Developing a new road deterioration model incorporating flooding

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Currently, there is no road deterioration (RD) model that can address pavement performance with flooding. Therefore, the aim of this work was to develop an RD model that considers flooding and pre- and post-flood strategies. The case study is road group(s) in Queensland, Australia, based on the 34 000 km road database of its main roads authority, as Queensland was severely affected by floods in 2011. This paper provides a brief literature review and proposes an approach to develop an RD model based on a non-homogeneous Markov transition probability matrix. The new RD models are developed for a number of road groups based on roughness and rutting data collected since 2000. Detailed results on the derived roughness-based and rutting-based RD models with flooding for two selected road groups are highlighted. The new RD models show significant pavement deterioration at different probabilities of flooding events, especially at higher probabilities. It is believed that these results will help road authorities in managing flood-damaged roads with appropriate treatments and optimum budget.

1. Introduction

The impact of natural disasters on road infrastructure is severe and has been seen worldwide in recent serious natural disasters such as the 2012 tsunami in Japan, hurricanes Katrina in 2005 and Sandy in 2012 in the USA and flooding in Australia in 2010–2011 and 2013. From a pavement management perspective, two conditions are expected for a road segment after a natural disaster like flooding: the road may be substantially damaged to such an extent that it should be reconstructed or the road may be serviceable after the disaster. In the latter case, the road structure may remain inundated for several days, which leads to a weakened base and subbase.

Studies on pavement responses due to flooding are limited. Helali et al. (2008) assessed the impact of hurricanes Katrina and Rita, occurring in 2005 in Louisiana in the USA, on pavement performance. Roads were submerged for weeks and heavy traffic loading was moving over these flooded roads. It was found that 90–190 mm of asphalt concrete as rehabilitation was required for the flooded road to enhance its structural strength. Helali et al. also found that flooded sections deteriorated more than the control sections, with 2.5–6.5 times higher deflection values. Another study revealed that the average pavement strength loss and subgrade modulus loss due to flooding were 18% and 25% respectively; flooded pavements experienced higher deflection and as a result had lower strength and modulus (Zhang et al., 2008). It can thus be concluded that flooding reduces the moduli of pavement layers and, as a consequence, pavement strength decreases and deflection increases. These factors indicate a poor pavement response to flooding.

The 2010/2011 flooding in Queensland, Australia, was the worst for 30 years. It affected 70% of the state – equal to the area of France and Germany combined. The indicative loss to the economy was about A$ 30 billion (2.5% of gross domestic product (GDP)) and road asset loss was around A$ 2.8 billion (PWC, 2011). The Queensland Department of Transport and Main Roads (TMR-QLD) is currently working on its largest programme (Operation Queenslanders, with a budget of $4.2 billion) to reconstruct 6709 km of roads (TMR, 2012). In general, Australia is affected by flooding due to low-lying areas in some places. The intensity of flooding and water ponding varies storm
2. Road deterioration (RD) models

A basic building block of a pavement management system (PMS) is a robust road deterioration (RD) model. However, no RD model exists that can address a flooding event in a pavement’s life cycle performance. Moreover, there is no cost-effective maintenance strategy to select an appropriate rehabilitation treatment as a post-flood strategy. In view of that, the aim of this work was to derive roughness-based and rutting-based RD models that consider flooding and pre- and post-flood strategies. It was intended to use 34,000 km of Queensland main road’s data as a case study to incorporate flooding in a PMS.

The study covers flood-damaged pavements that are saturated but the embankment and structure are intact (not completely damaged or washed away); that is, roads that are at moderate risk and need rehabilitation after flooding. In fact, these roads need proper attention after a flooding event.

The main focus of this paper is the development of a new RD model that can reflect the impact of flooding on road performance. Section 2 of the paper covers different types of RD models and determination of an RD model using a probabilistic method. The proposed approach for the RD modelling based on non-homogeneous Markov transition probability matrix (TPM) is highlighted in Section 3. Section 4 shows some major results on the derived roughness-based and rutting-based RD models for two selected road groups as examples. Finally, Section 5 summarises the findings of this paper.

2.1 Deterministic models

Deterministic models are a type of mathematical model in which outcomes are precisely determined through known relationships among states and events. These types of models are generally regression, mechanistic and mechanistic–empirical models.

