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Development of IRI Prediction Models for National Highways in Nepal

by

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A THESIS

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The undersigned certify that they have read, and recommended to the Institute of Engineering for acceptance, a thesis entitled **"Development of IRI prediction model for National Highways in Nepal"** submitted by **Taranath Sigdel** in partial fulfillment of the requirements for the degree of Master of Science in Transportation Engineering.

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ABSTRACT

Reliable predictions of pavement performance are essential for transportation agency to effective planning and management for maintenance, rehabilitation, and reconstruction of roads. International Roughness Index (IRI) is the most widely used pavement performance indicator. It reflects the overall pavement condition, riding quality and comfort level. Developments of pavement performance models are necessary for effective/ optimum pavement maintenance strategy. Modeling of IRI over time gives the performance of pavement over time. In the past decade correlation study between IRI and others performance indicators were made, however, most of them are not reliable for the prediction of roughness. In this study, IRI over time was modeled through both multiple linear regressions and the Artificial Neural Network (ANN) approach. The model was developed by using the pavement and traffic database stored in Department of Roads, Highway Management of Information System unit and climate data stored in Department of Hydrology and Meteorology. Rainfall, annual low temperature and high temperature days, commercial vehicle and initial IRI are considered as input parameters for modeling IRI. The final database consisted of 1682 sections with 3587 total observations based on which the generalized IRI prediction model for flexible pavements of national highways in Nepal was developed. The regression model yielded a coefficient of determination (R^2) value of 0.76 while the ANN model yielded a coefficient of determination (R^2) of 0.82 showing better fit to the data. Sensitivity analysis shows the initial IRI is most sensitive parameter with sensitive index 0.85 while low temperature days is found least sensitive variable among all. A generalized and six regional IRI predictions models considering specific terrain and traffic conditions were developed using ANN techniques. The R^2 values of the models are in a range 0.73 to 0.86 showing good fit to the data. The IRI trends over time as observed from the performance curves developed from the models follow S- shape patterns by both generalized and regional models. The performance curve reveals that the environmental factors are overshadowed by traffic factors in early stage of pavement.

Keywords: *International Roughness Index, Traffic and Environmental data, Artificial Neural Network, Flexible pavement, Performance Indicators.*

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LIST OF ACRONYMS AND ABBRIVIATIONS

AADT	Average Annual Daily Traffic
ANN	Artificial Neural Network
ASTM	American Society for Testing Materials
BI	Bump Integrator
BP	Back Propagation
CV	Commercial Vehicle
DHM	Department of Hydrology and Meteorology
DoR	Department of Roads
ESAL	Equivalent Single Axle Load
FY	Fiscal Year
GA	Genetic Algorithm
GEP	Gene Expression Programming
HDM	Highway Development and Management
HMIS	Highway Management Information System
IARMP	Integrated Annual Road Maintenance Program
IRI	International Roughness Index
LRN	Local Road Network
LVR	Low Volume Road
MEPDG	Mechanistic Empirical Pavement Design Guidelines
MERLIN	Machine for Evaluating Roughness using Low-cost Instrumentation
MoPIT	Ministry of Physical Infrastructure and Transport
NH	National Highways
PCI	Pavement Condition Index
PSD	Power Spectral Density
PSI	Present Serviceability
PSR	Present Serviceability Rating
PURELIN	Linear Trasform function
RBN	Roads Board Nepal

RCI	Road Condition Index
RMSE	Root Mean Square Error
SAI	Structural Adequacy Index
SDI	Surface Distress Index
SII	Strategic Importance Index
SN	Structural Number
SRN	Strategic Road Network
TANSIG	Hyperbolic tangent sigmoid transfer function
TGI	Traffic Group Index

CHAPTER ONE: INTRODUCTION

1.1 Background

Highway infrastructure is a backbone of economic development of a nation. However, for developing countries like Nepal, maintaining road pavements in smooth condition is one of the major challenges. Nepal Road Standard (NRS) 2070 provides administrative and technical classification for roads in Nepal (Department of Roads, DoR, 2013). Administrative classification of roads is intended to assign national importance and level of governance for overall management and method of financing. According to this classification, roads have been classified into National Highway, Feeders Roads, District Roads and Urban Roads. After the full phase implementation of the constitution of Nepal 2072, the classification of roads has been changed as National Highways, Provincial Roads and Local Roads. National Highways (NH) are major roads and provide linkage and connectivity throughout the country. Overall responsibility for development and maintenance of NH lies within Department of Roads (DoR) and Roads Board Nepal (RBN) under Ministry of Physical Infrastructure and Transport. Currently, Department of Roads, Nepal is using Surface Distress Index (SDI) and International Roughness Index (IRI) values to prioritize the roads for the maintenance interventions. SDI is pavement performance rating which is primarily based on subjective evaluation. IRI is based on vehicle response due to the interaction between pavement and vehicle and is a better performance indicator (Lu sun 2003). Therefore, development of pavement performance model with IRI as an index parameter and relating it to the major factors causing pavement distress is essential for development of efficient pavement management system with optimum utilization of the available resources.

A road pavement continuously deteriorates under the action of Traffic and Climate. The ability of the pavement to withstand the effect of traffic and climate over its design life is called performance of pavement. Pavements usually do not serve comfortably, safely, efficiently and economically during its design life. The reason behind this scenario is mainly due to early deterioration of road pavement. Deterioration mainly depends upon traffic volume, axle load characteristics, truck traffic, original design, material used, adopted construction technology, quality control on field, environmental conditions and age etc.

Pavement surface roughness is an important indicator of pavement performance. Prediction of future roughness gives an idea of future pavement performance, allowing engineers, Department of Roads, and other concerned agencies to plan for maintenance and rehabilitation. It reflects not only the condition of the pavement, but also the ride quality and comfort of road users. The increase in pavement roughness indicates that maintenance is required. A well-constructed newly laid pavement will also have some initial roughness, which will increase over time as the pavement deteriorates due to traffic movement and environmental factors.

ASTM E867 defines pavement roughness as "the deviation of the pavement surface from a true planar surface with characteristic dimensions that affect vehicle dynamics, ride quality dynamic load and drainage. In the 1970s the World Bank sponsored several large-scale research programs aimed at developing cost-effective maintenance alternatives for roadway pavements and developed the concept of International Roughness Index (IRI). IRI was an output of International Road Roughness experiment conducted in Brazil in 1982 by the World Bank. It is defined as 'the accumulated suspension vertical motion divided by the distance travelled as obtained from a mathematical model of a simulated quarter-car traversing a measured profile at 80 km/hr (ARA 2004). The pavement roughness or smoothness values are comprehensive pavement evaluation indicator that takes into account not only comfort and ride quality but also represent the presence of distress. The condition of pavement can be evaluated by thoroughly observing the type and severity of distress presence in pavement. But this method is time consuming and costly for both project level and network level.

It should be noted that the IRI is a numerical value that summarizes the roughness level, which influences vehicle response. IRI may not be suitable for all applications. IRI is particularly useful when a roughness measure relating to: overall vehicle operating cost, overall riding quality of pavement surface, overall surface condition, and dynamic wheel load effect is desired. Figure 1.1 shows the IRI scale for different types of road developed by World Bank.

The previous IRI models relied heavily on linear or non-linear regression techniques. In recent years, an Artificial Intelligence technique known as the Artificial Neural

Network (ANN) has been developed as a machine learning technique. ANNs deal with data which do not follow a casual mathematical relationship, the final solution is considered as a black box (Gurney 1997). ANNs provide quite accurate solution to develop empirical models for complex datasets with non-linear behaviors and not fitting at known mathematical functions (Ceylan et al. 2014).

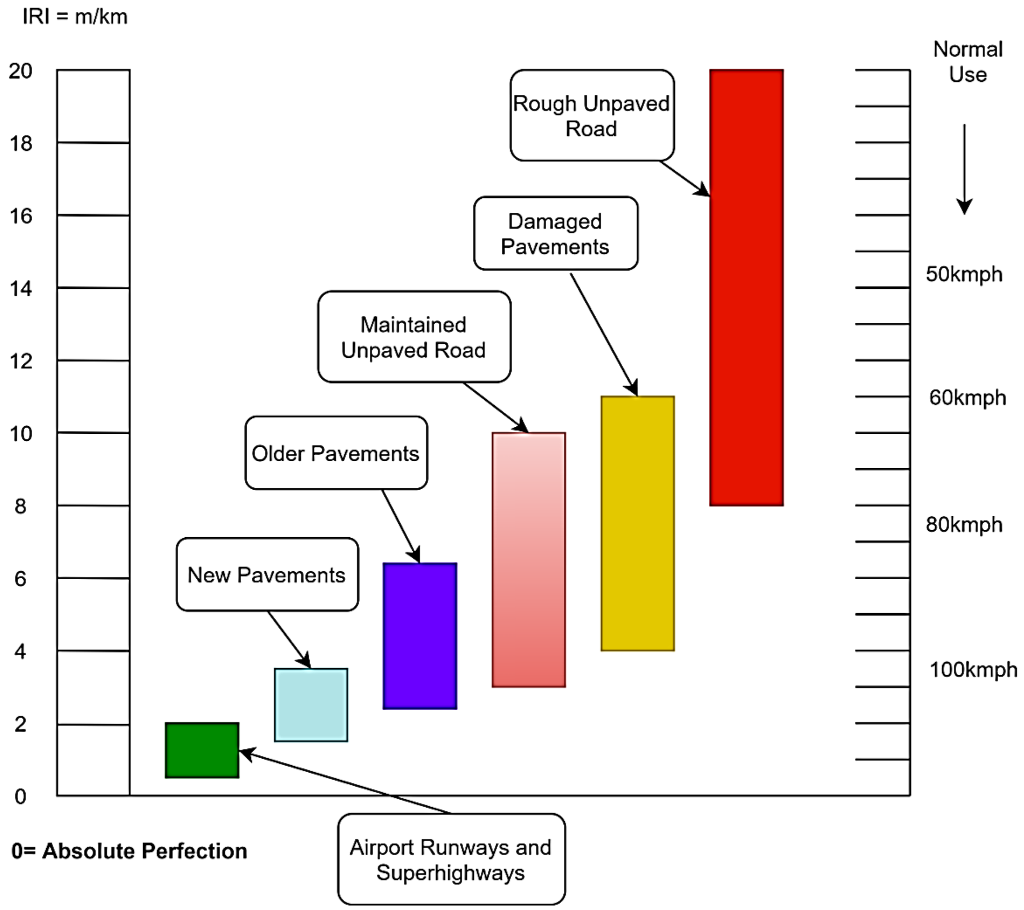

Figure 1.1 IRI Roughness Scale (World Bank technical paper 46)

In context of Nepal, there have been a few studies on pavement performance indicators. Maharjan (2012) developed SDI model to predict the periodic maintenance period of bituminous road in Nepal. However, this model took only time into account as an independent variable. Incorporating climate and traffic parameters is highly recommended to improve model reliability. IRI is one of the major performance indicator used by DoR for performance based maintenance contract (Mulmi 2013). However, to the knowledge of authors, none of the studies has made attempts towards development of IRI model as a pavement performance indicator. Therefore, this study is an initial step towards this direction and aims to develop an IRI prediction model for flexible pavements of national highways in Nepal. The model has significant potential to assist engineers, planners and concerned authorities in formulating plans and strategies for pavement maintenance and rehabilitation and reconstruction.

1.2 Problem Statement

Highways play a crucial role in socio-economic well-being at the national and local levels. The pavement is a key component of road infrastructure. Increasing traffic volume, heavy load and adverse climatic conditions causes' significant functional and structural deterioration of pavement. Development of roads in Nepal has been mainly carried out to provide basic accessibility and serviceability. A majority of the roads are low volume roads for which limited maintenance funding is available. Therefore, to keep the roads in smooth and serviceable condition in the best possible way, Government of Nepal, DoR is mainly using SDI as a functional performance indicator for the maintenance strategy. Many performance-based contracts have been also practiced in the past, but many of them did not worked well. A reason behind this could be due to a lack of an efficient performance prediction model. SDI is subjective rating of the pavement but IRI which is a direct measure of interaction between vehicle and pavement surface, is a better indicator of the pavement performance. More recently, DoR has also started practicing IRI based contracts for example an IRI based contract has been started for East West Highway improvement project with four years extended maintenance period. Therefore, development of an IRI prediction model specific to Nepal is crucial as it can significantly support in effective performance of such planning and maintenance practices, and is the major concern of this study. A number of performance models and roughness models were developed in the past but many of them consider limited number of parameters that result errors in prediction. Also, without sensitivity analysis of parameters, such models cannot be directly used for pavements in Nepal. So, development of a model considering the specific parameters in context of Nepal is vital and is the focus of this study.

