A STUDY OF ENVIRONMENTAL FACTORS ON PAVEMENT DETERIORATION USING THE HAZARD MODEL.

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Environmental factors must be considered to analyze how different climatic factors such as rainfall, temperature variations etc. affect the rate and extent of pavement deterioration. Climate of Nepal is dependent on the geographical features. The general climatic characteristic varies from alpine climate in the northern Himalayan region, temperate climate in the mid-hills to sub-tropical monsoon climate in the southern plain. Similarly, the monsoon is the essential part of Nepal's climate that occurs annually. Approximately 80 percent of the annual rainfall takes place during monsoon from June till September. Department of Roads (DOR) is the responsible agency established for the RAM of Strategic Road Network (SRN) in Nepal has challenges to maintain heavily traffic national highways to feeder roads with low traffic volume in varying climatic conditions such that to preserve and maximize the service periods of road assets. A review of environmental factors influencing pavement deterioration is important to road agencies for pavement design, construction materials selection and revising maintenance strategies. The Markov deterioration hazard model can be applied to estimate and forecast the deterioration process of the pavement. In the model, the deterioration process is described by transition probabilities. The deterioration states are categorized into several ranks based on inspection results and their deterioration rates are estimated by the hazard models. The application of the Markov deterioration hazard model for describing the pavement conditions of SRNs using the International Roughness Index data set from 2015 to 2022 and environmental factors as explanatory variables is presented in this paper.

Key Words: *Road asset management; Markov hazard model; Exponential hazard function; Pavement deterioration; Environmental factors*

1. INTRODUCTION

In recent years, road asset management has become increasingly important to road agencies in developing countries. A key objective of this concept is to implement a strategic management plan to minimize the life cycle cost of road assets by ensuring regular inspection, estimation of road degradation, and timely implementation of appropriate repair activities.

In Nepal, Department of Roads (DOR) established in 1962 is a service-oriented institution responsible for the construction and maintenance of Strategic Road Networks (SRNs) [1].SRN includes the National Highway, Feeder Roads, and Sub Urban Road Network of a total length of 14,656 km and 1,656 numbers of bridges excluding the under-construction and planned highway of approximately 3,536 km[2),3)]. DOR Strategy, July 1995 highlights the departmental policy document that was developed with the strategies to attain the end goal - "the reduction of total road transport cost". This depart-

mental end goal was also incorporated by the National Planning Commission into the 8th National Plan (1991/92). The total road transport costs are the sum of independent costs of road construction, road maintenance, and vehicle operating costs[4]. The comprehensive guideline of maintenance activities adopted by DOR to preserve the road in a serviceable state for road users and defer the need for high-cost road maintenance activities are well described in policy documents[5].

The annual budget for SRN maintenance is allocated by the Roads Board Nepal (RBN). Under the funding of RBN, the DOR has been collecting inspection data for International Roughness Index (IRI), Surface Distress Index (SDI), and Annual Average Daily Traffic (AADT) yearly. The traffic Survey involved traffic counting and analysis from 160 stations which are at the major nodal locations on the strategic road network of Nepal. Based on these data, the simple empirical method developed in 2005 is used to prepare the integrated annual road maintenance plan for all road division offices[6]. The Planned maintenance and the detailed methodology for the selection of the roads are explained in "Standard Procedure for Periodic Maintenance Planning", published in November 2005.

IRI is an internationally recognized standard for assessing road roughness. It is expressed in m/km. The standard procedure and roughness measuring devices are standardized by World Bank sponsored International Road Roughness Experiments conducted in Brazil in 1982[7]. The results are consistent and can be compared with other road sections locally and globally. The results of IRI can be correlated with ride quality and road user satisfaction. The annual road condition survey conducted for IRI in 2022 indicates 26 percent of the bituminous roads are in good condition (IRI < 4)[2].

DOR is facing the challenge of maintaining deteriorating SRN in fair to good condition. In the future aging road infrastructure and an increase in traffic volume will add up more difficulties to achieving satisfactory results. Timely predictions on maintenance demands of the road assets in the future along with the appropriate financial plans to implement the optimal repair strategy are important to overcome this challenge. In addition, the rate of deterioration of the road pavement is important for planning the appropriate maintenance approach. However, the pavement deterioration curve for the condition of Nepal is not available to forecast future deterioration.

Using road condition data from 2015 to 2022, and environmental factors as explanatory variables, a Markov deterioration hazard model is applied for forecasting the deterioration of SRN. The deterioration model can be applied to estimate the hazard rates and residual life of the pavement. Further, the average Markov transition probabilities (MTP) matrix, the hazard rate for each transition state, the life expectancy, and the expected deterioration path describing the average deterioration process during the life expectancy rating is presented in this paper.

2. METHODOLOGY

To forecast the deterioration progress of the pavement a statistical deterioration model based on past inspection results is applied. The Markov deterioration hazard model is a statistical model used to forecast the deterioration progress of pavement developed by Tsuda et al., 2006[8]. In this model, a rank order is assigned as a condition state depending on the result of the past inspection data. The MTP are estimated to represent the deterioration progress between the condition states. This model is widely preferred for sound maintenance strategies and budget management policies.

The road condition data for the study is acquired from Highway Management Information System Unit (HMIS) under Planning Branch within DOR. The road condition data is acquired from annual road inventory data recorded in the road register of SRN. The environmental data for rainfall and temperature data are purchased from the Department of Hydrology and Meteorology, Babarmahal, Kathmandu, Nepal. The data constitutes the location of meteorological station network and corresponding daily rainfall and temperature records. In this paper, the application of the Markov deterioration hazard model for deterioration forecasting of SRN in Nepal using the IRI data set and the environmental factors from 2015 to 2022 is presented.

(1) Model description

The Markov deterioration hazard model is the probabilistic model based on survival analysis and hazard function for multi-condition ratings. This model helps to predict the hazard rate, life expectancies, and deterioration curves of roads given the historical inspection results and other variables concerning various environmental impacts such as traffic volume, weather, temperature, axle loads, etc. These variables are termed explanatory variables. For the application of the Markov hazard model, the following assumptions must hold true.

