovian behaviour to calculate the transition probabilities [6]. A negative binomial regression which is a generalization of Poisson model was also used to relaxes the quality assumption between the mean and variance of the variables. Recently Markov based approach was applied to predict the future condition of water distribution network to use as a decision support system [7]. They check the validity of Markov property using Chi-square. Poisson probability distribution was used as well to compute the transition probabilities. another study was done to evaluate the fuzzy logic approach to rate the bridge conditions and to develop bridge condition rating [8]. Lastly, the fuzzy logic and probabilistic analysis was proposed to address the uncertainties in bridge condition assessment [9]. The proposed method integrated Monte Carlo simulation with evidential reasoning to enhance bridge condition rating.

Many literatures focused on pavement deterioration because of its important. Yang et al. presented an empirical study that compare the abilities of Markov chain and neural networks in modeling crack deterioration of flexible pavements using FDOT data [10]. Butt et al. developed a pavement performance and prediction model that passed on pavement condition index and the pavement age [1]. They also did a comparison between Markov model and constrained least-squares model. A series of models were developed for predicting the deterioration rate of pavement for the first 8 years of service [11]. Kobayashi et al. presented a methodology to estimate the Markov transition probabilities model to predict the deterioration of road sections [12]. Bianchini and Bandini proposed a neuro fuzzy model to predict the performance of flexible pavements using the parameters routinely collected by agencies to characterize the condition of an existing pavement [13]. Surendrakumar et al. applied the Markovian probability process to develop decision support system to expect the future condition of pavement sections [14]. Abaza (2004) developed a deterministic performance prediction model utilizes the serviceability concept adopted by AASHTO to be used in the management and rehabilitation of flexible pavements [15].

3. Data extraction
The data used in this paper was collected from the Long-Term Pavement Performance (LTPP) database which has been used by several researcher around the world. LTPP program is the largest pavement study ever conducted for US and Canada. It was initiated in 1987 as part of the Strategic Highway Research Program (SHRP) [16]. Later in 1992, The management of the program was transferred to the Federal Highway Administration (FHWA) which continue serving this role until now. The data of More than 2500 sections was collected by the LTPP program organization in cooperation with highway agencies. the data collected includes inventory, material testing, pavement performance monitoring, climate data, traffic, maintenance, and rehabilitation [16]. Before making the
data available to the public, it subjected to a wide range of quality control checks. At the end, the data is stored in an information management system (the LTPP database) which is the largest pavement performance database in the world [16]. Canadian pavement sections with no maintenance and rehabilitation were collected to be used in the model development. The total number of sections was 16 sections.

From the collected data, the employed performance indicator in this study was the international roughness index (IRI). IRI describes the vehicle vibrations caused by profile roughness and is linearly proportional to roadway roughness [17]. The lower the IRI value the flatter the paved profile and vice versa. There exists no upper limit on IRI, but in practice, IRI values above 8 m/km relate to pavements nearly impassable by vehicle except at reduced speed [17]. In this paper, the mean IRI data that was collected and organized to be used in calculating the condition of each section through its service life.

4. The model

4.1. Data analysis

Before developing the model, the data should be organized to be used. Therefore, the condition changes of each pavement section were calculated using the collected IRI values. The condition will be classified into five condition states from Very good to Poor based on the IRI ranges specified by FHWA, as shown in Table 1.

| State | Category     | IRI (m/km) | Interstate | Other road |
|-------|--------------|------------|------------|------------|
| 1     | Very good    | < 0.95     | < 0.95     |            |
| 2     | Good         | 0.95 – 1.49| 0.95 – 1.49|            |
| 3     | Fair         | 1.50 – 1.89| 1.50 – 2.69|            |
| 4     | Mediocre     | 1.90 – 2.69| 2.70 – 3.48|            |
| 5     | Poor         | 2.69 <     | 2.48 <     |            |

After calculating the condition changes of the 16 pavement sections, three sections were excluded. The reason for the first two sections was that both of them were found to be in a perfect condition during their service life where their conditions didn’t drop from the very good state. The third section was excluded as the inspector started calculating the IRI data of that section after more than 10 years from its construction date, which lead to a lot of missing data. The final number of the sections that will be used to develop the model is 13 sections. The sections information is summarized in Table 2.