1.3 Objective

This thesis study aims to develop International Roughness Index (IRI) prediction models for flexible pavements of national highways in Nepal. The detailed objectives are:

1. To identify all potential factors that affects road roughness condition of flexible pavements through critical review of relevant literature.
2. To develop generalized IRI prediction model for National Highways in Nepal using Artificial Neural Network and regression approaches and identify the one that provides a better fit.
3. To develop regional IRI prediction models for flexible pavements of national highways in Nepal.
4. To develop performance prediction curves based on developed models and provide planning suggestions.

1.4 Scope and Limitations of Study

This study focuses on predicting the periodic maintenance of bituminous pavement based on IRI values which can help in optimum pavement maintenance management.

- Due to lack of reliable pavement thickness data, the developed model can only predict the time of required maintenance (simple surface treatment/periodic maintenance/rehabilitation/fully reconstruction) but cannot predict the overlay thickness.
- Pavement roughness data, traffic data and environmental data in the study are obtained from secondary sources. So, there might be questions for the reliability of these data.
- Number of commercial vehicles is used instead of Equivalent Single Axle Load due to ambiguity in vehicle classification and vehicle damage factors.
- Air temperature is used as pavement temperature. Different relationship may exist between air temperature and pavement temperature for different region which has not been considered in this study.
- The analysis assumes similarity in material properties, compositions and construction practices over the different highway sections.

1.5 Organization of Report

This report has been organized into seven chapters as described below;

Chapter 1: Introduction

Discuss about International Roughness Index and need of the study.

Chapter 2: Literature Review

Consists of discussion on accessible literature on International Roughness Index and its modeling, new modeling approach in pavement engineering.

Chapter 3: Methodology

Includes data collection, model development using traditional statistical method and emerging machine learning approach.

Chapter 4: Generalized IRI prediction model

Presents the model developed by using Regression and ANN. Comparison is made between developed ANN and regression model.

Chapter 5: Regional IRI prediction models

Presents the six regional models developed by using ANN techniques.

Chapter 6: Performance curve and recommendation for maintenance planning

Include the performance curve for generalized model and all six regional models. Based on performance curve maintenance cycles in years is presented.

Chapter 7: Conclusion and Direction for future works

Conclude the findings and direction for future research.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

This chapter documents previous research and practices regarding pavement performance indicator such as IRI, PCI, PSI, SDI etc. The absence or presence of surface flaws that affect the riding quality of road users can be represented as pavement smoothness or roughness. Many researchers have conducted research on road deterioration models development. Pavement distress rating adopting different approaches is used to prioritize highway pavement projects, taking into account limited highway budgets. The criteria or pavement characteristics chosen to evaluate pavement condition as well as the equipment and procedures adopted vary widely.

2.2 Road Surface Performance Evaluation Indicators and Standards

Various indicators discussed in literature for evaluation of road surface conditions are:

2.2.1 International Roughness Index

International Road Roughness experiment was conducted in Brazil in 1982 by the World Bank. There are many approaches for measuring the road roughness index. All of these methods used for measurement can be classified into four different classes.

Class I equipment, such as rod and level, MERLIN, and others, provide extremely accurate data, allowing for exact road roughness measurement. Such procedures, on the other hand, are arduous and time-consuming. Class II devices, such as the Laser Road Surface Tester and the APJ Trailer, measure the road profile directly from each wheel track. When compared to Class I equipment, the accuracy of such procedures is quite low. The response of the vehicle or trailer utilized in the experiment, such as the Bump Integrator, is studied to determine the pavement roughness. Class III equipment is quite expensive, despite the fact that it provides a decent level of precision. Class IV method usually quantifies pavement roughness in terms of Present Serviceability Rating (Highway Research Board 1965; Sayers et al. 1985). PSR is defined as ‘the judgment of an observer as to the current ability of the pavement to serve the traffic it is meant to serve’ (Henry, 2000); the observers ride over the test track, and the ride quality is rated on a quantitative scale to generate the PSR score. The rating scale ranges from 0 (essentially impassable) to 5 (excellent). As road roughness largely affects the ride quality, PSR and roughness are said to be related. Different pavement performance indicator used by municipal and federal agencies is present in Table 2.1. 85% of provincial agencies in Canada use IRI as a pavement performance indicator (Tighe, 2013).

Table 2.1 Percent of pavement performance indicators used in Canada (Tighe, 2013).

Condition Indicator	Percent of Agencies Using Specific Indices	
	Municipalities (%)	Provincial/ Federal/ Territorial (%)
Road Condition Index (RCI)	40	54
International Roughness Index (IRI)	60	85
Structural Adequacy Index (SAI)	47	31
Surface Distress Index (SDI)	73	69
Composite Index	60	62

Different IRI and SDI values which is use to access the pavement surface condition and required intervention as suggested by Hamdi et. al (2017) is presented in Table 2.2.

Table 2.2 Surface condition, IRI and SDI index and Type of treatment (Hamdi et. al 2017).

Surface Condition	IRI scale	SDI scale	Type of treatment
Good	IRI <= 4	SDI <=50	Routine maintenance
Fair	IRI > 4 & IRI <=8	SDI> 50 & SDI<=100	Periodic maintenance
Poor	IRI >8 &IRI <= 12	SDI> 100 & SDI <= 150	Rehabilitation
Bad	IRI > 12	SDI > 150	Reconstruction

2.2.2 Pavement Condition Index (PCI)

The Pavement Condition Index assesses the state of a road network's surface. The PCI assigns a number rating to road segments inside the network, with 0 being the worst possible condition and 100 representing the greatest. The pavement distress index (PCI) assesses the kind, amount, and severity of pavement surface distresses (usually cracks and rutting). The PCI is a subjective inspection and observation-based approach of evaluation. It is not a difficult or time-consuming task. The road network is driven by knowledgeable and experienced public works personnel who examine its status in a systematic manner. For evaluation and utilization, the observations are recorded into a database. The PCI should be performed once a year to assess changes in road conditions. The PCI informs public works officials about the current state of the road network as well as the pace of deterioration over time.

2.2.3 Power Spectral Density (PSD)

In the unit frequency range, the power spectral density indicates the signal's finite mean square value. The displacement power spectral density and velocity power spectral density are primarily utilized to represent the vibration statistical characteristics produced by road roughness in the most recent international standard ISO8608-2016.

2.2.4 Profile Index

The profile index is used to assess the tire track's road roughness as assessed by the cross-section measurement equipment. The seven meter crossbar is employed as a reference displacement in the actual measurement, and the vertical undulation of the surveying wheel is recorded using a tape recorder in a particular ratio to generate a longitudinal sectional image of the road surface.

2.2.5 Present Serviceability Index (PSI)

PSI was developed in the early 1960s and constituted the first comprehensive effort to establish performance standards based upon considerations of riding quality (Carey and Irick, 1960; Highway Research Board, 1962). A panel of highway users from different backgrounds evaluated 74 pavement sections and rate them on a five-point discrete scale (0 for poor; 5 for excellent). The rating was averaged for each section converting the discrete rating into a continuous rating referred to as the Present Serviceability Rating (PSR). PSI ranges in integer scale from 0 (completely disintegrated) to 100 (newly constructed or resurfaced).

2.3 Review on IRI Measurement Devices

Roughness measuring devices are classified by ASTM E950-94 standards into four groups according to their accuracy and method to determine IRI.
Example of roughness measuring Instruments are:

Table 2.3 Roughness measuring instruments.

Class	Class Name	Equipment
1	Precision Profiles	Laser Profiler: Non-contact lightweight profiling devices and portable laser profilers. Manually operated devices: TRL beam, ROMDAS, Walking profiler.
2	Other Profilometric methods	APL profilometer, Optical profiler, GMR etc.
3	IRI estimation from correlation equations	Roughometer, Bump integrator, Roadmaster, rolling straightedge
4	Subjective ratings/ Uncalibrated measurements	Visual observation, Key code rating system, Ride over section.

2.4 Previous IRI Prediction Models

The available pavement surface roughness progression and its deterioration models are generally classified into probabilistic, deterministic and biologically inspired models (Hudson *et al*. 1997, Yang *et al*. 2003). Probabilistic model consists of Markov Chain Process (MCP). Deterministic models consist of: empirical models, mechanistic models and empirical–mechanistic models. Empirical models are based on the statistical models and require a large amount of data. Mechanistic models are based on mechanics theories such as the elastic layer theory, finite element analysis and fracture mechanics. Empirical–mechanistic models are a combination of empirical methods and mechanistic approaches and biologically inspired models consist of artificial intelligence techniques such as Artificial Neural Network (ANN), Genetic Algorithm (GA) etc. Some of the most relevant efforts in developing roughness prediction models are discussed below.

Attoh-Okine (1994) developed a roughness progression model for flexible pavements using Artificial Neural Networks. Input parameter for this study was traffic data (AADT, ESAL), pavement surface type and its thickness. Moreover, climate zone is classified as dry non freeze zone, wet not freeze zone and wet freeze. Back propagation ANN technique was used to develop the model. However, the study shows improvement of model to desirable accuracy can be achieved using the different influencing parameter. Francesca La Torre et. al (1998) developed a roughness prediction model by using ANN technique. This study utilizes the ANN approach to predict the future International Roughness Index (IRI) year by year up to a maximum pavement age of 20 years. Input parameters are E- value, thickness, precipitation and ESAL. The ANN was developed as a Microsoft Windows95 based software tool.

Jyh-Dong Lin et. al (2003) studied the correlation between International Roughness Index (IRI) and pavement distress by Neural Network method. To calculate total change in IRI over given period of time, sum of incremental change in IRI due to environment, cracking, rutting, pothole and structure were considered. A back-propagation neural network was applied in this research. It was found that severe potholes, digging/patching, and rutting have the highest correlation to IRI. Man-holes, stripping, and corrugation have less correlation. Cracking, alligator cracking, bleeding, and road level are the least related to IRI.

Al-Suleiman and Shiyab (2003) developed two IRI regression models for Dubai (one for the slow lanes and the other for the fast lanes) considering pavement age as the independent variable where an exponential relationship was deduced as given by Equations 2.1 and 2.2.

$$IRI_s = 0.796 * e^{0.0539*age} \tag{2.1}$$

$$IRI_f = 0.824 * e^{0.0359*age} \tag{2.2}$$

Nima Kargah- Ostadi (2009) developed network level pavement roughness prediction model for rehabilitation recommendation. In this study, a model for changes in International Roughness Index (IRI) over time is developed through ANN pattern recognition. The factors deemed were initial roughness, pavement age, traffic, climatic conditions (average annual precipitation and average annual freezing index), pavement structural properties, subgrade properties (moisture content and percent passing No. 200 sieve), drainage type and conditions. Traffic factor is found insignificant for IRI. MATLAB ANN Toolbox was employed for the modeling. ANN model performed successfully in predicting IRI trends. Thube (2012) developed ANN-based pavement deterioration models for low volume roads in India. The study showed implementation of a pavement condition prediction methodology using ANN to forecast cracking, raveling, rutting and roughness for Low Volume Roads (LVR) in India. ANN models with different architectures were trained and tested to suggest the optimum ANN model. The study results suggest that ANN models satisfactorily forecast future individual distresses. The input variables: traffic, pavement age (calculated from the date of construction or most recent rehabilitation), dominant climatic conditions, and structural capacity. The performance of the suggested ANN models is also compared to the calibrated HDM-4 models. The ANN models show a higher goodness of fit regarding the predictability of distresses than that of HDM-4 calibrated distresses.