Assumptions of the Markov model are : (a) there have been no maintenance and repair activities imposed and no measurement errors during the inspection period and (b) the deterioration process of the road section occurs naturally as its condition state

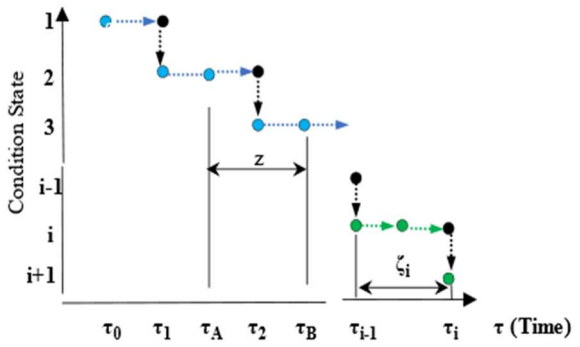


Fig.1 Deterioration process and inspection.

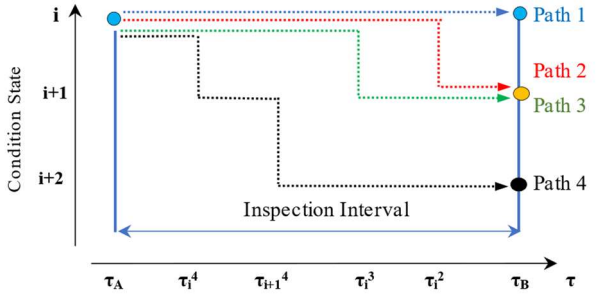


Fig.2 Condition states and possible deterioration paths (Kobayashi et al. 2010)

getting worsens over the year[9].

This deterioration process is explained graphically in **Fig.1** with blue round marks. At time τ_0 the condition state is in a good state with $i = 1$. Over the year condition state, i $(i = 1, 2, \dots, J)$ deteriorates and falls into a worse condition. Inspection is carried out at τ_A and τ_B. The condition state at inspection points is known but there is difficulty to trace exactly when the condition states transitioned, τ_1 and τ_2 in the **Fig.1**, between the two inspection points. Thus, it is noted that condition state 2 at any arbitrary future time τ_1 cannot be deterministically predicted. Moreover, the condition state at each time point in the time axis is restricted to the time at which the inspection is done.

In **Fig.1**, τ represents the calendar time. The deterioration of the road pavement starts immediately after its opening to public use at an initial time τ_0. The condition state is expressed by ranks representing condition state variable i $(i = 1, 2, \dots, J)$, where $i = 1$ represents the good or new situation. The increments of condition state i indicates progressing deterioration and $i = J$ indicate its service limit (absorbing state of the Markov chain). In **Fig.1** with green round marks, for each discrete time τ_i $(i = 1, 2, \dots, J)$, on the x-axis, we can observe the condition state changing from i to $i + 1$. Therefore, τ_i refers to the time at which the transition from condition state i to $i + 1$ occurs.

The data regarding the deterioration process can be obtained from the periodic inspection results. Since the continuous monitoring and inspection of infrastructure is difficult and cost-consuming, therefore normal practice is to conduct discrete periodic inspections during the service life of the infrastructure. The model assumes two periodic inspections at times τ_A and τ_B on the time axis such that its interval is denoted by Z $(Z = \tau_B - \tau_A)$.

Fig.1 also explains the deterioration path of pavement condition using the concept of the Markov chain. When the deterioration condition state changes from i to $i + 1$ (refer to green round marks) at τ_i, the duration it remained at condition state i can be expressed by ζ_i $(\zeta_i = \tau_i - \tau_{i-1})$. The life expectancy of a condition state i is assumed to be a stochastic variable with a probability density function $f_i(\zeta_i)$ and distribution function $F_i(\zeta_i)$. The distribution function $F_i(\zeta_i)$ represents the cumulative probability of the transition in the condition state for i to $i + 1$, when i is set at the initial point $y_i = 0$ (time τ_{i-1}). The cumulative probability $F_i(y_i)$ of a transition in the condition state i during the time points interval $y_i = 0\ to\ y_i \in [0, \infty]$ is defined as:

$$F_i(y_i) = \int_0^{y_i} f_i\ (\zeta_i) d\zeta_i \tag{1}$$

Accordingly, the survival function $R_i(y_i)$ becomes $R_i(y_i)$ = Prob$\{\zeta_i \geq y_i\}$ = $1 - F_i(y_i)$. By using the exponential hazard function, it is possible to represent the deterioration process that satisfies the Markov condition. The probability density $\lambda_i(y_i)$, which is referred to as the hazard function, is defined in the domain $[0, \infty]$ as:

$$\lambda_i(y_i) = \frac{f_i(y_i)}{R_i(y_i)} = \frac{\frac{dR_i(y_i)}{dy_i}}{R_i(y_i)} = \frac{e}{dy_i}\ (-logR_i(y_i)) \tag{2}$$

Using the hazard function $\lambda_i(y_i) = \theta_i$, the probability $R_i(y_i)$ that the life expectancy of the condition state i remains longer than y_i and its probability density function $f_i(\zeta_i)$ are expressed by the following

$$R_i(y_i) = \exp\left[-\int_0^{y_i} \lambda_i(u) du\right] = \exp\left(-\theta_i y_i\right) \tag{3}$$

$$f_i(\zeta_i) = \theta_i \exp\left(-\theta_i \zeta_i\right) \tag{4}$$

Referring to **Fig.2**, it is supposed that at time τ_A, the condition state observed by inspection is i $(i = 1, 2, \dots, J - 1)$. The deterioration process in future times is uncertain. Among the infinite set of possible scenarios describing the deterioration path, only one path is finally realized. For simplicity, there are four possible sample paths described as follows:

Path 1 indicates no transition in condition state i during the periodic inspection interval. Path 2 indicates the transition of the pavement from condition state i to $i+1$ at time τ_i^2. Path 3 indicates the transition of the pavement from condition state i to $i+1$at time τ_i^3. Path 4 indicates the transition of the pavement from condition state i to $i+1$ and $i+2$ at time τ_i^4 and τ_{i+1}^4 respectively. The condition state observed at τ_B is $i+2$. The transitions in the condition state are observed only at the time of periodic inspections (at τ_A and τ_B) and it is not possible to obtain information about the time in which those transitions occurred (τ_i^4, τ_{i+1}^4, τ_i^3, τ_i^2 etc.)