Regression analysis is a statistical approach based on historical data, which uses one or more independent variables to obtain a dependent variable. However, it needs a large database for better modelling as it can work only within the range of input data. Madanat et al. (1995) thus concluded that statistical regression is not a suitable method to assess pavement uncertainty.

Mechanistic models predict cause and effect to provide the best results, which are primarily based on theory (i.e. stress, strain and deflection). This type of model uses large numbers of variables (e.g. material properties, environmental conditions, geometric elements, loading characteristics, etc.) and can only predict basic material responses (FHWA, 1990). Panthi (2009) and Gucbilmez and Yuce (1995) concluded that mechanistic models are complex in nature and mainly relate to pavement design parameters.

Similar to the mechanistic model, a mechanistic–empirical model is based on a cause-and-effect relationship but its predictions are better and easy to work with a final empirical model. However, the method depends on field data for the development of an empirical model and works within a fixed domain of independent variables. It uses material properties, environmental conditions, geometric elements, loading characteristics, etc., which are not often available in a PMS (FHWA, 1990; Gucbilmez and Yuce, 1995). The well-known PMS tools (HDM-III; highway development and management model HDM-4 and ARRB, etc.) are mechanistic–empirical models (Martin and Thoresen, 1998; Odoki and Kerali, 2000; Paterson, 1987).

2.2 Probabilistic models

Probabilistic models predict RD to capture the uncertainty of traffic and environmental variables. Several studies have highlighted the importance of probabilistic models as they are useful in dealing with uncertainty related to pavement behaviour (Li, 1997; Madanat et al., 1995; Ortiz-Garcia et al., 2006; Tack and Chou, 2002).

Generally, probabilistic models are of two types, the Markov process and survival curves. A survival curve is easy to derive, but
it only provides a probability of failure versus age relationship. Moreover, considerable error may be expected if only a small group is used (FHWA, 1990).

A Markov chain is a mathematical system that undergoes transitions from one state to another, where the next state depends only on the current state and not on the sequence of events that preceded it. Markov chains have been used for infrastructure deterioration predictions of bridges (Fu and Debraj, 2008; Ranjith et al., 2011), roads (Abaza and Ashur, 1999; Hudson et al., 1998; Lethanh and Adey, 2012; Li, 1997; Li and Haas, 1998; Madanat et al., 1995; Ortiz-Garcia et al., 2006; Panthi, 2009; Tack and Chou, 2002; Wang et al., 1994), waste water (Hyeon-shik et al., 2006), rail (Ferreira and Murray, 1997; Shafahi and Hakhameushi, 2009) and pipelines (Sinha and Mark, 2004).

One of the major advantages of using the Markov model is that it has the capacity to integrate pavement deterioration rates and maintenance and rehabilitation improvement variables into a single entity, the transition matrix. As a result, accurate pavement deterioration predictions using stochastic and dynamic load modelling and optimal maintenance strategies can be easily derived (Butt et al., 1994; Chun et al., 2012; Li, 1997).

The Markov chain may or may not be time dependent. A time-independent Markov chain is known as a homogeneous TPM. However, it is not realistic as pavement deterioration and behaviour vary with time (Fu and Debraj, 2008). When the transition probability is assumed to change with time, then a non-homogeneous Markov chain results; this is called a non-homogeneous TPM. Non-homogeneous TPMs represent real RD. Detailed algorithms of homogeneous and non-homogeneous TPMs have been highlighted by Khan et al. (2012).

2.3 Methods of deriving a non-homogeneous TPM

In general, deterministic models provide an outcome using physical and functional factors of pavement, but they are difficult to develop and relate to basic pavement responses. On the other hand, probabilistic methods can be used to obtain actual pavement performance. Pavement deterioration is dependent on material characteristics, loading and environment, all of them being stochastic in nature. Therefore, it is sensible to use probabilistic models (Chun et al., 2012; Li, 1997) because they can predict uncertainty in pavement performance due to traffic and environmental variables. In view of that, the current work aimed to use the probabilistic method (Markov chain, i.e. a non-homogeneous TPM) for RD modelling.