| Sec | State     | Section ID | Construction date | Roadway Functional Class | Age [Yrs] |
|-----|-----------|------------|-------------------|--------------------------|-----------|
| 1   | Ontario   | A340       | 06/01/1981        | Other                    | 11        |
| 2   | Saskatchewan | 0901       | 09/01/1996        | Other                    | 12        |
| 3   | Saskatchewan | 0902       | 09/01/1996        | Other                    | 12        |
| 4   | Saskatchewan | 0903       | 09/01/1996        | Other                    | 12        |
| 5   | Saskatchewan | 0959       | 09/01/1996        | Other                    | 12        |
| 6   | Saskatchewan | 0960       | 09/01/1996        | Other                    | 12        |
| 7   | Saskatchewan | 0962       | 09/01/1996        | Other                    | 12        |
| 9   | Quebec    | A340       | 06/01/1981        | Interstate               | 14        |
| 10  | Ontario   | 2812       | 06/01/1981        | Other                    | 17        |
| 11  | Ontario   | 0901       | 06/01/1997        | Other                    | 19        |
| 12  | Ontario   | 0902       | 06/01/1997        | Other                    | 19        |
| 13  | Newfoundland | 1801      | 09/01/1984        | Interstate               | 22        |
| 13  | Quebec    | 3002       | 06/01/1979        | Other                    | 39        |

The historical condition state on each year for a period of 20 years of each section was summarized in Table 3. It is shown that the total number of transitions is 144.
Table 3. Historical condition states for sections.

| Sec | Age [Yrs] | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 |
|-----|-----------|---|---|---|---|---|---|---|---|---|----|----|----|----|----|----|----|----|----|----|----|
| 1   | 11        | x | x | x | x | x | x | x | 3 | 3 | 4 | x | x | x | x | x | x | x | x | x | x |
| 2   | 12        | 1 | 1 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 |
| 3   | 12        | 1 | 1 | 1 | 2 | 2 | 2 | 2 | 2 | 2 | 3 | 3 | x | x | x | x | x | x | x | x | x |
| 4   | 12        | 1 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | x | x | x | x | x | x | x |
| 5   | 12        | 1 | 2 | 2 | 2 | 2 | 2 | 3 | 3 | 3 | 3 | x | x | x | x | x | x | x | x | x |
| 6   | 12        | 1 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 |
| 7   | 12        | 1 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | x | x | x | x | x | x |
| 8   | 14        | x | x | x | x | x | x | x | 3 | 3 | 3 | 3 | 3 | 4 | 4 | 4 | 5 | 5 | 5 | 5 | 5 |
| 9   | 17        | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 2 | 2 | 2 | 2 | 2 | 3 | 3 | 3 | 3 | 3 | 3 | x |
| 10  | 19        | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 3 | 3 | 3 | 3 | 3 | 4 | x |
| 11  | 19        | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 2 | 3 | 3 |
| 12  | 22        | x | x | x | x | 3 | 4 | 4 | 4 | 4 | 4 | 4 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 |
| 13  | 39        | x | x | x | x | x | x | x | x | x | x | x | x | 4 | 5 | 5 | 5 | 5 | 5 | 5 | 5 |

4.2. Markov chain framework.

There are two different basic types of deterioration models: Deterministic and stochastic. Deterministic model is basically a formula, none of the used variables are random, and the output of the model is fully determined using the parameters value. On the other hand, Stochastic model depends on random variables and represents an event where uncertainty is present. Since deterioration is an independent and random event, stochastic models are typically used. Markov chain is one of well-known stochastic model that have been used in modelling the deterioration of infrastructure facilities.

Markov chain was developed in 1906 by Andrei Markov to help decision makers analyze transition between states [7]. It is a process that has a discrete number of states, and the sequence of possible events is described. In Markov process, the probability of each event depends only on the state reached in the present regardless what was the past state as shown in Eq. 1.

\[
P(X_j) = P(X_{t+1} = i_{t+1}|X_t = i_t, X_{t-1} = i_{t-1}, ..., X_1 = i_1, X_0 = i_0) = P(X_{t+1} = i_{t+1}|X_t = i_t)
\]  

(1)

Where \(P(X_j)\) is the probability of the future condition, it is the state in time \(t\) (present), and \(j\) is the future state. In Markov chain deterioration modeling the probabilities of transitioning from state \(i\) to state \(j\) called the transition probability and denoted by \(P_{ij}\), all the transition probabilities will be presents in a matrix form. This matrix is called the transition probability matrix and denoted by \(P\). it is the base of the Markov process. The final form of the matrix is shown in Eq. 2.