(2) Markov transition probability

The transition process of the condition state for road pavement is uncertain and forecasting future states cannot be done deterministically. The MTP is used to represent the uncertain transition of the condition state during two points in time. In other words, MTP are defined to forecast the deterioration of pavement using the periodic inspection process shown in **Fig.2**. The observed condition state of the component at time τ_A is expressed by using the condition state variable $h(\tau_A)$. If the condition state observed at time $\tau_A = i$, a Markov transition probability, given a condition state $h(\tau_A) = i$ observed at time τ_A, defines the probability that the condition state at a future time τ_B will change to $h(\tau_B) = j$, that is

$$\text{Prob}[h(\tau_B) = j | h(\tau_A) = i] = \pi_{ij} \quad (5)$$

The MTP matrix can be defined by using the transition probabilities between each pair of condition states (i, j) as:

$$\prod = \begin{pmatrix} \pi_{11} & \cdots & \pi_{1J} \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \pi_{JJ} \end{pmatrix} \quad (6)$$

Where, $\pi_{ij} \geq 0$,

$\pi_{ij} = 0$ (when $i > j$) since the model does not consider the repair and $\sum_{j=1}^{J} \pi_{ij} = 1$.

The final state of deterioration is expressed by condition state J, which remains an absorbing state in the Markov chain if no repair is carried out. In this case $\pi_{JJ} = 1$.

(3) Determination of Markov transition probability

From **Fig.2** various deterioration paths are possible that are broadly classified into π_{ii} , π_{ii+1}, π_{ij} and π_{iJ}. The MTP for these possible paths are based on the exponential hazard model can be explained for the three cases considering the condition state observed at periodic inspection time point as shown in **Fig.3**.

Case 1: The condition state i does not change during the inspection interval Z: For a condition state i obtained at the inspection time point y_A, the probability that the same condition state is observed at a time point y_B (= $y_A + z$) is expressed by:

$$\pi_{i\,i} = \text{Prob}[h(y_B) = i \mid h(y_A) = i]$$

$$= \exp(-\theta_i Z) \quad (7a)$$

The equation (7a) indicates that π_{ii} is dependent only on the hazard rate (θ_i) and inspection interval (Z). This shows it is also possible to estimate transition probability without using the deterministic value of the time points y_A and y_B.

Case 2 : The condition state changes from i to $i+1$ during the inspection interval Z : For a condition state i observed at inspection time point y_A to change to condition state $i+1$ at time point y_B, the transition is assumed to occur as 1) the condition state i remains constant between a time point y_A to a time point $s_i = y_A + z_i$, ($z_i \in [0, Z]$), 2) the condition state changes to $i+1$ at the time point $y_A + z_i$, and 3) it remains constant between $y_A + z_i$ and y_B. Although the exact time in which the condition state transition from i to $i+1$ cannot be traced by periodic inspection, it is assumed that the transition occurs at a time point $\bar{s_1} \in [y_A, y_B]$. The MTP that the condition state change from i to $i+1$ during the time points y_A and y_B is expressed by:

$$\pi_{i\,i+1} = \text{Prob}[h(y_B) = i+1 \mid h(y_A) = i]$$

$$= \frac{\theta_i}{\theta_i - \theta_{i+1}} \{-\exp(-\theta_i Z) + \exp(-\theta_{i+1} Z)\} \quad (7b)$$

where, $\pi_{i\,i+1} < 1$

Case 3 : The condition state changes from i to j ($j \geq i+2$) during the inspection interval Z : For a condition state i observed at the inspection time point y_A to change to condition state j at the time point y_B, the transition is assumed to occur as: 1) the condition state i remains constant between a time point y_A, $\bar{s}_i = y_A + \bar{z}_i \in [y_A, y_B]$, 2) the condition state changes to $i+1$ at the time point $\bar{s_i} = y_A + \bar{z}_i$, 3) the condition state $i+1$ remains

constant during the time interval $\bar{s}_i = y_A + \bar{z}_i$, $\bar{s}_{i+1} = \bar{s}_i + \bar{z}_{i+1}$ $(\bar{s}_{i+1} \leq y_B)$, and at this time point changes to $i+2$. After repeating the same process 4) the condition state changes to j at some time point $\bar{s}_{j-1}$ $(\leq y_B)$ remains constant until the time point y_B.

The MTP that the condition state change from i to j $(j \geq j+2)$ during the time points y_A and y_B is expressed by:

$$\pi_{ij} = \text{Prob}[h(y_B) = j \mid h(y_A) = i] = \sum_{k=i}^{j} \prod_{m=i}^{k-1} \frac{\theta_m}{\theta_m - \theta_k} \prod_{m=k}^{j-1} \frac{\theta_m}{\theta_{m+1} - \theta_k} \exp(-\theta_k Z) \quad (7c)$$

where,

$\prod_{m=i}^{k-1} \frac{\theta_m}{\theta_m - \theta_k} = 1, at\ (k \leq i+1)$ and

$\prod_{m=k}^{j-1} \frac{\theta_m}{\theta_{m+1} - \theta_k} = 1\ at\ (k \geq j)$.