El-Hakim (2013) developed International Roughness index prediction for rigid pavements an artificial neural network application. In this study, an ANN model was developed to predict the IRI for Jointed Plain Concrete Pavement (JPCP) sections. The inputs for this model are: initial IRI value, pavement age, transverse cracking, percent joints spalled, flexible and rigid patching areas, total joint faulting, freezing index, and percent subgrade passing No. 200 U.S. sieve. The Neuro Solutions 5 software with TanhAxon transfer function was used for the model development. The bias in the predicted IRI values using the ANN model was significantly lower compared to the MEPDG regression model.

Ceylan et. al (2014) studied application of neural networks in pavement engineering. It provides a state-of-the-art survey of neural network applications in pavement engineering. There are different types of neural network types such as back-propagation algorithms, radial basis function network, probabilistic neural networks, and generalized regression neural networks. More recently, hybrid neural network approaches, in combination with global optimization techniques or other machine learning techniques, have become popular in addressing complex pavement engineering issues.

Mazari et. al (2016) predict the pavement roughness using a hybrid gene expression programming-neural network technique. The application of a hybrid technique which combines the gene expression programming (GEP) and ANN. The developed algorithm showed reasonable performance for prediction of IRI using traffic parameters and structural properties of pavement. First the model was developed by using gene expression programming and then improves by using GEP-ANN approach. The hybrid method was found to effectively predict the IRI. The contribution of SN parameter in prediction of IRI was not significant. Equation 2.3 represents final model developed in the study.

$$IRIp = (AGE_0 + \Delta ESAL + ESAL_0^2)\frac{IRI}{64.4+AGE} + \left(4.09 - 2\Delta AGE - \frac{5.53}{IRI}\right)^{-1} + \left[\exp(\Delta AGE) - ESAL_0 - \frac{1}{IRI} - 13.58\right]^{-1} \quad (2.3)$$

Hossain et. al (2017) predict the International Roughness Index of flexible pavements from climate and traffic data using artificial neural network modeling. It predicts the International Roughness Index (IRI) for flexible pavements using climate and traffic data by employing Artificial Neural Network (ANN) modeling. LTPP database was used to extract the climate and traffic volume data for flexible pavements. The ANN model trained with PURELIN transfer function. The sensitivity analysis was performed in this study to check the parameter that impacts the prediction and annual average temperature was found most sensitive.

Abdelaziz et. al (2018) developed International Roughness Index prediction model for flexible pavements. ANNs emerged as an efficient tool for modeling purposes hence; it was adopted in this research to predict IRI in terms of pavement distresses. The models in general related the IRI to pavement distresses, site conditions, climatic conditions and structural parameter, such as traffic level, layers thicknesses. The ANN model was developed using MATLAB version R2013a (MATLAB 2013). After several modeling trials, a Feed Forward Back propagation neural network was adopted. The network architecture is composed of one input layer including five neurons (inputs), one output layer including one neuron (output) and one hidden layer in between with ten neurons.

Shakya M. (2013) develops a relationship between IRI measurement using MERLIN and profilometric method suggested in WB technical paper number 46. He also suggest that smart phone can be also be used to estimate road roughness. Maharjan M. (2015) develops a SDI model considering time as independent variables. Separate model was developed for hill area and plain area. Main findings of this study were, the pavement deterioration in Terai region is mainly depends on traffic but in hill region deterioration is more dependent on climate factor than traffic factors. This study recommends that by incorporating traffic and climate factor enhance the model reliability.

2.5 Road Maintenance Practice in Nepal

This section presents the overview on Road maintenance practice in Nepal, types of maintenance, Ranking and prioritizes procedure for maintenance works and DoR's strategy.

2.5.1 Background Information

The Government of Nepal has given road transport development a high priority, and as a result, the roads sub-sector is receiving a significant amount of government funding. Prior to the 1990s, more roads were built in response to public demand and less emphasis was placed on maintaining existing highways. More than half of the major highways were in poor condition by the end of 1992, necessitating immediate rehabilitation. As a result, in the ninth five-year plan (1992–1997), the government established a road subsector target, and since then, more emphasis has been placed on road maintenance and asset protection. In order to restore the road network to a sustainable condition, increased emphasis was placed on planned maintenance methods. Furthermore, the GoN has established the Road Fund Board Act 2002 in order to increase the funding for maintenance activities. The Roads Board Nepal (RBN) has been established and is empowered to collect service and fuel levy fees that are not included in the government's revenue stream and fully utilized for road maintenance works.

2.5.2 DoR's Strategy

Periodic maintenance, which includes re-gravelling gravel roads and cyclic resealing bitumen roads, is an important part of planned maintenance. Cyclic resealing, in particular, is thought to be the most cost-effective procedure for improving the serviceability of bitumen roads in Nepal. It entails applying a seal to all roads in the period of 5-8 years, depending on the environment and traffic. Because all resealing has a high economic rate of return, the cyclic resealing philosophy is to reseal 12 months ahead of schedule rather than one day late. Prioritization of the road for maintenance works is depends upon four parameters namely road age, visual survey rating, traffic volume and strategic importance.

2.5.3 Prioritize and Ranking for Maintenance

The recommended resealing interval of 5-8 years for each road. The management procedures and planning guidelines for periodic maintenance were developed under the Strengthened Maintenance Divisions Program, and are based upon current DoR Policy. At first, Determine maintenance cycle **T** in years to find out which roads are to be resurfaced every 5, 6, or 7years based upon traffic volume and terrain shown in Table 2.4.

Table 2.4 DoR's Nominated Maintenance Cycle.

Years	Traffic volume	
Terrian Type	up to 1500 (Low to Moderate)	> 1500 (High)
Plains	7	6
Rolling	7	6
Hills	6	5

Prioritize for the section is based on ranking index which is obtained by adding Traffic Group Index, Road Condition Index and Strategic Importance. Each index is obtained from table 2.5, 2.6 and 2.7 respectively.

Table 2.5 Traffic Group Index (TGI).

	Traffic Group vpd		
Traffic	<250	250-1500	>1500
TGI	0.15	0.5	0.9

Table 2.6 Road Condition Index (RCI).

	Road Condition Index		
SDI or IRI	(SDI= 0-1.7) or (IRI= 6m/km)	1.8-3.0 or 6-8m/km	3.1-5.0 or >8m/km
Condition	Good	Fair	Poor
RCI	0.02	0.3	1

Table 2.7 Strategic Importance Index (SII).

	Strategic Importance		
Importance	Low	Medium	High
SII	0	0.3	0.6

Ranking Index (RI) = TGI + RCI + SII

Roads for resealing are ranked with the highest value of Ranking Index (RI) first. The list forms part of the Region's Annual Road Maintenance Plan, along with a list of roads that require resealing in later years and a list of those needing rehabilitation now.

2.6 Summary of Literature Review and Research Contribution

Accuracy of database and the correct choice of the influencing variables are vital for IRI modeling. The models in literature have considered several independent variables that affect IRI including traffic factors, environment factors, material properties and pavement layer properties. However, most studies are specific to a single or few factors and there are limited studies that consider all these factors in one model. The reasons behind this limitation are: The collection of pavement distress data is time consuming and labor intensive. Structural data collections sometimes need specimens that can be collected by destructive test such as coring. The collection of materials test data requires the use of sophisticated laboratory equipment and a skilled technician. To overcome these limitations and progress my study, accumulated value of rainfall, maximum temperature and minimum temperature are used as environmental factor, commercial vehicle used as traffic factor, initial IRI and age after the last maintenance time is used to develop the models. Moreover, the dependency within the variables has been often ignored, and literature specific to Nepal is lacking. SDI as a performance indicator was developed by considering time as independent variable. So, need to incorporate traffic factor and environmental factor for estimation of reliable performance of pavement. Therefore, this thesis study aims to contribute to these gaps in the literature through development of an IRI model for national highways of Nepal by using both regression and ANN technique, considering all these potential factors in one model. Further, six different regional models are developed by ANN techniques for better maintenance planning in regional level.

CHAPTER THREE: METHODOLOGY

3.1 General

The research methodology followed in this research starts with critical review of the relevant literature. In this study, the predictability of International Roughness Index (IRI) of flexible pavements has been tested using regression method and Artificial Neural Network (ANN) method. A generalized IRI prediction model for flexible pavements of national highways in Nepal has been proposed following the method that provides better model fit. This is followed by development of regional models considering the specific regional factors that influence the pavement condition. Detail methodology used to develop the models is described in the successive sections of this chapter.

3.2 Framework of Study

Development of roughness model requires considerable amount of effort in data collection, observation, processing, and development and validation of the model. Figure 3.1 summarize the methodological framework used in this study for the development of the IRI prediction models. Data were collected from three different sources. Road roughness data and traffic data were collected from DoR, HMIS unit. Climate data was collected from DHM and road maintenance data was obtained from Roads Board Nepal's annual road maintenance program report. Since data were collected from different sources, so it is necessary to matching the observation date and picking only those records which have complete set of data of selected independent variables. Section classification was made and model was developed by regression and ANN techniques. Comparison study between ANN and regression model also performed to find out the reliable modeling technique.

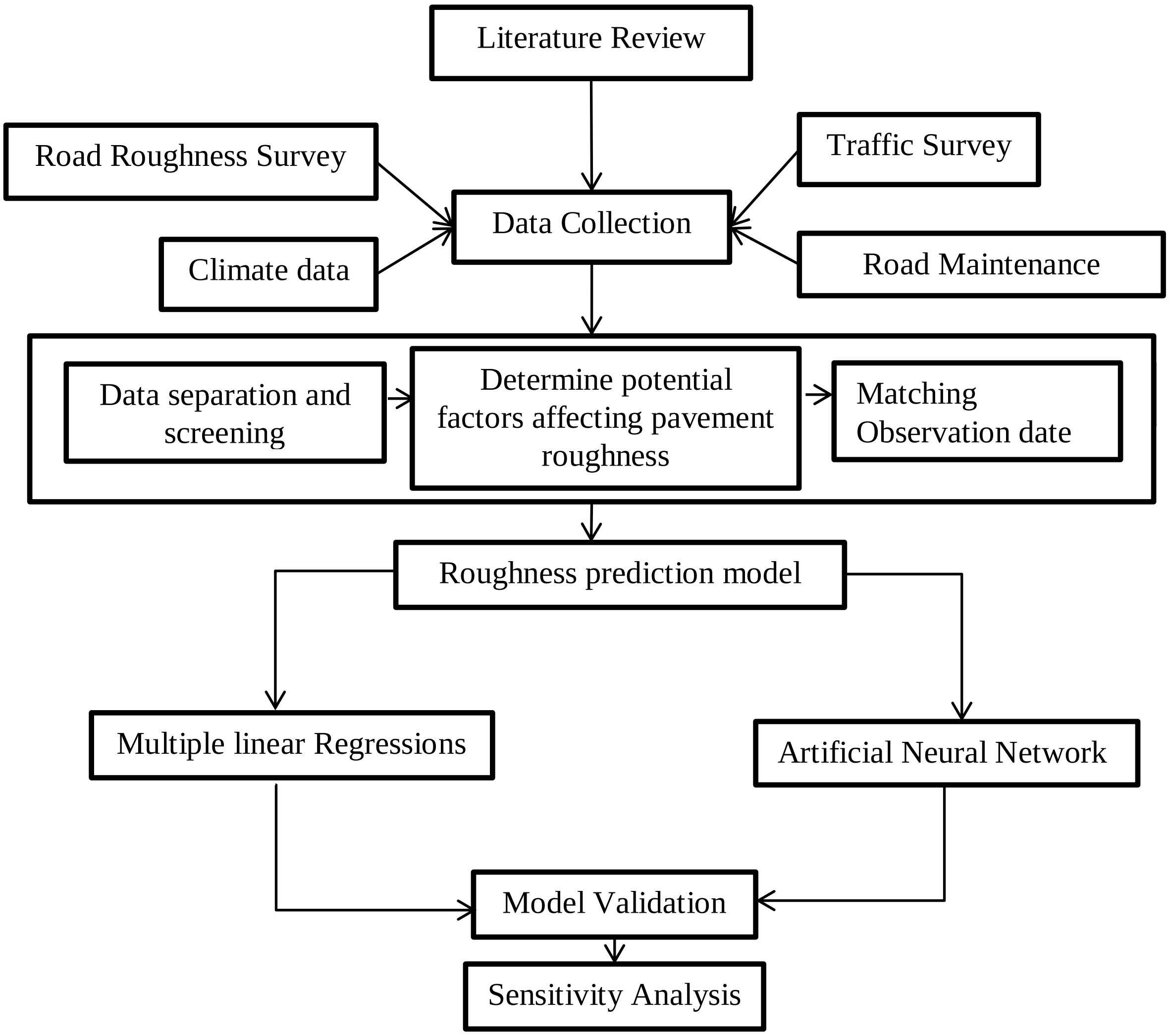

Figure 3.1 Flow chart of the research methodology.