Generally, six methods are used to derive non-homogeneous TPMs for RD modelling: the percentage transition method, the minimum error method, the probit model, conversion from a deterministic model, the Bayesian technique and the multi-stage hazard model; detailed features of these methods are discussed by Khan et al. (2012). The current study uses the percentage transition method as it could help to generate several flooding and non-flooding TPMs from real data using pavement deterioration trends and can address inherent pavement deterioration.

3. Methodology

The proposed probabilistic roughness-based and rutting-based RD models were generated with a non-homogeneous TPM using the percentage transition method. In the analysis, pavement performance with flooding is represented with roughness and rutting data. These two factors are vital for representing pavement structural and functional responses, and they are widely used. Roughness is related to pavement structural and functional conditions, traffic loading and environmental factors, and has a direct relationship with vehicle operating costs, accidents and comfort (Odoki and Kerali, 2000; Prozzi, 2001). On the other hand, rutting is linked to pavement structural condition, skid resistance and accidents. Both roughness- and rutting-based RD models were thus used.

The percentage transition method uses real data to derive TPMs for representative road groups. It estimates transitions from one state to another in the next year, and generates a TPM. This method can address explanatory variables and inherent pavement deterioration. This study uses the international roughness index (IRI) and rutting distribution data to derive non-homogeneous TPMs with and without flooding. Monte Carlo simulation is then used for generating roughness- and rutting-based RD models.

To develop RD models for a road group, IRI and rutting versus time graphs with observed data are needed. These trends will ensure how many TPMs are necessary to obtain a final TPM for simulation. Generally, a new TPM is generated when there is a change in deterioration trend. A final TPM is derived for the years with no flooding from several TPMs and one TPM is used to reflect a flood. The final two TPMs – that is a TPM without flood and a TPM with flood – are then used in the simulation.

The current simulation was undertaken in Matlab. In each simulation, a set of random variables is used to compare with flooding probability and to determine if the normal TPM or a flood TPM should be utilised. The chance of selecting a flood TPM depends on the chance of a flood occurrence. A second random variable is generated to estimate the future state of a road. The final TPM is averaged over all the simulated states. After all the simulations are completed, RD models are generated for different probabilities of flooding. In the current RD modelling, this procedure is continued for 10,000 trials over a 20-year period.

TMR-QLD has records of detailed road inventory, road conditions, traffic and pavement historical data for its road network. The 34 000 km road database covers roughness and rutting data for about 10–12 years. RD as a result of flooding (with IRI and rutting data) is also captured in the database. Data quality checking was performed to obtain reliable road condition data through correcting missing data, zero values and assessing
deterioration trends. It was therefore possible to develop IRI and rutting deterioration trends with and without flooding TPMs for each road group and, ultimately, an RD model that reflects flooding.

The current study developed 27 road groups using TMR-QLD’s 34,000 km road data based on pavement type, traffic loading and pavement strength. The road grouping considers three types of pavement – flexible, composite and rigid. Similarly, traffic loading is divided into three types (high, medium and low) and pavement strength into three categories (strong, fair and poor). The new specific RD model is valid for a specific road group and, as a result, all of these RD models are suitable for the whole road network.

The development process of RD models with flooding is summarised in Table 1. Figure 1 shows the overall approach in deriving RD models for the 27 road groups. Roughness and rutting versus time are assessed to obtain trends on pavement performance for a road group, and with and without flooding TPMs are generated from the change in trends. These TPMs are used in the Monte Carlo simulation to obtain roughness- and rutting-based RD models for a road group. Details for deriving the TPM are given by Khan et al. (2012). Moreover, incremental changes in roughness ($\Delta$IRI) and rutting ($\Delta$rutting) were generated for different probabilities of flooding.

Figure 2 shows the simulation process (code used) to obtain RD models for different flooding probabilities. As already mentioned, random variables are generated to select either with or without...
flood TPMs. Then, another set of random variables is used to compare with the condition states. After 10,000 trials for a 20-year period, the average RD model is obtained.

4. Case study
Two road groups out of 27 are chosen here to demonstrate the numerical results of an RD model incorporating flooding. The two road groups are a flexible pavement with low traffic loading and high strength (F-LT-S) and a flexible pavement with low traffic loading and poor strength (F-LT-P). Some key features of these road groups are given in Table 2.