In equation (7c) , π_{ij} $[0 < \pi_{ij} < 1]$, and π_{iJ} is arranged using the MTP conditions as follows:

$$\pi_{iJ} = 1 - \sum_{j=1}^{j-1} \pi_{ij} \quad (7d)$$

In equation (7a) ~ (7d) the multistage exponential hazard model has been defined. However, considering the explanatory variable to estimate hazard rate θ_i which is defined as the function of explanatory variables $\mathbf{x^k}$ and unknown parameters $\boldsymbol{\beta_i}$. where $\beta_i = (\beta_{i.1}, \ldots, \beta_{i.m})$ and $\boldsymbol{m} = (1, 2, \ldots, M)$ is the number of explanatory variable and $k = (1, 2, \ldots, K)$ is an individual sample of inspection data.

$$\theta_i^k = f(\boldsymbol{x^k}: \boldsymbol{\beta_i}) \quad (8)$$

In summary, the elements of MTP matrix π_{iJ} are estimated using $\pi_{iJ}\,(Z^k, \boldsymbol{x^k}: \boldsymbol{\beta_i})$. The unknown parameter $\boldsymbol{\beta_i}$ $(i = 1, 2, \ldots, J-1)$ is determined with Bayesian estimation method to obtain the hazard function $\theta_i^k (i = 1, 2, \ldots, J-1)$, the life expectancy of each condition state i can be defined by means of the survival function $R_i(y_i^k)$.

$$LE_i^k = \int_0^\infty \exp(-\theta_i^k y_i^k) dy_i^k = \frac{1}{\theta_i^k} \quad (9)$$

Life expectancy from i to J can be estimated using

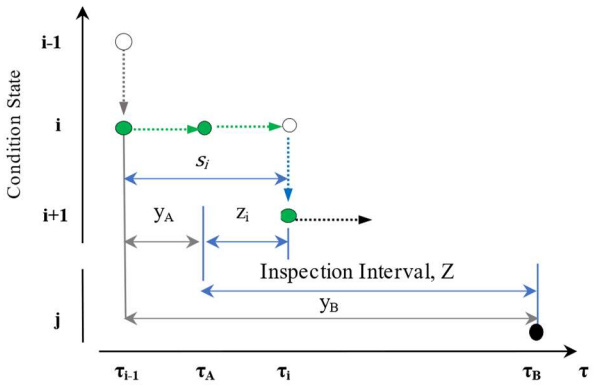


Fig.3 Periodic inspection practice of the condition state.

$$LE_i^J = \sum_{i=1}^{J-1} LE_i^k \quad (10)$$

The MTP matrix $\prod$ defined in equation (6) can be composed by aggregating π_{ij} from equation (7a) – (7d). For detailed description it is recommended to refer the reference Tsuda et al., 2006[8].

4) Determination of unknown parameter β using Bayesian estimation.

Bayesian estimation is an iterative method of statistical inference that involves using prior knowledge and data to estimate the parameters of a model. In the context of a Markov hazard model, Bayesian estimation can be particularly useful to estimate the unknown parameter $\boldsymbol{\beta_i}$ for several reasons. They are (a) Incorporation of prior knowledge: In Bayesian estimation, it allows us to use prior knowledge about the parameters of the model to inform our estimates. This can be particularly useful in case of some prior knowledge about the parameters that we are trying to estimate. (b) Robustness to small sample sizes: Bayesian estimation can be more robust to small sample sizes compared to classical methods, as it allows us to incorporate prior knowledge and make use of partial information. (c) Quantification of uncertainty: Bayesian estimation allows us to quantify the uncertainty associated with estimates, which can be useful for decision making and risk assessment. And (d) Flexibility: Bayesian estimation is generally more flexible compared to classical methods, as it allows to specify different prior distributions and consider different model structures.

In Bayesian statistics, the posterior distribution of parameters is estimated by using a likelihood function, inspection data and an assumed prior distribution of the model parameters. Hence, the posterior distribution $\pi(\boldsymbol{\beta}|\boldsymbol{\xi})$ is proportional to the likelihood function $L(\boldsymbol{\beta}|\boldsymbol{\xi})$ and prior distribution $\pi(\boldsymbol{\beta})$[10]. That is:

$$\pi(\boldsymbol{\beta}|\boldsymbol{\xi}) \propto L(\boldsymbol{\beta}|\boldsymbol{\xi})\, \pi(\boldsymbol{\beta}) \quad (11)$$

where, $\boldsymbol{\beta}$ is a probabilistic random variable with prior probability density function $\pi(\boldsymbol{\beta})$ and $\boldsymbol{\xi}$ is the observed inspection data. The posterior probability density function of unknown parameter $\boldsymbol{\beta}$ can be defined by the simplest form of Bayes Theorem as:

$$\pi(\boldsymbol{\beta}|\boldsymbol{\xi}) = \frac{L\,(\boldsymbol{\beta}|\boldsymbol{\xi})\;\pi(\boldsymbol{\beta})}{\int L\,(\boldsymbol{\beta}|\boldsymbol{\xi})\pi(\boldsymbol{\beta})\,d\beta} \tag{12}$$

Where, $L(\boldsymbol{\xi}) = \int L(\boldsymbol{\beta}|\boldsymbol{\xi})\pi(\boldsymbol{\beta})d\beta$ is the marginal probability of $\boldsymbol{\xi}$, called the normalizing constant.

In conclusion, Bayesian estimation can be a useful method for estimating the parameters of a Markov hazard model, particularly with limited data or prior knowledge that need to incorporate into estimates.

The Bayesian method for estimation can be summarized in 3 steps:
Step 1: Define the prior probability distribution $\pi(\boldsymbol{\beta})$. **Step 2**: Define the likelihood function $L(\boldsymbol{\beta}|\boldsymbol{\xi})$ by using newly obtained data $\bar{\boldsymbol{\xi}}$. **Step 3**: Modify the prior distribution $\pi(\boldsymbol{\beta})$ using the Bayes' rule and update the posterior distribution $\pi(\boldsymbol{\beta}|\boldsymbol{\xi})$ for parameter $\boldsymbol{\beta}$.