3.3 Data Collection

In Nepal, there are 80 national highways that make a total length of 14,913 km (Department of Roads DoR, 2021a). Among them thirteen national highways were considered in this study. Figure 3.2 shows the roads under study. The selected sections include a wide range of temperature, rainfall and traffic variation.

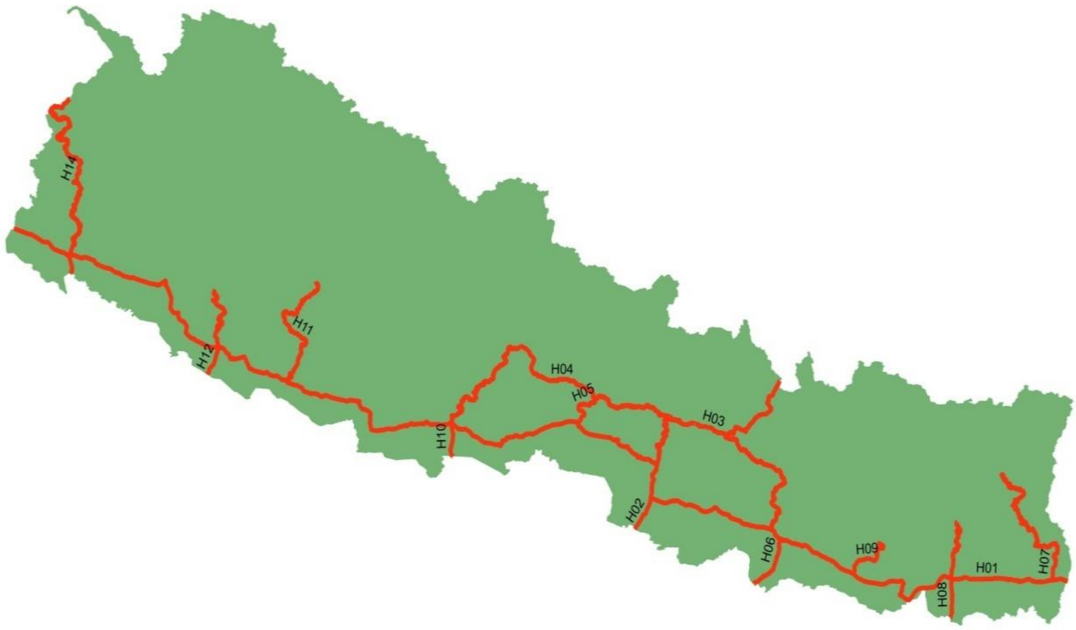

Figure 3.2 Highway sections considered for model development.

The measurement of IRI value by DoR started from FY 1995/96, but the systematic web based online database system was initiated only after FY 2012/13. The IRI data collected by DoR Highway Management Information System (HMIS) units covers about 3397 km length of national highway. The four years IRI data of national highways in Nepal provided by DoR HMIS unit (DoR, 2021b) is used in this study. Planning Branch of DoR has been carrying out the manual traffic count since 1996. The first manual traffic count was carried out by Maintenance Rehabilitation Coordination Unit (MRCU) in 1994. The commercial vehicle/ truck traffic used in the current study is based on the traffic data collected by DoR establishing the 160 traffic count stations throughout the national highways of Nepal. Figure 3.3 shows the traffic count stations. Pavement sections were chosen where maintenance activities were just conducted to improve the pavement condition. Some section with higher values of initial IRI were also chosen to see the significance of initial IRI. Pavements that had a maintenance operation were identified by analyzing the maintenance record kept at Roads Board Nepal, RBN (RBN, 2016) and tallying it with the DoR database. Average annual rainfall, daily maximum, minimum and average temperature information for FY 2013/14 to 2016/17 was obtained from Department of Hydrology and Meteorology, Nepal.

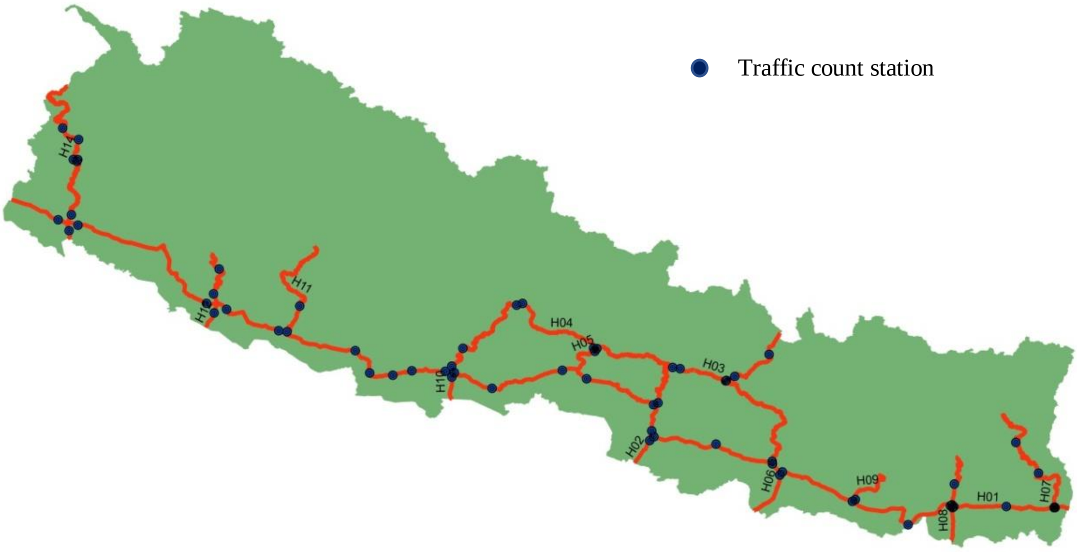

Figure 3.3 Traffic count stations

3.4 Data Processing

Data preparation is the process of cleaning and transforming raw data prior to processing and analysis. It is an important step prior to processing and often involves reformatting data, making corrections to data and the combining of data sets to enrich data. IRI data obtained from DoR contains some unusual data. Some section shows decline of IRI but no records on maintenance, rehabilitation, interventions are found in RBN's report. These unusual records can be misleading and may cause error in the model development. Therefore, the road link which have unexplained decline in IRI values were eliminated and were not used in the analysis. Hence preprocessing of IRI data was done with the help of maintenance record from RBN and by comparing IRI of consecutive years in DoR database.

The traffic on a road link was obtained based on the traffic data collected at the corresponding survey stations. Commercial vehicle was obtained by adding number of multi axle truck, heavy truck and light truck. Annual rainfall in mm collected in the gauge station was distributed in the roadway section by creating a buffer of appropriate radius not exceeding 10 km using GIS ArcMap. The temperature in degree centigrade (°C) was converted into degree centigrade days (°C days) to achieve cumulative effect over the days. The number of days having average temperature less than 25°C is termed as cold days and average temperature greater than 25°C is termed as hot day. Low temperature days for model input were obtained by multiplying number of cold days with average temperature of cold days. High temperature days for model input was obtained by multiplying number of hot days with average temperature of hot days.

3.5 Classification of Pavement into Different Groups

For development of the overall generalized model that can be used for IRI prediction of all national highways of Nepal, the traffic, climatic and IRI measurement data of national highways of both Terai and Hilly region are considered which included information of 3588 highway sections as shown in Table 3.1 that accounts for a total length of 1682 km. To further develop more specific regional models considering the specific climatic and traffic conditions, the pavement sections have been further classified into different data groups as shown in Figure 3.4 on the basis of traffic level and terrain characteristics. Sections in Terai group are from low altitude high temperature region and that in Hilly groups are from high altitude low temperature regions. Furthermore, the sections with commercial vehicular traffic of 1500 commercial vehicles per day are classified as sections with high traffic and are otherwise classified as low traffic sections. Therefore, for regional model development, 6 data groups that are Terai, and Hilly regions (based on temperature differences); and Terai with high traffic, Terai with low traffic, Hilly with high traffic, and Hilly with low traffic (based on temperature traffic combinations) are considered as given in Table 3.1. The table also list outs the number of sections and total road length under each data group.

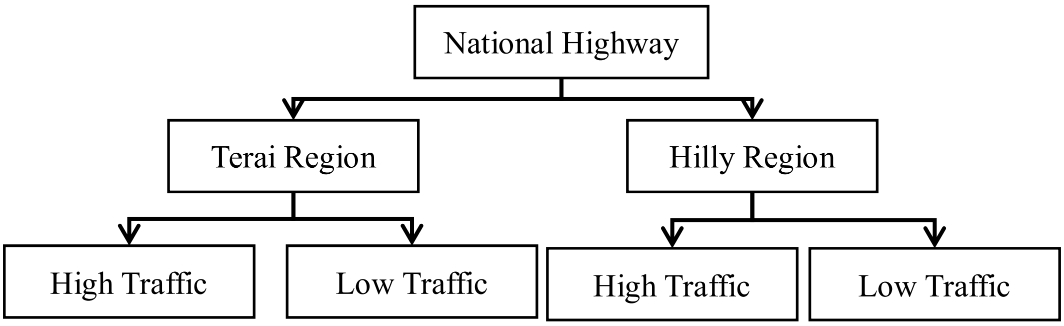

Figure 3.4: Sectional zoning based on Terrain and Traffic

Table 3.1 Data groups based on terrain and traffic combinations

Data Group	Model	Road length (km)	No. of section considered
1	Overall generalized model	1682	3587
2	Terai region	939	1987
3	Hill region	743	1601
4	Terai region low traffic sections	851	1802
5	Terai region high traffic sections	88	185
6	Hill region low traffic sections	604	1300
7	Hill region high traffic sections	139	301

3.6 Identification of Independent Variables

Based on the literature survey, and study of database available for the sections, this study defines IRI as a function of initial IRI, temperature, rainfall, and the number of commercial vehicles as shown in Equation (3.1). Initial IRI is the values which are obtained just after the resealing of the pavement. The effect of temperature is represented in terms of annual number of days with low temperature (below 25°C) and annual number of days with higher temperature (greater than 25°C). Most of the literature used average annual air temperature. But in this study two temperature parameter viz. numbers of days with high temperature and days with low temperature have been used to quantify the effect of high and low temperature separately. Majority of the database shows AADT indifferent to IRI increase. Also, most literature shows IRI is largely affected by commercial vehicles rather than AADT values. Therefore, number of commercial vehicles was considered to include effect of traffic on the road roughness. Since detail axle loading distribution of the considered commercial vehicle types was not available, the effect of varying axle loading was not considered. Also, due to the lack of reliable design data, structural data was not considered in the model development. Moreover, as discussed in Chapter 2, literatures show insignificant effect of Structural Number parameter on road roughness, therefore will have little effect on model's efficiency on IRI prediction.

$$\mathrm{IRI} = \mathrm{f}\,[\,\mathrm{IRI_0}, \mathrm{RF}, \mathrm{TD_l}, \mathrm{TD_h}, \mathrm{CV}\,] \tag{3.1}$$

Where,

IRI: International Roughness Index / Performance function (m/Km)

IRI_0: Initial roughness after the application of maintenance (m/km)

RF: Rainfall (mm)

TD_l: Low temperature days (°C days)

TD_h: High temperature days (°C days)

CV: Number of commercial vehicle

3.7 IRI Prediction Model

IRI prediction model was developed based on the collected data. The collected data were carefully observed and filtered so that only the reliable data values will be incorporated for the development of model. To reduce the unexplained variability on prediction of IRI, pavements sections are classified into different groups having similar characteristics with similar roughness progression rate. Both regression-based and ANN based models were developed and compared to identify the one with better fit.