It is worth noting that the TMR-QLD road database was used for road grouping and derivation of with and without flooding TPMs.
from the observed roughness and rutting data. After statistical analysis of 34,000 km of road data, loading and strength ranges are set for road grouping. The criteria set for the three types of loading are low (<1 mesa (million equivalent single axle loading in design life)), medium (1–10 mesa) and high (>10 mesa). The three types of pavement strength are calculated from the available pavement age, seal age and pavement depth data. To obtain a hypothetical strength value, the relationship

\[
\text{Strength} = \frac{1}{A_p} \times \frac{1}{A_s} \times D_p
\]

is assumed, in which \(A_p\) is pavement age, \(A_s\) is seal age and \(D_p\) is pavement depth. After obtaining these data, pavements are grouped into three strength categories – poor (<1), fair (1–5) and strong (>5).

Figure 3 shows the developed roughness-based and rutting-based RD models for the two road groups. A comparison is given between observed and predicted pavement performances using roughness and rutting data, which seem to be reasonable. The observed 1 year with and without flooding data are averaged from the respective yearly flooding and non-flooding data. In Figure 3, observed non-flooding data are shown in year 1 and flooding is considered in year 2. However, the simulation considers flooding in year 1, hence the RD models with flooding show abrupt jumps at the first year. Therefore, the predicted and observed results do not match accurately, though their trends seem to be all right. Roughness and rutting increase predictions due to flooding (at year 2) are closer to the observed data for F-LT-P. It is worth mentioning that IRI = 5 and rutting = 25 mm are considered as ultimate values in the analysis, as practised by TMR-QLD.

Figure 4 shows the pavement performance with flooding (using IRI and rutting versus time) at different flooding probabilities for the two road groups. All are shown starting from year 1, although the roughness increase is not properly predicted at year 1 for F-LT-S. These results reveal that the highest impact on pavement performance up to a certain period may be observed at the highest probability of flooding (i.e. the higher the probability of flooding, the poorer is the pavement performance). For example, a 50% probability of flooding has more effect on pavement performance than a 10% probability of flooding. Monte Carlo simulation was used for all these predictions. It is noted that, after a certain period, the RD models become flat; therefore, the first 7 years of results have been considered to show the RD model’s scenario with different flooding probabilities.

Figure 4(a) shows a high roughness impact range at different flooding probabilities for F-LT-S, whereas a low impact range is observed for F-LTP. This is contrary to the case when rutting-based RD models are assessed, where F-LT-P has a higher impact range. In general, a higher strength road should perform better than a poor road. The roughness-based...
RD models for the two road groups reveal that if first year impact is considered then F-LT-S performs better than F-LT-P. However, this is not valid for the remaining 6 years where the stronger pavement shows less deterioration up to 10% probability of flooding, but beyond that it performs less well. It is worth mentioning that the stronger road performs better at different flooding probabilities when rutting-based RD models are compared (see Figures 4(b) and 4(d)).

Figure 5 shows $\Delta$IRI and $\Delta$rutting versus time at different probabilities of flooding for F-LT-S, which are presented to show pavement performance for 3 years and at the first year. In general, the highest probability of flooding has the highest effect on pavement performance, and the lowest probability has the lowest impact. The roughness increase in the first year for different probabilities of flooding lies in between 0-48IRI and 0-58IRI, and rutting is increased in the range 0-66-3-37 mm. As an example, 0-48IRI, 0-49IRI, 0-53IRI and 0-58IRI increases in roughness are observed in year 1 at 0%, 10%, 50% and 100% probability of flooding events respectively. Similarly, rutting increases of 0-66, 0-94, 2-02 and 3-37 mm are found for 0%, 10%, 50% and 100% probability of flooding respectively.

Similarly, $\Delta$IRI and $\Delta$rutting versus time at different probabilities of flooding for F-LT-P are shown in Figure 6. Pavement performance trends with flooding are the same for both road groups. The roughness increase in the first year for different probabilities of flooding is between 0-62IRI and 0-85IRI and rutting increases in the range 0-92-3-53 mm. Increases in roughness of 0-62IRI, 0-64IRI, 0-73IRI and 0-85IRI and rutting increases of 0-92, 1-16, 2-22 and 3-53 mm are observed in year 1 for 0%, 10%, 50% and 100% flooding event probabilities respectively. $\Delta$IRI and $\Delta$rutting thus increase at higher rates for the poorer pavement; as a result, the stronger road performs better during flooding. This information is useful from a practical point of view as it can assist asset management engineers to plan necessary treatments and budgets for after-flood rehabilitation. Moreover, investigations of inherent roughness and rutting increases due to flooding are also useful.