In this paper, we suppose that the observed data is defined by $\bar{\boldsymbol{\xi}} = (\bar{\xi}^1, \ldots, \bar{\xi}^k)$ and the inspection information of the inspection sample k is $\bar{\boldsymbol{\xi}}^{\boldsymbol{k}} = (\bar{\delta}_{ij}^k, \bar{\boldsymbol{z}}^{\boldsymbol{k}}, \bar{\boldsymbol{x}}^{\boldsymbol{k}})$. (The likelihood function $L(\boldsymbol{\beta}|\boldsymbol{\xi})$ based on Bayes Rule is defined by using $\pi_{ij}(z)$ such that:

$$L(\boldsymbol{\beta}|\boldsymbol{\xi}) = \prod_{i=1}^{J-1}\prod_{j=i}^{J}\prod_{k=1}^{K}\{\sum_{h=i}^{j}\prod_{l=i}^{h-1}\frac{\theta_l^k}{\theta_l^k-\theta_h^k} \cdot \prod_{l=h}^{j-1}\frac{\theta_l^k}{\theta_{l+1}^k-\theta_h^k}\exp\left(-\theta_h^k\bar{z}^k\right)\}^{\bar{\delta}_{ij}^k} \tag{13}$$

where, $\bar{\delta}_{ij}^k$ is a dummy variable, whose value is 1 when $h(\tau_A^k) = i$ and $h(\tau_B^k) = j$, otherwise 0.

Referring to step 1, to define the prior probability density distribution function of unknown parameter $\boldsymbol{\beta}$, we defined a conjugate prior probability density function and assume that the prior probability density distribution function of unknown parameter $\boldsymbol{\beta}$ follows the conjugate multidimensional normal distribution such that $\boldsymbol{\beta_i} \sim \boldsymbol{N_M}\,(\mu_i, \sum_i)$. This assumption is essential to overcome the computational problems related to the non-convergence of estimation results and to derive a similar function for the posterior probability density function. Thus, we can express the probability density function of the M-dimensional normal distribution $\boldsymbol{N_M}\,(\mu_i, \sum_i)$ as:

$$g(\boldsymbol{\beta}_i|\mu_i, \boldsymbol{\Sigma_i}) = \frac{1}{(2\pi)^{\frac{M}{2}}\sqrt{|\Sigma_i|}} \cdot \exp\left\{-\frac{1}{2}\,(\boldsymbol{\beta}_i - \mu_i)\,\boldsymbol{\Sigma}_i^{-1}(\boldsymbol{\beta_i} - \mu_i)'\right\} \tag{14}$$

where, μ_i represents the prior expectation vector (or mean) of $\boldsymbol{N_M}\,(\mu_i, \sum_i)$ and $\boldsymbol{\Sigma_i}$ is the prior variance – covariance matrix. The symbol $'$ denotes the transpose. Substituting the value from equation (13) and equation (14), the posterior density function $\pi(\boldsymbol{\beta}|\boldsymbol{\xi})$ in equation (11) can be defined as:

$$\pi(\boldsymbol{\beta}|\bar{\boldsymbol{\xi}}) \propto L\,(\boldsymbol{\beta}|\bar{\boldsymbol{\xi}}) \cdot \prod_{i=1}^{J-1} g(\boldsymbol{\beta_i}|\mu_i, \boldsymbol{\Sigma_i}) \propto \prod_{i=1}^{J-1}\prod_{j=i}^{J}\prod_{k=1}^{K}\{\sum_{h=i}^{j}\prod_{l=i}^{h-1}\frac{\theta_l^k}{\theta_l^k-\theta_h^k} \cdot \prod_{l=h}^{j-1}\frac{\theta_l^k}{\theta_{l+1}^k-\theta_h^k}\exp\left(-\theta_h^k\bar{z}^k\right)\}^{\bar{\delta}_{ij}^k} \cdot \frac{1}{(2\pi)^{\frac{M}{2}}\sqrt{|\Sigma_i|}}\exp\left\{-\frac{1}{2}\,(\beta_i - \mu_i)\,\Sigma_i^{-1}(\beta_i - \mu_i)'\right\} \tag{15}$$

However, the normalizing constant $L(\boldsymbol{\xi}) = \int L(\boldsymbol{\beta}|\boldsymbol{\xi})\prod_{i=1}^{j-1} g(\boldsymbol{\beta_i}|\mu_i, \boldsymbol{\Sigma_i})d\boldsymbol{\beta}$ is difficult to calculate. To overcome such limitation, we use Metropolis – Hastings algorithm often known as M-H algorithm in Markov chain Monte Carlo (MCMC) simulation to directly obtain the statistical value regarding the posterior distribution of parameters [14]. This method is suitable and can be applied when the normalizing constant for density function is not known or difficult to calculate[11]. The M-H algorithm operates as follows:

Step 1: Define the initial value of the parameter vector $\beta(0)$. **Step 2**: Calculate current probability density $\pi(\beta(n))$ by using current $\beta(n)$. **Step 3**: Find a candidate value as $\tilde{\beta}(n) = \beta(n) + \varepsilon(n) \sim N\,(0, \sigma^2)$ where $\boldsymbol{\varepsilon}$ is the step width of the random walks. **Step 4**: Calculate the proposal density by using $\tilde{\beta}(n)$ as a candidate parameter $\pi\left(\tilde{\beta}(n)\right)$. **Step 5**: Apply the updating rule by comparing $\pi(\tilde{\beta}(n))$ and $\pi(\beta(n))$ with the following conditions.

$$\beta(n+1) = \begin{cases} \pi\left(\tilde{\beta}(n)\right) > \pi(\beta(n)), \beta(n+1) = \tilde{\beta}(n) \\ \pi\left(\tilde{\beta}(n)\right) \le \pi(\beta(n)), \begin{cases} R \le r, \beta(n+1) = \tilde{\beta}(n) \\ Else, \beta(n+1) = \beta(n) \end{cases} \end{cases} \tag{16}$$

Table 1 Road Condition based on IRI

IRI Range	Condition	Condition State Ranking
<4	Good	1
4-6	Fair	2
6-8	Poor	3
>8	Bad	4

Table 2 Zone based on average temperature.