3.7.1 Regression Based IRI Model

Regression analysis is widely used to develop the relationship between a dependent variable and one or more independent variables as they are easy to construct and interpret. In this study, an IRI model based on multiple linear regression is also developed and compared with the one developed using ANN technique. Multiple linear regression is performed when there is more than one independent or explanatory variables. Mathematically, a multiple regression model takes the form as given in Equation (3.2) where y is a dependent variable, $x_1, x_2, x_3, \dots, x_n$ are the independent variables and $\beta_0, \beta_1, \beta_2, \beta_3, \dots, \beta_n$ are the regression coefficients and Ɛ is the residual error.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots + \beta_n x_n + \mathcal{E} \tag{3.2}$$

Where,

y: Dependent variable

$x_1, x_2, x_3, \dots, x_n$: Independent variables

$\beta_0, \beta_1, \beta_2, \beta_3, \dots, \beta_n$: Regression coefficients

Ɛ : Residual error

Independent variables should show a minimum correlation with each other. If the independent variables are highly correlated with each other, it will be difficult to assess the true relationships between the dependent and independent variables. Hence correlation study is mandatory before the model develop.

3.7.2 ANN Based IRI Model

Development of IRI model using ANN follows data collection and preparation for training, creating network, configuring the network, initializing the weight and biases, training network, validating the network and using the network. The ANN Toolbox in MATLAB R2019b (MathWorks, 2021) was used for the modeling. Data collection in general does not fall under the scope of Neural Network Toolbox. To store all the information first the network object was created. Neural network consists of input layer, hidden layer and output layer. Each node of hidden layer and output layers are called computation nodes or processing units simply called neurons. The connecting link between inputs and processing units are called synapses. The synapses are characterized by their synaptic weights, which is assigned initially in random way.

Network Architecture:

One of the most vital tasks in constructing the ANNs is the choice of the number of hidden layers and the number of neurons. Optimum numbers of neurons are found by hit and trial methods (Devi et al., 2012). In this study, a number of tests were performed with varying number of hidden layers and varying number of neurons in the hidden layer to make the appropriate choice of the layers and neurons. After several trials, a simple ANN network with one hidden layer and 10 neurons was selected for model development in this study as it showed least RMSE and maximum R^2 values in the trials. Figure 3.5 shows the network structure of the proposed ANN-based IRI model with 5-10-1 network architecture. Rectangles in the figure represent input and output, circles denote the neurons in the hidden layer and arrows represent the connecting links. As shown in Figure 3.6, the logarithmic sigmoid function is used in the hidden layer and linear activation function is used at the output layer. Since all of the input parameters have different unit, to have uniformly distributed variables in a defined range [-1 1] of numbers, the “mapminmax” pre-processing function in the MATLAB program is used so that all the values would be normalized to the range. In this way, the problem becomes easier for the neural network to solve, and the network outputs will be within the desired range.

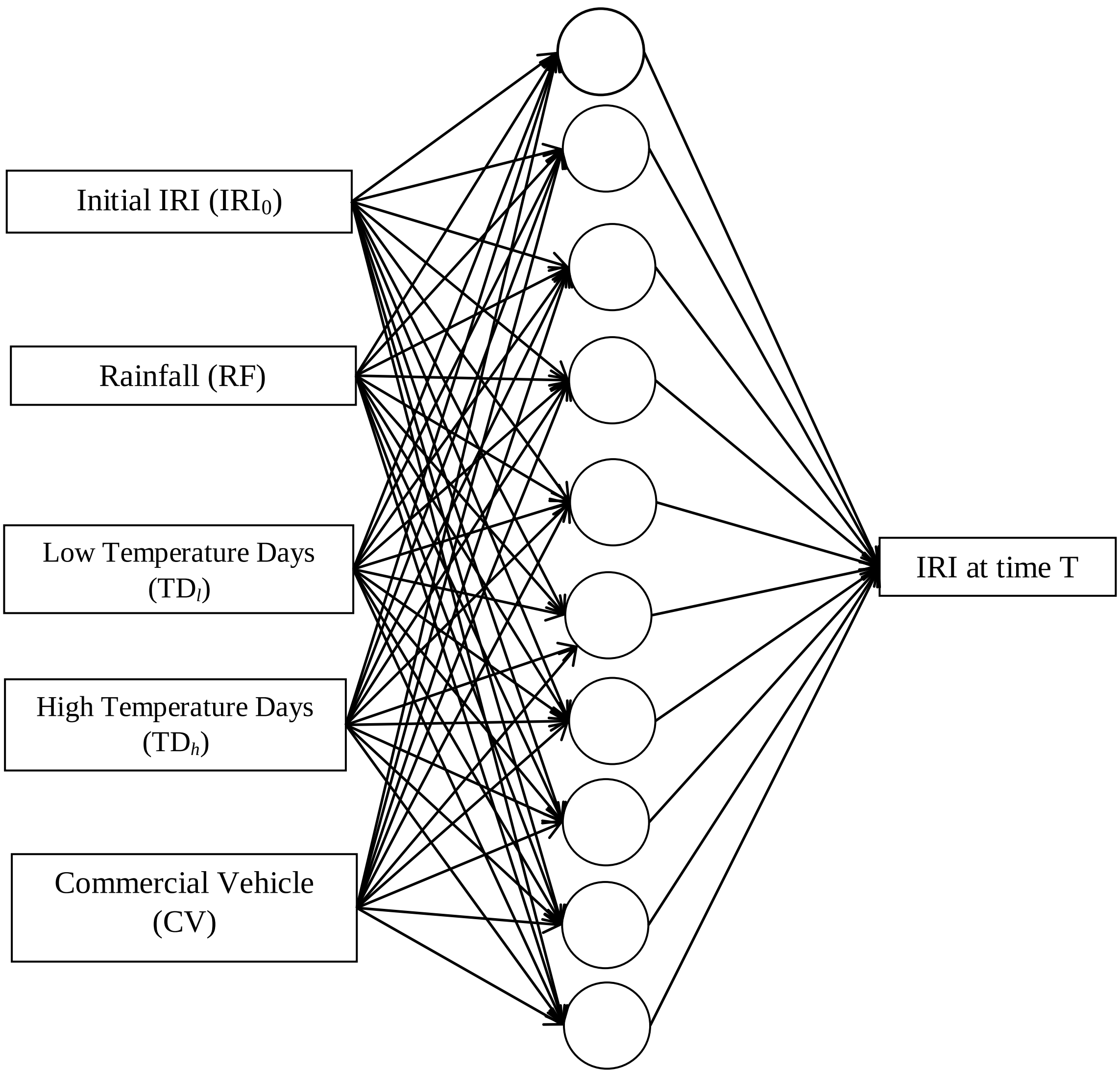

Figure 3.5: The 5-10-1 ANN model

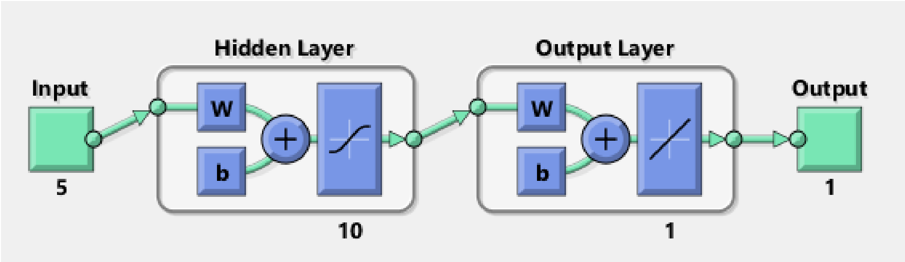

Figure 3.6: Neural network architecture as modeled by MATLAB

The training set and validation set is employed to construct the model; the testing set is used for measuring the model predictive performance. Due to the randomness in data selection, single run of experiment cannot reliably express the true predictive performance of model. Hence multiple runs are made to develop model. There is no any hard and fast rule for the number of runs to be made, but multiple runs are made based on minimum predictive variability.

ANN Iteration Process

ANN model development undergoes an iterative process. First of all it is necessary to calculate the weight and bias matrix. For this purpose, feed forward back propagation algorithm is used. Figure 3.7 shows the feed forward back propagation network. I is the input and O is the output matrix. b_1 and b_2 are the biases for input hidden layer and output layer. W is synaptic weight for each connection.

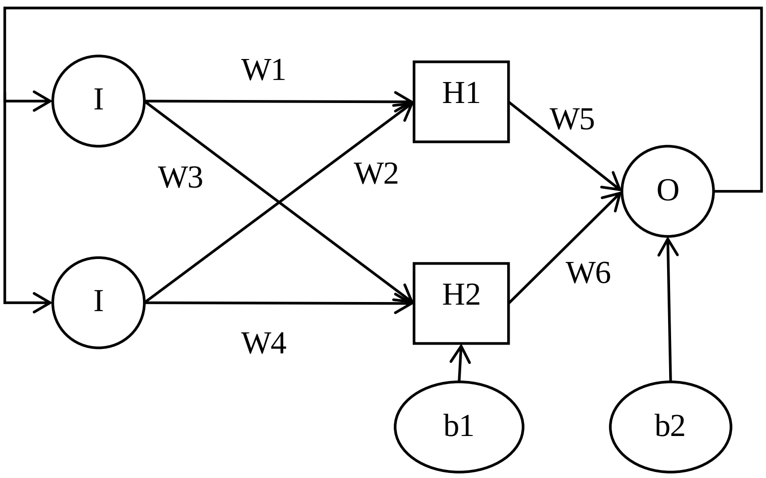

Figure 3.7 Feed forward back propagation neural network/ iteration process

At first calculation proceed from forward direction. Equations (3.3) to (3.5) show feed forward calculation. Input for hidden layers H_1 and H_2 are calculated using Equation (3.3). The value obtained in the hidden layer is then passed through transfer function as shown in Equation (3.4). Finally, the output from the hidden layer is treated with synaptic weight and biases at output layer as shown in Equation (3.5) and transferred through the linear function to achieve the result. Result thus obtained is compared with the target set up and error is computed using Equation (3.6). If the error is beyond the permissible limit, back propagation is performed to adjust the weightage and bias as per Equations (3.7) and (3.8). The iteration continues until the stopping criterion is fulfilled.

$$H_1 = w_1 * i_1 + w_2 * i_2 + b_1 \tag{3.3}$$

$$H_{1out} = tansig(H_1) \tag{3.4}$$

$$Output = H_{1out} * w_5 + H_{2out} * w_6 + b_2 \tag{3.5}$$

$$Error = \sum [0.5 * (target - output)^2] \tag{3.6}$$

$$\frac{\partial E}{\partial W} = \frac{\partial E}{\partial O} * \frac{\partial O}{\partial N} * \frac{\partial N}{\partial W} \tag{3.7}$$

$$W_{new} = W_{old} - \alpha * \frac{\partial E}{\partial W} \tag{3.8}$$

Where,

H_1, H_2: Input for hidden layer

i_1, i_2: Inputs

w_1, w_2, w_5, w_6: Synaptic weights

b_1, b_2: Bias

$\frac{\partial E}{\partial O}$: Derivatives of total error with respect to output node

$\frac{\partial O}{\partial N}$: Partial Derivatives of Output with respect to its activation function

$\frac{\partial N}{\partial W}$: Partial derivative of the output node with respect to the weight change

α: Learning rate

After the completion of the iterative process, feed forward neural network is used for the prediction of IRI. Feed forward networks often have one or more hidden layers. In this study, one hidden layer with tansig neurons followed by an output layer of linear neurons has been adopted. Figure 3.8 shows the feed forward neural network with five input variables, one hidden layer with ten neurons and output layer with only one neuron. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear relationships between input and output vectors. Finally, the IRI values can be obtained based on the weight matrices and the bias matrices as given by Equation (3.9).

$$IRI_{predict} = \left[W_2 * \left\{\frac{2}{1 + e^{-2(W_1 * I + B_1)}} - 1\right\}\right] + B_2 \tag{3.9}$$