\[
P = \begin{bmatrix}
P_{11} & P_{12} & \cdots & P_{1j} \\
P_{21} & P_{22} & \cdots & P_{2j} \\
\vdots & \vdots & \ddots & \vdots \\
P_{I1} & P_{I2} & \cdots & P_{Ij}
\end{bmatrix}
\]

(2)

The time step between states should be specified because it defines the transition period for the transition probability matrix. The transition probability matrix will represent the states and the probability of transitioning between states. The final matrix is developed for one time step. To find the transition matrix after \(n\) time step \(P_t\) the transition probability matrix \(P\) should be multiply by itself \(n\) times, or simply \(P\) can be raised to the power \(n\) as shown in Eq. 3.

\[
P_t = P^n.
\]  

(3)

4.3. Percentage prediction method.

Transition probabilities of the Markov chain models can be calculated using different methods from the condition data. Some of these methods are presented in literatures such as the percentage
prediction [4], regression-based optimization [1], Poisson distribution [7], and negative binomial models [6] etc. In this paper, Since the transition probabilities is computed for the sections with no maintenance and rehabilitation which is normal deterioration and developing the model will based in 13 sections only, all the sections will either transit to the next lower condition or stay in the same condition. The simple prediction method will be used to calculate the transition probabilities and develop the transition probability matrix. For other situation, other methods mentioned before can be used as well. The probability of transitioning from state \(i\) to state \(j\) can be computed using Eq. 4.

\[
P_{ij} = \frac{N_{ij}}{\sum_{j=1}^{n} N_{ij}}
\]  

(4)

4.4. Markov process.

After developing the transition probability matrix, it will be used to forecast the future condition through the Markov process. The present condition will be presented in terms of vector called the initial condition vector \((P_0)\). The probability vector of transitioning to state \(j\) after \(n\) time step \((P_n)\) will be calculated through multiplying the transition probability matrix after \(n\) time step by the initial condition vector as shown in Eq. 5.

\[
P_j = P_n \times P_0
\]  

(5)

By using \(P_j\) the expected value (Ev) of condition state can be obtained and the expected condition value of any facility after any number of years can be predicted easily by Eq. 6.

\[
Ev = \sum_{j=1}^{s} j \times P_j(j)
\]  

(6)

4.5. Developing the model.

In this paper, developing the deterioration model of Canadian pavement sections using Markov process will be summarized in the following steps:

- Step 1: Select the time step, it was chosen to be one year.
- Step 2: Calculate how many transitions from state \(i\) moving to state \(j\), summarized in Table 4.

Table 4. The total number of transitions in each state

| Expected From State | 1   | 2   | 3   | 4   | 5   |
|---------------------|-----|-----|-----|-----|-----|
| To state            |     |     |     |     |     |
| 1                   | 21  | 8   | 0   | 0   | 0   |
| 2                   | 0   | 60  | 5   | 0   | 0   |
| 3                   | 0   | 0   | 20  | 5   | 0   |
| 4                   | 0   | 0   | 0   | 7   | 2   |
| 5                   | 0   | 0   | 0   | 0   | 16  |

- Step 3: Calculate the transition probability using percentage prediction method, as follow:

\[
P_{ij} = 21/29 = 0.72414
\]

Make sure that the summation of each row should equal to 1. in other words, the summation of probabilities transit from state \(i\) should equal to 1.
- Step 4: Represent the transition probability in a matrix form.

\[
P = \begin{bmatrix}
0.72414 & 0.27586 & 0 & 0 & 0 \\
0 & 0.92308 & 0.07123 & 0 & 0 \\
0 & 0 & 0.80000 & 0.20000 & 0 \\
0 & 0 & 0 & 0.77778 & 0.22222 \\
0 & 0 & 0 & 0 & 1
\end{bmatrix}
\]
• Step 5: Use the transition probability matrix to calculate the future condition through Markov process.

After developing the transition probability matrix, the expected value of conditions will be calculated through Markov chain process mentioned before. Ten trails were done to check the validation of the model using 5 Canadian sections other than the ones used to develop the model. The information of these sections and the condition changes are summarized in Table 5.