Average Temperature Range	Zone
< 10°C	I
10°C – 15°C	II
15°C – 20°C	III
20°C – 25°C	IV
25°C – 30°C	V

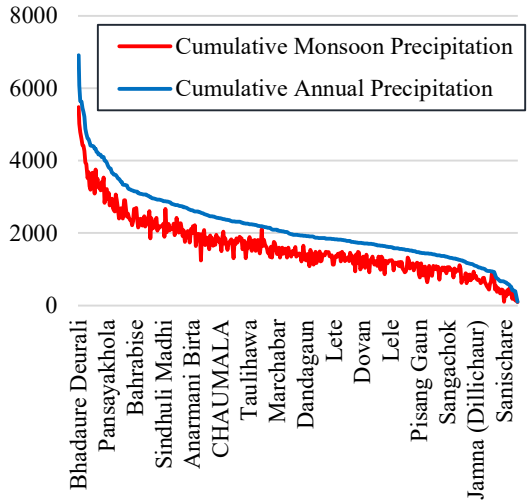


Fig.4 Rainfall in mm, 2021

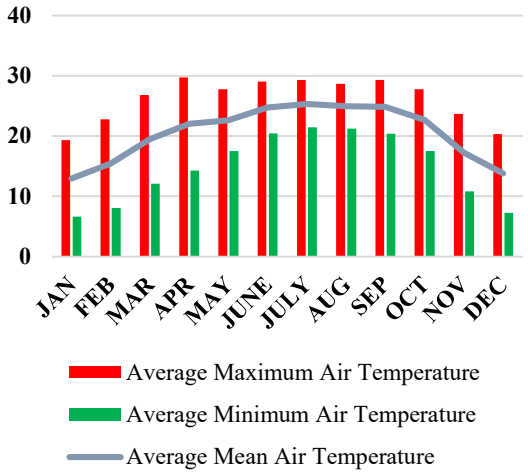


Fig.5 Monthly Climatology of Average Maximum Air Temperature, Average Minimum Air Temperature and Average Mean Air Temperature, 2021

Where, $r = \pi\left(\tilde{\beta}(n)\right)/\pi(\beta(n))$, and R is a standard uniform for $R \sim U(0,1)$.

Then sufficiently large numbers of iterations from step 2 to step 5 are done, until sequence $\beta(n)$ becomes a stationary condition (that is close to convergence). Burn-in samples are cut, and the average of sample parameters are taken.

The M-H algorithm also generates Markov chains as the transition probabilities from $\beta(n)$ to $\beta(n+1)$ that independent of $\beta(0)$. The MCMC does not include any method to confirm that the initial value $\beta(0)$ reaches stationary distribution. To check theMarkov chain reaches the convergence to a maximum, Geweke's test is used. Geweke's test takes two sample groups (n_1, n_2) from the first 10% and the last 50% of the Markov chain. If the mean of the two groups is equal, it indicates the chain is stationary. A modified z-test can be used to compare the two samples and the resulting statistics are termed as Geweke's z-score. The detailed description of M-H algorithm and Geweke's test to confirm the convergence of the Markov chain can be referred to Han et. al., (2014)[12].

3. EMPIRICAL ANALYSIS

Among the four measures identified for a performance measure, DOR considers the following two primary measures: i) surface roughness and ii) surface distress of pavement to determine how well the pavement is performing and meets the serviceability requirement of the road. The Bayesian estimation for the Markov hazard model is carried out with the actual inspection data based on one of the two performance measures of road pavement of SRNs. The inspection data set corresponding to road roughness includes the result of two inspection intervals: Z, and characteristic variable: x. To apply MTP the condition rating shown in **Table 1** is used to rate the pavement based on IRI.

In this study, environmental factors like cumulative monsoon rainfall (C_m) and average temperature (T_a) are considered as environmental characteristic variables respectively. There are primarily two types of pavement (a) Surface treatment over granular base (STGB) and (b) Asphalt Material over granular base (AMGB). These two categories of pavement are represented by 0 and 1 respectively as categorical explanatory variables. For analysis, all quantitative value of the characteristic variable is normalized so that the maximum value becomes 1. The total number of 3,209 sets of road section data based

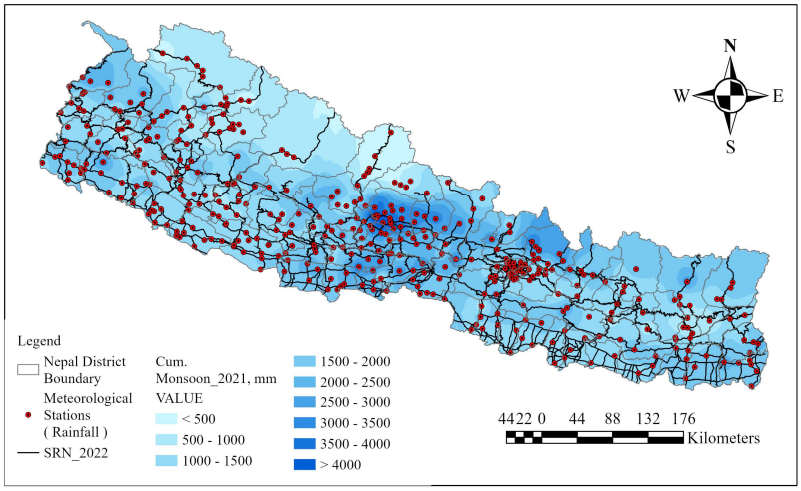


Fig.6 SRN and Cumulative Monsoon Rainfall Distribution, mm, 2021

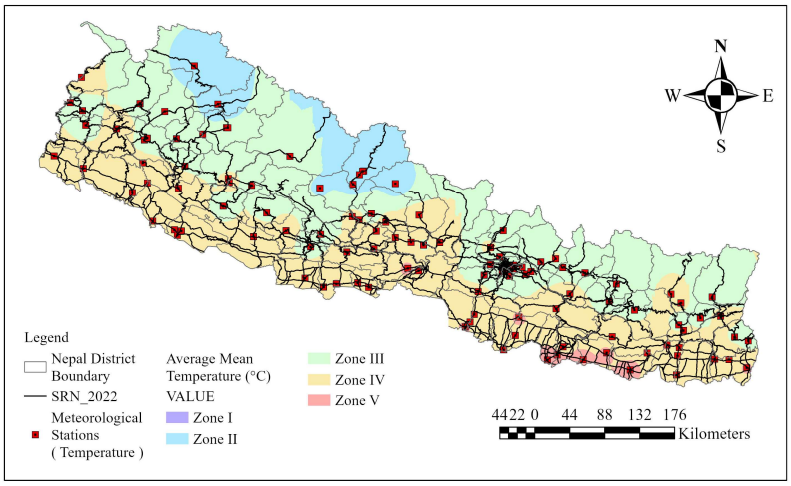


Fig.7 SRN and Average Temperature Distribution, °C, 2021

on IRI satisfying the Markov condition were analyzed. These data sets are used in this paper to estimate the parameters of the exponential hazard function.