Where,

W_1: Weight matrix for input layer

W_2: Weight matrix for output layer

B_1, B_2: Bias matrix for hidden layer and output layer

I: Normalized input matrix

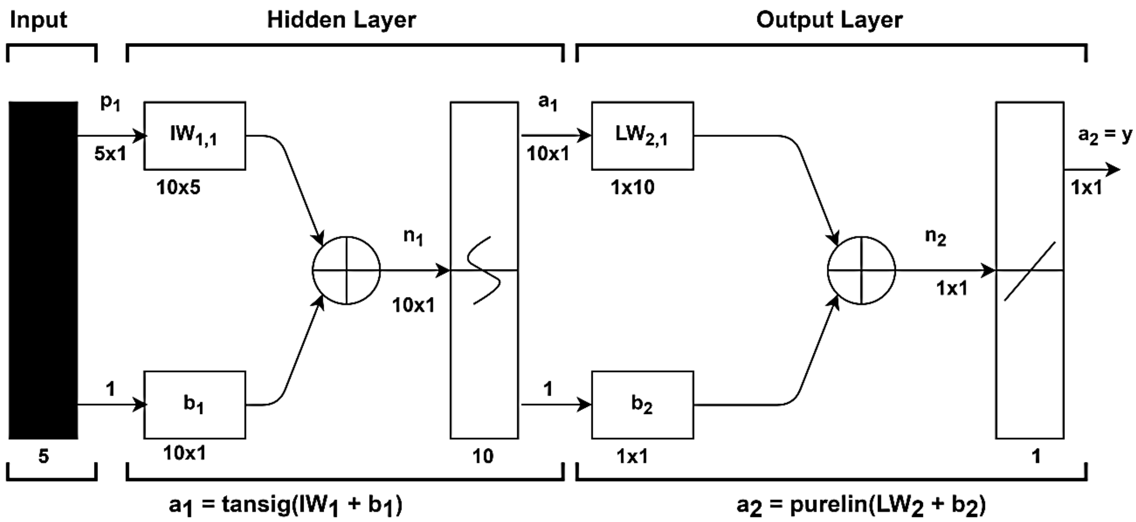

Figure 3.8: Feed forward neural network

CHAPTER FOUR: GENERALIZED IRI PREDICTION MODEL

4.1 General

International Roughness Index (IRI) prediction models were developed using both multiple linear regression and Artificial Neural Network (ANN) techniques discussed in Chapter 3. This chapter presents the results of testing and validations and shows a comparison between the two models in terms of goodness of fit and proposes a generalized model that can be used for IRI prediction of national highways of Nepal. All 3588 data records from various regions of Nepal were used in the development of the generalized model. Coefficient of determination R^2 value and Root Mean Square Error (RMSE) value are used to compare the performance of the models.

4.2 Performance of Regression Based IRI Model

Prior to the model development, relation between individual independent variables was checked by developing correlation coefficient matrix. Correlation and regression analysis in this study was performed using Microsoft Excel 2010 with solver add-ins. Table 4.1 shows the correlation between the five independent variables considered in the study. As the table shows the correlation coefficients for the variables are between 0.01 to 0.63. Therefore, the variables are found to be weakly and, in some cases, moderated correlated indicating absence of strong multicollinearity between the independent variables. Therefore, all five independent variables are considered for the development of the regression model.

Table 4.1 Pearson's correlation coefficient matrix

Variables	IRI_0	RF	TD_l	TD_h	CV
IRI_0	1.00	0.03	-0.02	0.01	-0.20
RF	0.03	1.00	0.60	0.63	0.31
TD_l	-0.02	0.60	1.00	0.58	0.38
TD_h	0.01	0.63	0.58	1.00	0.43
CV	-0.20	0.31	0.38	0.43	1.00

For the development of the IRI prediction model, the dataset was randomly sorted and split into two sets, referred to as the “in-sample” and “out-of-sample” data. The in-sample group composed of 85% of the dataset and was utilized to develop the regression model. The remaining 15% the dataset, referred to as the “out-of-sample” or “testing data” was utilized to assess the regression model’s prediction efficiency.

Multiple linear regression over the in-sample data was carried out using Microsoft Excel to find the relationship between the IRI and the defined five independent variables. Statistical tests were carried out at the level of significance of 5%. An Analysis of Variance (ANOVA) was performed on the regression results to assess the adequacy of the proposed model. This analysis was conducted with the null hypothesis that the IRI is not related to IRI_0, CV, RF, TD_l and TD_h while the alternate hypothesis is that the IRI is related to the aforementioned variables. Furthermore, the regression coefficient of each of the independent variables was evaluated by another hypothesis test in which the null hypothesis is that the coefficient equals zero and the alternate hypothesis is that it does not equal zero. Tables 4.2 and 4.3 summarize the results of the ANOVA test and hypothesis test on the regression coefficients, respectively. The table shows p-values for the test statistics of all the five independent variables are less than 0.05 indicating that all the five variables considered in the study have statistically significant relationship with the IRI value. The intercept and partial regression coefficients for each parameter are given in the table. The RMSE of the model is 2.41 and the adjusted R^2 value is 0.76 which implies that about 76% of variation in IRI can be explained by the initial IRI, traffic and the climatic factors.

Table 4.2 ANOVA test results

	Degree of freedom	Sum of squares	Mean of squares	*F* Statistics	p- value
Regression	5	28391.52	5678.30	2351.88	0
Residual	3582	8648.26	2.41		
Total	3587	37039.77			

Table 4.3 Test statistics and regression coefficients

	Coefficients	Standard Error	t Statistics	p-value	Lower 95%	Upper 95%
Intercept	-1.615	0.106	-15.24	7.34E-51	-1.82	-1.41
IRI_0	1.306	0.013	100.90	0	1.28	1.33
RF	0.00015	2.6E-05	5.85	5.22E-09	0.00010	0.00020
TD_l	0.00018	1.54E-05	11.43	9.61E-30	0.00015	0.00021
TD_h	7.9E-05	8.93E-06	8.82	1.78E-18	6.12E-05	9.63E-05
CV	0.00018	2.5E-05	7.14	1.14E-12	0.00013	0.00023

Based on the test results of the multiple linear regression analysis, the IRI prediction model for pavements of national highways in Nepal can be expressed as given in Equation (4.1). Partial regression coefficients for all five independent variables are positive. Therefore, the pavement roughness or the IRI value increases with increase in the initial roughness or IRI, commercial vehicle traffic, rainfall, and accumulated low and high temperature days.

$$IRI = -1.615 + 1.306\, IRI_0 + 0.00015\, RF + 0.00018\, TD_l + 0.000079\, TD_h + 0.00018\, CV \quad (4.1)$$

4.3 Performance of ANN Based IRI Model

The ANN based IRI model was developed and analyzed using ANN Toolbox in MATLAB R2019b. Of the total dataset of 3587 data records, 70% (2511 records) were used for training, 15% (538 records) were used for validation and the rest 15% were used for testing. Table 4.4 shows the results of training, validation, testing and overall performance of the developed ANN model. There is no any specific method to decide the network architecture. Here, RMSE of different network architecture is calculated and compared and the network architecture which produced lowest RMSE that is predicts IRI value closest to the actual IRI values was selected.

The goodness-of-fit results of the corresponding models in terms of R^2 values are given in the Table 4.4. Moreover, the predicted and measured IRI values are further presented in Figure 4.1 to show the predicting capability of the ANN model. Vertical distance of the plotted data from the fit line reflects the residual error. Same patterns can be seen for training, testing and validation. The overall model shows most data are concentrated near the fit line and the corresponding R^2 value is 0.81 which reflects a good fit of the model to the actual values.

Table 4.4 Summary of RMSE and R^2 values

5-10-1 ANN model	Record	RMSE	R^2
Training	2512	1.960	0.80
Validation	538	2.072	0.79
Testing	538	1.767	0.85
Overall	3588	2.072	0.81

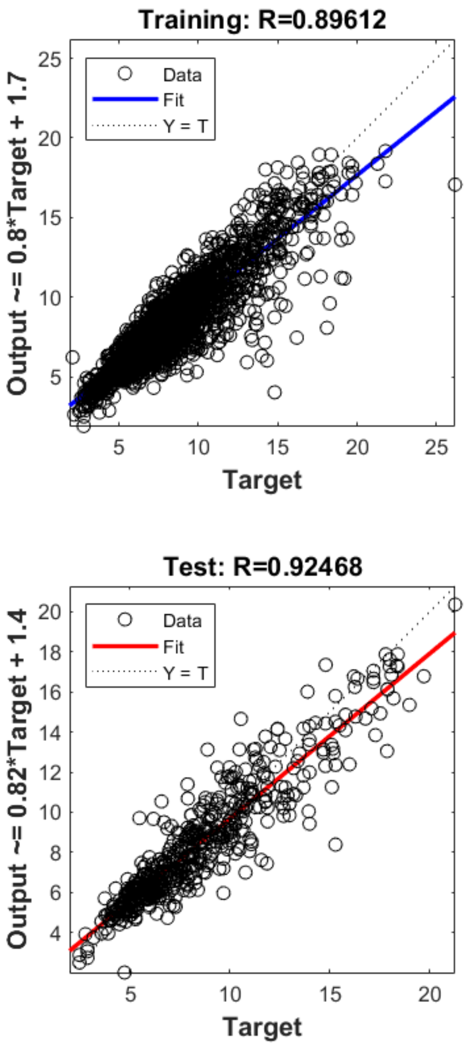

Figure 4.1 Predicted and measured IRI values.

Only R^2 value cannot give the full picture of predicting capability of model. So R^2 value with combination of residual plot is considered in this study. Error histogram for the model is present in Figure 4.2. As the figure shows, the error histogram is more or less normally distributed which indicates that it is reasonable to assume that the random errors for these processes are drawn from approximately normal distributions. Therefore, there is a strong linear relationship between the residuals and the theoretical values.

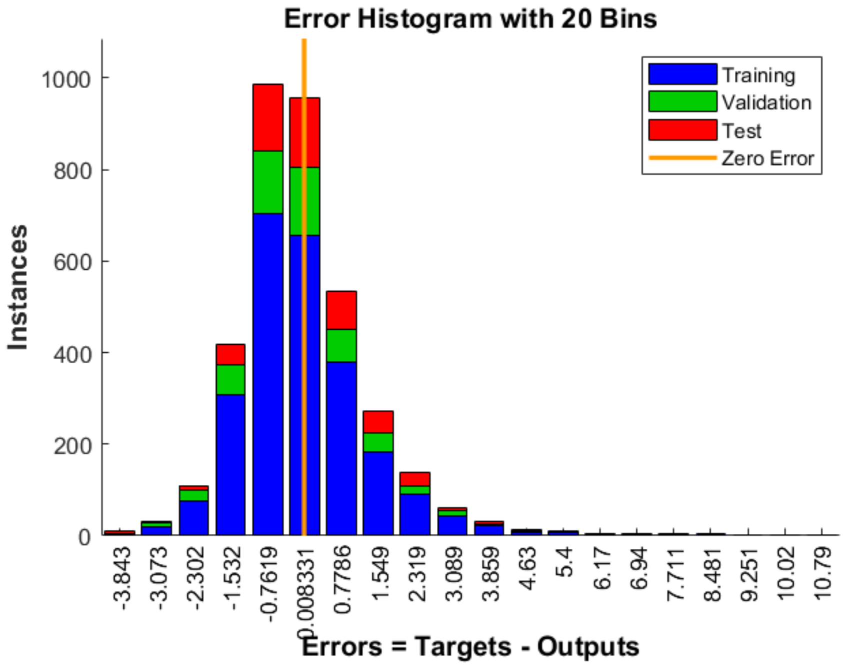

Figure 4.2 Error histogram

Over fitting of model can yield better result for given training, testing and validation data set but poor prediction capability for raw dataset. This is mainly due to machine learning technique may learn noise as a concept for given data set. But same type and level of noise may not present in raw dataset. Figure 4.3 shows that the performance of model during training, testing and validation phase. The iteration process was stopped at 27th iteration when performance curve of all phase comes close to each other and becomes parallel to prevent the problem of under fit and over fit. The best performance with a mean square error value of 1.883 was found on 21st iteration.