In practical applications, these results are important for selecting an optimum treatment for after-flood rehabilitation for a specific road group. For example, using the roughness-based RD model with 50% flooding probability for F-LT-S, the second year roughness is found to be 1-43IRI. If funding is ensured at the second year, then the optimum treatment (derived from a PMS tool like HDM-4) may be a thin overlay to ensure that the road
condition is good. However, if funding is not secured until the third year due to budget constraints, which is a reality, then the roughness-based RD model for this road group with 50% flooding probability shows that the new roughness value would be 2.30IRI at that time. As a result, the selected thin overlay may not be appropriate in the third year as the road has further deteriorated and a thick overlay may be needed to improve the road condition.

Similarly, rutting-based RD models may be used together with roughness-based RD models for appropriate treatment selection for a road group.

In fact, TMR-QLD did not receive all the necessary funding in the second year (in 2012) for after-flood rehabilitation in Queensland and the authority is still working on projects to manage the 2011 flood-damaged roads. Therefore, in practice, it is essential to use RD models with different flooding probabilities for a specific road group to determine current road condition states at the second, third and fourth year, etc. so that an appropriate treatment is chosen for after-flood rehabilitation.

Figure 4. Roughness-based and rutting-based RD models with different probabilities of flooding for two road groups

5. Conclusion
A flooding event may significantly weaken pavement structure and it is essential to select appropriate treatments for after-flood rehabilitation. The study of pavement performance with flooding is therefore an important element of a PMS, but there are no existing RD models that can address flooding. In view of that, the current study aimed to develop RD models incorporating flooding and pre- and post-flood strategies. The scope of the work covered saturated pavements that require rehabilitation with or without partial reconstruction as a post-flood treatment. As Queensland had experienced severe road damage due to the 2011 flooding, the study used the 34 000 km road database of TMR-QLD as a case study.

This paper has presented the development of new roughness-based and rutting-based RD models with flooding. It is proposed that probabilistic models with non-homogeneous Markov chains are much better for RD modelling because of uncertainties in pavement performance, materials and traffic loading. The per-
A percentage transition method was employed to develop with and without flood TPMs from the observed data for a road group to use in the Monte Carlo simulation for RD modelling. The proposed methodologies and simulation approach were discussed in this paper. Results from two specific road groups are used in this paper as examples. Similar trends between observed and predicted data were obtained, although the results do not match closely due to prediction of flooding at year 1 instead of the second year as considered for the observed data. As expected, the generated RD models with higher probabilities of flooding show increased rates of deterioration. It was observed that ΔIRI and Δrutting are high in the initial years due to flooding events, and are higher with greater flooding probabilities. Moreover, it was shown that a stronger road performs better during flooding. These roughness- and rutting-based RD models can predict pavement performance for different flooding probabilities. Each RD model is valid for its representative roads, and the developed roughness- and rutting-based RD models are transferrable to any probability of flooding events.

Moreover, these RD models are useful in the selection of optimum treatment for after-flood rehabilitation for a specific road group. A road’s condition definitely deteriorates in the second, third and fourth years post-flooding, and this was observed in the generated RD models. Therefore, depending on these roughness-based and rutting-based RD models and the availability of funding at different years along with a PMS tool like HDM-4, a road authority could select an appropriate treatment to rehabilitate a flood-damaged road. Furthermore, these models are helpful for a road authority to ensure cost-effective road asset preservation after flooding events, and this is an important advancement of a PMS.

Figure 5. ΔIRI and Δrutting versus time due to different probabilities of flooding for F-LT-S.
It is planned to use the derived RD models as input in HDM-4 for developing pre- and post-flood road maintenance strategies for each group. As a case study, 20-, 50- and 100-year flood maps would be used with the new RD models. In the future, investigations could be carried out to determine the causes of incremental changes in roughness and rutting after flooding events.

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REFERENCES


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