(1) Surface roughness

Surface roughness is closely related to the pavement condition and the vehicle operating cost increases with an increase in the roughness of the IRI expressed in m/km is used to provide a common scale for recording road roughness. A vehicle-mounted Bump Integrator is a response-type instrument to measure the surface roughness annually[13]. The road condition and the condition state based on IRI are shown in **Table 1**.

(2) Rainfall

Rainfall is an important environmental factor having damaging effects on road pavement. In Nepal, the monsoon is the major source of rainfall. There are more than 1,000 meteorological stations over Nepal for rainfall observation under the Department of Hydrology and Meteorology. The meteorological stations having a complete set of rainfall records throughout the year are only considered for the study. For example, in the year 2021, rainfall data from 435 out of 1,010 meteorological stations are considered for study.

The daily rainfall measurement data by the meteorological station network is summed to determine the cumulative annual monsoon rainfall (C_m) at each station. Inverse distance weighting (IDW), a GIS application to interpolate between stations of known rainfall value, is used to generate cumulative rainfall distribution (mm) over Nepal. A plot of the cumulative annual rainfall and cumulative monsoon rainfall measurements from 435 meteorological stations in 2021 is shown in **Fig.4**. **Fig.6** shows the location of meteorological stations, SRN and Cumulative Monsoon Rainfall Distribution in millimetres for year 2021. Approximately 80 percent of the annual rainfall takes place from June till September[14)–16)].

(3) Temperature

The general climatic characteristic of Nepal is broadly divided into 3 groups.
(i) Sub-tropical monsoon climate in southern plain region with hot, humid summer with heavy monsoon. (ii) Temperate climate in the hilly region with mild to warm summer and cool to cold winters. (iii) Alpine climate in northern Himalayan region with cold and harsh winter with heavy snowfall. Nepal can be divided into different zones according to altitude, ranging from the Terai region in the south at less than 500 m above sea level to the high Himalayan region in the north at over 5,000 m. Average temperatures ranges from a peak of over 40°C in the south down to below freezing point in highest mountains[17]. Temperature varies considerably both climatically and according to altitude of Nepal. The daily temperature variations are recorded using 115 meteorological stations throughout the country. IDW is used to interpolate between stations of known temperature value and generate temperature zones as described in **Table 2** with average temperature range (°C) over Nepal.

A plot of monthly climatology of average maximum air temperature, average minimum air temperature and average mean air temperature, 2021 from 115 meteorological stations in 2022 is shown in **Fig.5**. **Fig.7** shows the location of meteorological stations for temperature recording, SRN and average temperature distribution in °C for the year 2021.

4. RESULTS

(1) Average Markov transition probability

The MTP matrix for each sample is estimated by using the exponential hazard model and the average MTP matrix is determined which are presented in **Table 3**.

For IRI, there are 4 rating and 3 explanatory variables, this gives a total of 12 unknown parameters $\boldsymbol{\beta}$. The Bayesian estimated results of the unknown parameter $\boldsymbol{\beta}$ for IRI are shown in **Table 3** with the respective Geweke's test value of each explanatory variable in parenthesis.

(2) Hazard rate and life expectancy

The hazard rate for each transition is estimated using equation (8). Since the two major types of pavements STGB and AMGB differ in pavement thickness, strength, construction technology and cost etc. the hazard rate are estimated separately. The life expectancies for each transition are estimated using equation for two major types of pavements STGB and AMGB are (9) and they are graphically represented in **Fig.8.**

Table 3 MTP Matrix from estimation results - IRI

Rating	1	2	3	4
1	0.659	0.274	0.059	0.008
2	-	0.658	0.288	0.054
3	-	-	0.724	0.276
4	-	-	-	1

Table 4 Exponential Hazard Model Results

Rating	Const. β_0	C_m β_{i1}	T_a β_{i2}	P. Type β_{i3}
1	-1.094 (-0.654)	-0.525 (1.365)	1.497 (-1.105)	-0.498 (0.298)
2	0.741 (-0.741)	-1.462 (1.877)	-2.209 (-1.097)	-0.832 (0.1148)
3	-1.015 (-1.791)	0.1009 (-0.163)	0.009 (-1.208)	-0.565 (-0.603)

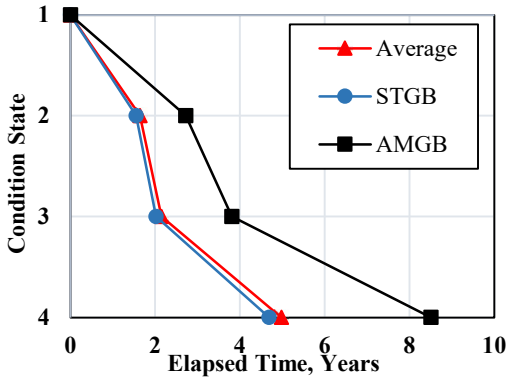


Fig.8 Expected deterioration path for pavement

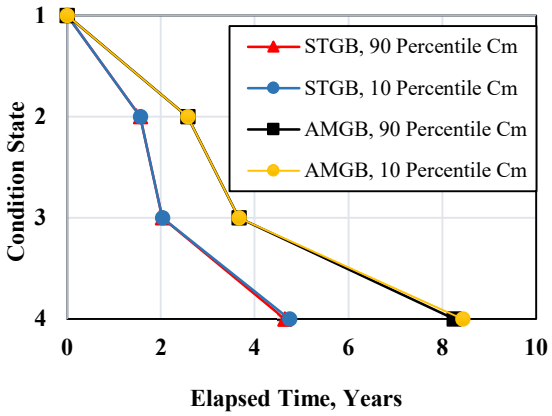


Fig.9 Expected deterioration path of pavement for cumulative monsoon.