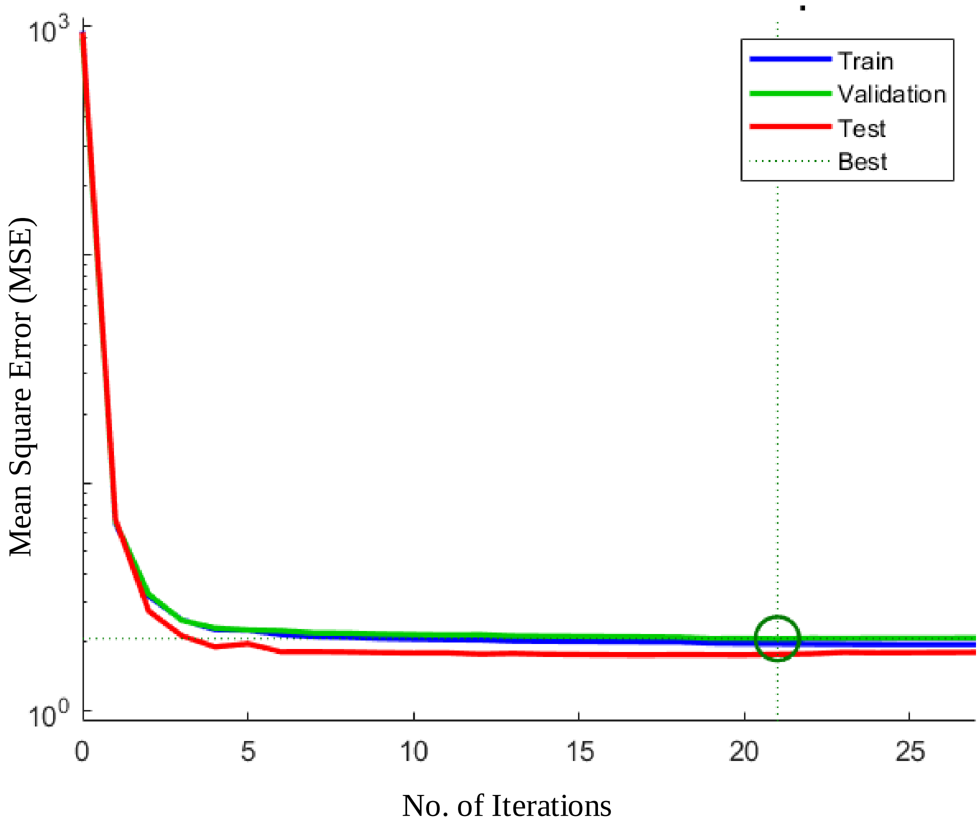

Figure 4.3 Performance of NN model during training stage

Equation (4.2) shows the proposed ANN-based IRI prediction model where the F values can be calculated using tansig function as given in Equation (4.3) based on the E_i values calculated using Equation (4.4). E_i is calculation made on hidden layer and can be obtained using weight and bias values given in Table 4.5.

$$IRI = -0.044\,F_1 + 0.157\,F_2 - 1.759\,F_3 + 1.482\,F_4 + 0.086\,F_5 - 1.633F_6 + 0.319\,F_7 - 0.059\,F_8 - 0.151\,F_9 + 0.100\,F_{10} - 0.993 \tag{4.2}$$

$$F_i = \left\{\frac{2}{1 + e^{-2E_i}} - 1\right\} \tag{4.3}$$

$$E_i = W_{1i}\,IRI_0 + W_{2i}\,RF + W_{3i}\,TD_l + W_{4i}\,TD_h + W_{5i}\,CV + B_{1i} \tag{4.4}$$

Table 4.5 Weight and bias values between input layer and hidden layer for IRI prediction

i	W_{1i}	W_{2i}	W_{3i}	W_{4i}	W_{5i}	B_{1i}
1	1.741676	-5.09804	-4.12269	-2.00759387	-1.11765	-2.80545
2	-1.47704	-1.3544	-0.62207	1.023464261	-0.60719	1.662769
3	0.154723	3.686755	-1.09845	-2.62955538	-0.71215	-0.60837
4	-0.00258	4.260955	-1.30963	-2.792024	-0.47803	-0.24602
5	2.251212	-1.22448	4.242625	3.037961995	0.881512	-1.97129
6	-0.72099	0.148343	0.095984	0.020560047	-0.05162	-0.65083
7	-4.53677	3.840627	-0.25607	-1.23558487	-3.03923	-5.06072
8	-4.85601	-3.97331	-1.25562	1.302140828	-0.65422	-3.45069
9	-1.32584	-2.12319	-0.07824	2.991264795	2.578206	2.378986
10	-0.18551	2.096902	5.110288	1.308647592	-1.63661	3.250539

4.4 Comparison of Regression Model and ANN Model

Both regression and artificial intelligence based techniques have been used in literature for development of roughness prediction models. Regression models are simpler and easier to interpret while the later models unlike the former models are unaffected by the multicollinearity between the variables and are also able to incorporate linear, nonlinear and other complex relationships between the dependent and the independent variables. Table 4.6 shows a comparison of performance of the regression based and the ANN based IRI prediction models developed in Sections 4.2 and 4.3. As can be seen in the table, the residual mean squared values of 2.375 and means squared error of ANN model is 1.883. Also R^2 value of ANN model is 0.82 which is better in comparison to that of the regression based model which is obtained to be 0.76. So, the overall performance of ANN based model is found to better compared to that of the regression model. Therefore, the ANN-based IRI prediction model represented by Equations (4.2) to (4.4) can be used as the generalized IRI prediction model for flexible pavements of national highways in Nepal.

Table 4.6 Comparison of regression and ANN based IRI prediction model

Model	R^2	RMSE
Regression	0.76	2.41
ANN	0.82	1.883

4.5 Sensitivity Analysis

Sensitivity analysis is an important step for the study having multiple inputs. The sensitivity index reflects the parameter which is most important and which parameter has less significant. In this study single value sensitivity index as given in Chang and Liao (2012) was used to find the most significant and least significant parameter. The sensitivity index can be obtained using Equation (4.5).

$$S = \left(\frac{O_2 - O_1}{I_2 - I_1}\right)\left(\frac{I_{avg}}{O_{avg}}\right) \tag{4.5}$$

Where,

S: Sensitivity index;

I_1, I_2: Smallest and the largest input values, respectively

O_1, O_2: Model output values corresponding to I_1 and I_2, respectively

I_{avg}, O_{avg}: Average I_1, I_2 and average O_1, O_2, respectively

Table 4.7 shows the results of sensitivity test which shows that the initial IRI is the most sensitive parameter whereas low temperature days is the least sensitive parameter for the prediction of IRI. Effect of high temperature days, number of commercial vehicle and annual rainfall amount are in sequential order. Rutting performance of bituminous road is very weak in high temperature. It should be noted that the sensitivity analysis in Table 4.7 is performed for the generalized IRI model, which contains a large number of sections with low traffic volume for which the impact of environmental factors is observed to be critical but this might be different if high volumes roads are considered separately. The result obtained is also consistent with the sensitivity analysis in the literature.

Table 4.7 Sensitivity analysis of input parameters

Input Parameter	Sensitivity Index
IRI_0	0.85
RF	0.39
TD_l	0.20
TD_h	0.53
CV	0.45

CHAPTER FIVE: REGIONAL IRI PREDICTION MODELS

5.1 General

Pavement sections of national highways of Nepal are subjected to wide range of traffic and climatic variation. The generalized model developed in Chapter 4 gives the general trend of IRI over time applicable to all the pavement sections of national highways of Nepal. For the better predictability of IRI, regional models considering specific climatic and traffic conditions as previously discussed in Chapter 3 are developed. Literature and test results for generalized model shows the better performance of ANN-based model as compared to regression model. Hence, the regional models are developed using ANN approach.

5.2 IRI Prediction Model for Terai Region

There are 1987 data records that fall under Terai region. Of this total dataset, 70% (1391 records) were used for training, 15% (298 records) were used for validation and the rest 15% were used for testing. Equation (5.1) shows the IRI prediction model Terai Region. The F values can calculate using tansig function as given in Equation (5.2) based on E_i values obtained from Equation (5.3). The weight and bias values to determine the E_i values are given in Table 5.1.

$$\begin{aligned} IRI = &-1.365\, F_1 - 0.0278\, F_2 - 0.6331\, F_3 + 0.4466\, F_4 + 1.3222\, F_5 + \\ &0.8016\, F_6 - 0.2173\, F_7 - 0.9437\, F_8 - 0.1038\, F_9 - 1.1888\, F_{10} - 0.3302 \end{aligned} \tag{5.1}$$

$$F_i = \left\{\frac{2}{1 + e^{-2E_i}} - 1\right\} \tag{5.2}$$

$$E_i = W_{1i}\, IRI_0 + W_{2i}\, RF + W_{3i}\, TD_l + W_{4i}\, TD_h + W_{5i}\, CV + B_{1i} \tag{5.3}$$

Table 5.1 Weight and bias values for IRI prediction in Terai region

i	W_{1i}	W_{2i}	W_{3i}	W_{4i}	W_{5i}	B_{1i}
1	0.6172	-0.0761	0.4771	0.7436	-3.2517	-3.9417
2	-0.9202	2.5861	1.8753	2.1012	-1.5165	0.3901
3	-0.8920	2.3014	1.4515	1.3325	2.1198	2.1966
4	0.2555	-2.4559	1.5455	-0.5556	-1.7159	0.4433
5	0.7730	-0.1692	0.0216	-0.1243	-0.1419	0.0219
6	-0.0879	1.7634	-0.3613	0.5082	1.2173	-0.5063
7	-0.8075	2.8075	0.2901	1.2608	1.5299	-1.0888
8	0.4201	-1.6288	-0.9785	-1.0473	-0.6789	-1.1744
9	1.9430	-0.4858	2.3825	0.7504	-3.9003	0.8416
10	0.1821	0.4850	-0.0503	-2.9662	2.4533	4.8700

Figure 5.1 shows the predicting capability of the proposed regional model. As the figure shows, most data are concentrated near the fit line during all three phases of model development. R^2 value of the model as shown in the figure is 0.77.

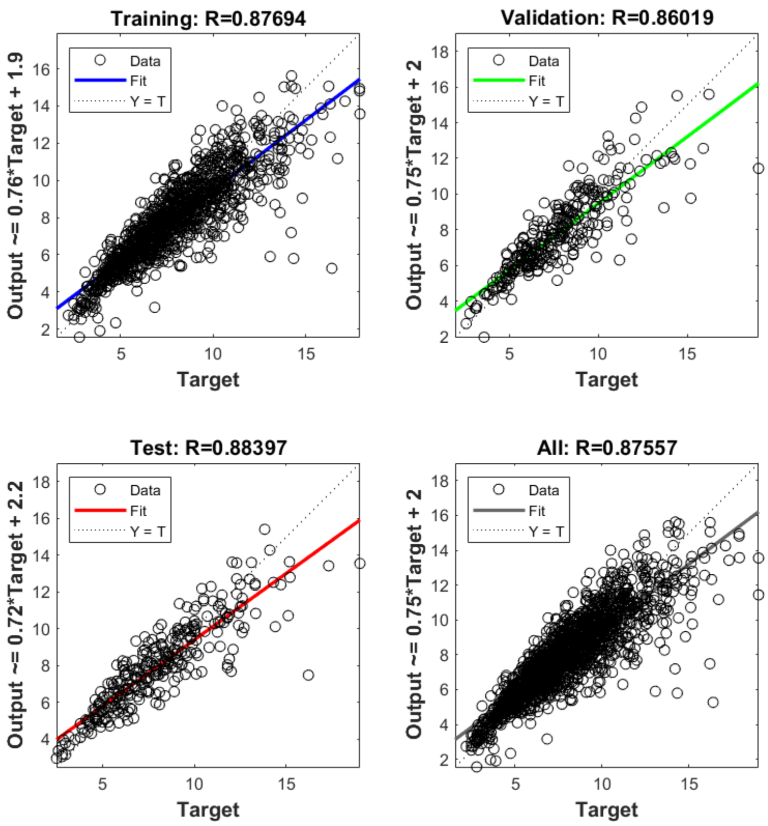

Figure 5.1 Goodness-of-fit of the IRI prediction model for Terai region

5.3 IRI Prediction Model for Hilly Region

There are 1601 data records that falls under Hilly region. Of this total data set, 70% were used for training, 15% were used for validation and the rest 15% were used for testing. Equation (5.4) shows the IRI prediction model for Hilly region. The F values can be obtained using tansig function as given in Equation 5.5 based on the E_i values that can be calculated from Equation (5.6) using weight and bias values given in Table 5.2.

$$IRI = -0.124\,F_1 - 0.130\,F_2 - 0.098\,F_3 - 0.334\,F_4 - 0.146\,F_5 - 0.074\,F_6 + 0.083\,F_7 - 0.149\,F_8 - 0.404\,F_9 - 0.389\,F_{10} - 0.147 \quad (5.4)$$

$$F_i = \left\{\frac{2}{1+e^{-2E_i}} - 1\right\} \quad (5.5)$$

$$E_i = W_{1i}\,IRI_0 + W_{2i}\,RF + W_{3i}\,TD_l + W_{4i}\,TD_h + W_{5i}\,CV + B_{1i} \quad (5.6)$$

Table5.2 Weight and bias values for IRI prediction in Hilly region

i	W_{1i}	W_{2i}	W_{3i}	W_{4i}	W_{5i}	B_{1i}
1	0.7306	1.1559	1.7469	-0.1278	3.1733	4.0245
2	1.6622	-0.0356	-2.8925	-0.9982	1.1460	-0.4461
3	1.2310	2.0563	-1.6476	-2.9553	0.1899	0.6043
4	-0.6684	-0.1897	-0.8648	0.3930	-1.0826	-1.1391
5	-0.9511	2.5900	-0.5045	-0.1086	-2.7335	-0.9774
6	0.6822	-2.9330	1.2528	-1.5292	-1.5572	-0.9353
7	5.6559	-2.8605	1.3945	0.9291	-0.0661	1.2498
8	-0.6101	5.5419	-3.0579	-1.4722	-1.5135	-0.8912
9	-1.2794	0.9078	0.2336	-0.7861	0.1753	0.8796
10	-1.0520	-2.1545	1.0048	0.8037	0.7759	-1.2782

Figure 5.2 shows the predicting capability of the proposed IRI prediction model for Hilly region. Most data are concentrated near the fit line and the R^2 value of the model as shown in the figure is 0.83 indicating a good model fit.