### Table 5. Historical condition for the testing sections.

| Sec.ID | Age [Yrs] | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 |
|--------|-----------|---|---|---|---|---|---|---|---|---|----|----|----|----|----|----|----|----|----|----|----|
| 1801   | 11        | 2 | 2 | 2 | 3 | 3 | 3 | 3 | 3 | 3 | 3  | 4  | 4  | 4  | 4  | 4  | 4  | 4  | 4  | 4  | 4  |
| 1125   | 12        | 4 | 4 | 4 | 5 | 5  | 5 | 5 | 5 | 5 | 5  | 5  | 5  | 5  | 5  | 5  | 5  | 5  | 5  | 5  | 5  |
| 1645   | 12        | 1 | 1 | 1 | 2 | 2  | 2 | 2 | 2 | 2 | 2  | 2  | 2  | 2  | 2  | 2  | 2  | 2  | 2  | 2  | 2  |
| A350   | 12        | 3 | 3 | 3 | 3 | 4  | 4 | 4 | 4 | 4 | 4  | 5  | 5  | 5  | 5  | 5  | 5  | 5  | 5  | 5  | 5  |
| 3016   | 12        | 5 | 5 | 5 | 5 | 5  | 5 | 5 | 5 | 5 | 5  | 5  | 5  | 5  | 5  | 5  | 5  | 5  | 5  | 5  | 5  |

Before starting the calculation, it must be known that the n time step was randomly selected with taking into consideration the inspection done for how many years for each section.

• For the first trial:
  - For section 1801, it was observed that in the fifth year when the inspector started the inspection, the section was initially in state 2, so this condition will be presented as a vector which is the initial condition vector \( P_0 = [0\ 1\ 0\ 0\ 0] \).
  - Based on the section age and the inspection period, the n time step was chosen to be 10 years.
  - Using the transition probability matrix computed in previous steps, the probability vector of deteriorating after 10-time steps is:
    \[ P_j = P_{10} \cdot P_0 = [0\ 0.4492\ 0.2136\ 0.1684\ 0.1688] \]
  - The expected value: \( \text{Ev} = (1\times0) + (2\times0.4492) + (3\times0.2136) + (4\times0.1684) + (5\times0.1688) \equiv 3 \)
  - The expected condition of the section after 10 years is to be in condition 3. Table 6 contains another 9 trials that were done, and the expected values were compared with the observed values.

### Table 6. Historical condition for the testing sections.

| Section ID | n time step | Current value | Expected value | Observed value |
|------------|-------------|---------------|----------------|---------------|
| 1801       | 10          | 2             | 3              | 3             |
| 1801       | 15          | 2             | 4              | 4             |
| 1125       | 2           | 4             | 4              | 4             |
| 1125       | 5           | 4             | 5              | 5             |
| 1654       | 7           | 1             | 2              | 2             |
| 1654       | 15          | 1             | 3              | 2             |
| A350       | 1           | 3             | 3              | 3             |
| A350       | 8           | 3             | 4              | 4             |
| A350       | 12          | 3             | 5              | 5             |
| 3016       | 3           | 5             | 5              | 5             |

From the obtained values, it was found that 90% of the results were correct. This shows that the model can be used to predict the future condition of any pavement section with a very good degree of accuracy. This can help the decision makers to predict the condition of the pavement section, rank them, and prepare any maintenance and rehabilitation needs on that time accordingly.

### 5. Conclusion

Predicting the future condition of pavement sections can help the decision makers to choose the appropriate maintenance or rehabilitation on the right time. This paper presented an approach for the prediction of the condition of pavement section using Markov chain and based on the IRI data extracted from the LTPP database. The data of sixteen sections in Canada with no maintenance or rehabilitation was collected. After excluding three sections due to missing information, the rest was
used to develop the model. The transition probabilities were computed using the simple percentage prediction method and the transition probability matrix was developed. Five Canadian sections other than the ones used to develop the model were used to check the validation of the developed model. The results were 90% accurate compared to actual conditions reported in LTPP which showed that the developed model has sufficient degree of accuracy. To conclude, the results illustrate that Markov chain using the IRI data produced an enhanced stochastic deterioration model for pavement infrastructure. In addition, the percentage prediction method is used because of its simplicity in calculating the transition probabilities. Future work may include the expansion of the current model using additional LTPP data from USA and comparing the proposed model results with results produced by other deterioration models such as deterministic and artificial intelligence models.

6. References

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