To understand the change in condition state over time visually, it is convenient to express the deterioration process by curves. The expected deterioration path can be represented by a curve describing the average deterioration process during the life expectancy rating as shown in **Fig.8, Fig.9** and **Fig.10**. The results of the study for the effect of monsoons on pavement deterioration are also presented. The expected deterioration path for the 90th percentile and 10th percentile cumulative monsoon for two major types of pavements STGB and AMGB is shown in **Fig.9.** Similarly, the expected deterioration path of pavements in different zones based on temperature is shown in **Fig.10.**

Further, it is also important to understand the time series variation of the condition state distribution of the entire infrastructure system or in our case the entire strategic road network for effective planning of asset management. The time-series variation of the condition state distribution is analyzed using the MTP. Let us consider a case where the entire road network is new at initial time t ($t = 0$). The condition state ranking of all equals to 1 (IRI < 4) and we define the initial value of the state vector as $X_t = (1, 0, 0)$. Then using the MTP the time-series variation of the condition state is calculated for consecutive 10 times. Since the inspection interval is 1 year, repeating the calculation 10 times will represent the condition state distribution over a period of 10 years.

Fig.11 shows the transition of the condition state distribution when MTP in **Table 3** is estimated using the IRI for condition state ranking. From **Fig.11** we can observe the at the deterioration process and increasing occupancy rates of higher condition states with elapse of time. Referring to **Fig.11**, after 5 years, there are approximately 7.2%, 20.6%, 33.2% and 39.0% of the entire road network will be in good, fair, poor and bad condition considering IRI respectively demanding huge capital reinvestment to reinstate into good condition.

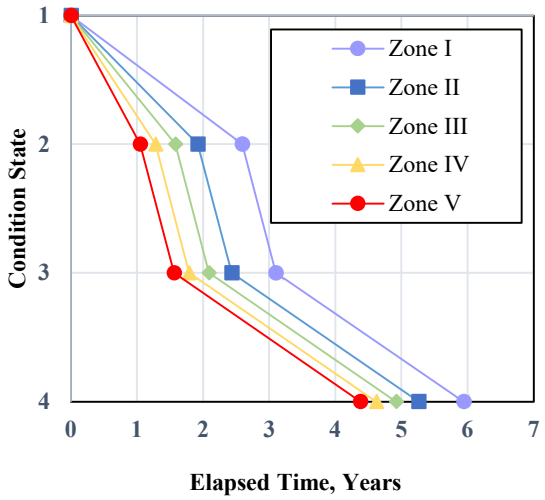


Fig.10 Expected deterioration path of pavement for cumulative monsoon.

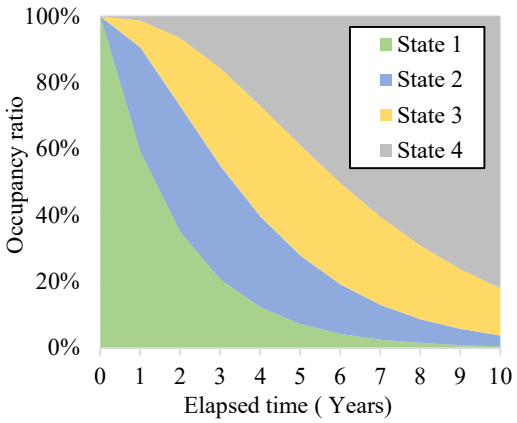


Fig.11 Transition of the condition state distribution

4. DISCUSSION

The road pavement mainly deteriorates under environmental factors. The environmental parameter i.e., cumulative monsoon rainfall (C_m) measured in mm, shows deterioration action on the pavement in the later condition states. Similarly, average temperature (T_a) measured in °C, shows deterioration action on the pavement in the initial and later condition states. The deterioration process of the pavement is estimated including only the positive values of unknown parameter $\boldsymbol{\beta}$ for environmental explanatory variables.

Periodic maintenance complemented by routine and recurrent maintenance work is performed to improve and extend the service life of the pavement. There are two major types of pavements in Nepal STGB and AMGB. The current practice suggests an interval of 5-8 years for periodic maintenance irrespective of pavement type[6].

The deterioration curves indicate that the rate of deterioration is high, and this interval is leading to further degradation of the road condition beyond the scope of periodic maintenance. This is more significant for STGB type roads which will demand expensive maintenance alternatives such as rehabilitation and reconstruction in future to reinstate into good condition.

The life expectancies of STGB and life expectancies of AMGB type roads are shown graphically in **Fig.8**, **Fig.9** and **Fig.10**. The average deterioration period in years during the life expectancy of the rating i.e., from the time the rating is reached to the next rating is attained is known. This information can provide an actual time frame to plan efficient

inspection intervals and maintenance planning.

5. CONCLUSION

In addition to the construction of new road infrastructure, it is also necessary to implement the concepts of road asset management for effective and efficient utilization of road assets during their service life in the future. In this study, Markov deterioration hazard model is applied for deterioration forecasting of SRN in Nepal. The study indicates the deterioration rate is high. The total life expectancy of entire road network considering IRI is 4.98 years. The deterioration curves presented in **Fig.8, Fig.9** and **Fig.10** can be used to forecast the future condition state of the road network and predict the remaining life expectancies.

However, there are still many aspects for future study. First, the study is limited to environmental factors only. The traffic parameter with reliable data sets can be included in this study for improved results. Second, the study can be extended using pavement temperature as explanatory variables in future studies. Third, the study presents the average deterioration process of the entire road network, but the road network itself is composed of heterogenous road infrastructures that can be grouped into different infrastructure groups considering categorical variables. By using the mixed Markov deterioration hazard model, the deterioration characteristics of individual groups of road infrastructure can be studied. It is expected to include the above-mentioned explanatory variables in the future with sufficient inspection data to expand the study for improved forecasting of the deterioration process of road infrastructure.

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