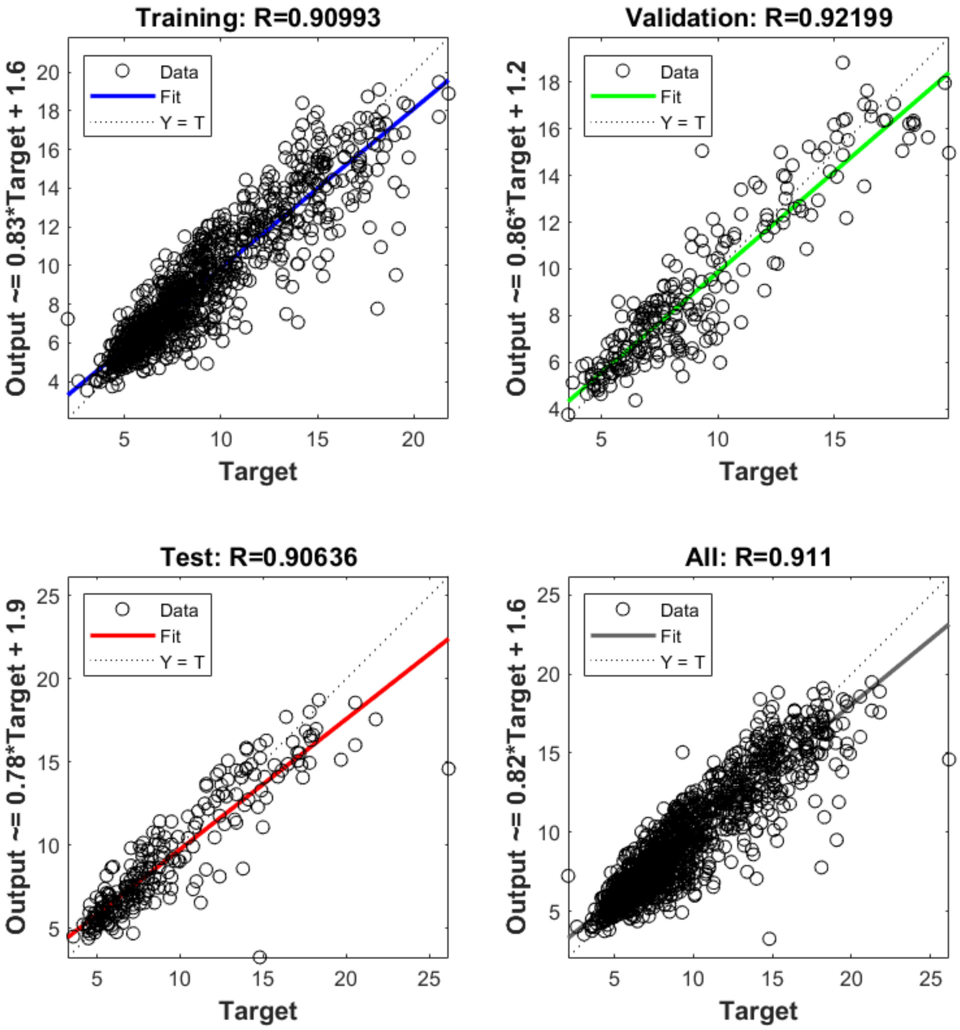

Figure 5.2 Goodness-of-fit of the IRI prediction model for Hilly region

5.4 IRI Prediction Model for Terai Region with Low Traffic

There are 1802 data records that fall under this category. Of this total data set, 70% of the data were used for training, 15% of data were used for validation and the rest 15% were used for testing. Equation (5.7) shows the IRI prediction model for Terai region with low traffic. The *F* values can be obtained using tansig function as given in Equation (5.8) based on E_i values that can be calculated from Equation (5.9) using weight and bias values given in Table 5.3.

$$IRI = 0.233\ F_1 - 0.251\ F_2 + 0.467\ F_3 - 0.343\ F_4 + 0.663\ F_5 - 0.214\ F_6 + 0.658\ F_7 - 1.206\ F_8 + 1.099\ F_9 - 1.190\ F_{10} - 1.308 \quad (5.7)$$

$$F_i = \left\{\frac{2}{1+e^{-2E_i}} - 1\right\} \tag{5.8}$$

$$E_i = W_{1i}\, IRI_0 + W_{2i}\, RF + W_{3i}\, TD_l + W_{4i}\, TD_h + W_{5i}\, CV + B_{1i} \tag{5.9}$$

Table5.3 Weight and bias values for IRI prediction in Terai region with low traffic

i	W_{1i}	W_{2i}	W_{3i}	W_{4i}	W_{5i}	B_{1i}
1	0.5970	1.3400	4.2938	1.1117	-0.8765	-2.1375
2	-1.6268	0.0550	-1.5380	-3.1307	2.2623	0.3299
3	1.4790	0.4274	1.7527	-3.5560	-1.1007	-1.0699
4	-0.5120	-1.9748	-2.8770	4.9816	-2.6518	-0.5111
5	1.3476	-0.3589	-0.2905	0.4668	0.5579	0.3134
6	-0.5705	3.1519	-0.1816	-1.7546	0.3933	-1.8278
7	-0.2072	-0.8643	-0.7395	-0.0940	-2.4904	1.0864
8	1.5137	0.3076	1.1256	1.4650	1.9767	2.2391
9	2.2430	1.1702	2.1269	1.6794	2.2477	3.0864
10	0.4366	0.3168	1.0429	-1.1043	-0.8297	-1.1558

Figure 5.3 shows the predicting capability of the proposed IRI prediction model for Terai region with low traffic. Most data are concentrated near the fit line and R^2 value of the overall model is 0.79.

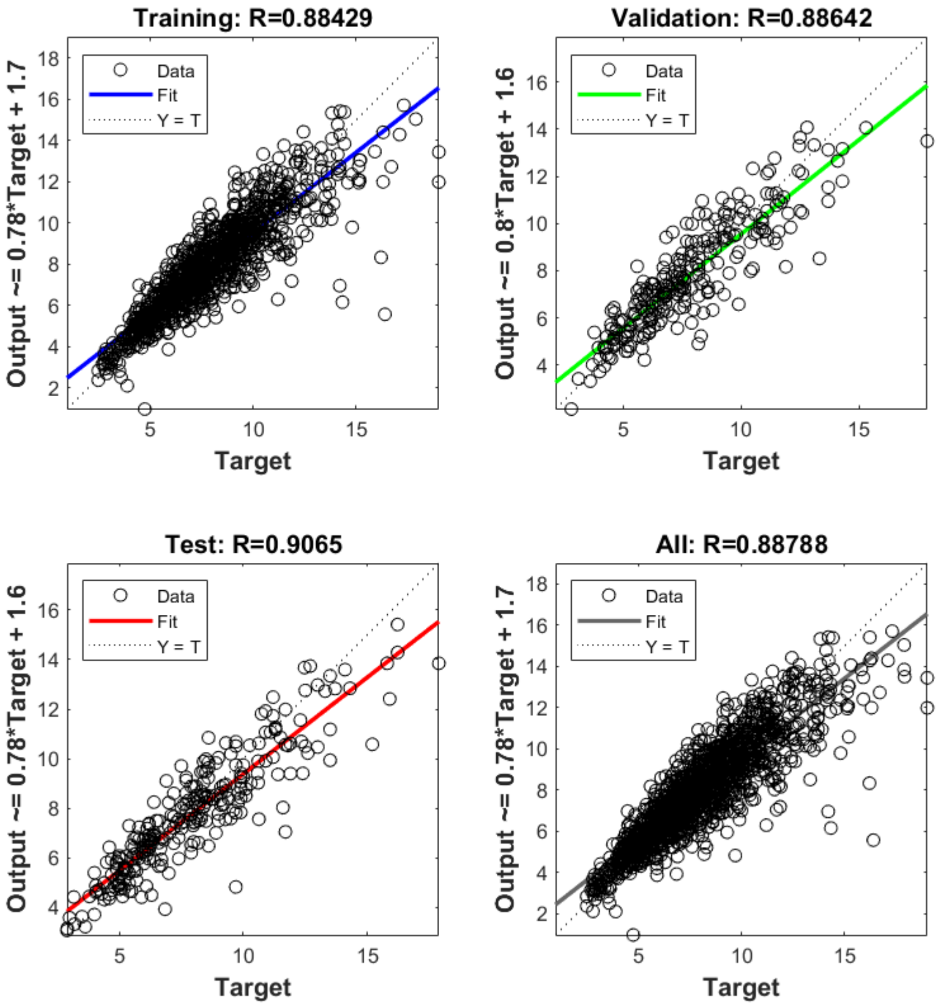

Figure 5.3 Goodness-of-fit of the IRI prediction model for Terai region with low traffic

5.5 IRI Prediction Model for Terai Region with High Traffic

There are 185 data records that falls under this category which is comparatively less than that in other categories. Of the total data set, 70% of the data were used for training, 15% of data were used for validation and the rest 15% were used for testing. Equation (5.10) shows the IRI prediction model for Terai region with high traffic. The *F* values can be calculated using tansig function as given in Equation (5.11) based on E_i values calculated from Equation (5.12) using weight and bias values given in Table 5.4.

$$IRI = -0.104\ F_1 - 0.120\ F_2 + 0.241\ F_3 + 0.267\ F_4 - 0.472\ F_5 - 0.252\ F_6 + 0.367\ F_7 - 0.399\ F_8 + 0.348\ F_9 + 0.170\ F_{10} - 0.339 \quad (5.10)$$

$$F_i = \left\{\frac{2}{1 + e^{-2E_i}} - 1\right\} \quad (5.11)$$

$$E_i = W_{1i}\ IRI_0 + W_{2i}\ RF + W_{3i}\ TD_l + W_{4i}\ TD_h + W_{5i}\ CV + B_{1i} \quad (5.12)$$

Table5.4 Weight and bias values for IRI prediction in Terai region with high traffic

i	W_{1i}	W_{2i}	W_{3i}	W_{4i}	W_{5i}	B_{1i}
1	0.7565	1.8157	1.5623	1.2954	0.2357	1.4000
2	1.5958	-1.1445	-0.8730	-1.2336	0.9575	-2.3414
3	1.7519	-2.0893	-0.7859	1.3576	0.9928	0.1641
4	1.8311	0.7059	0.9743	1.8672	0.9083	-1.2313
5	-0.1854	-1.3270	0.6241	0.3519	0.0036	1.2434
6	0.3111	0.6939	1.4709	1.9297	-0.7581	-0.5812
7	0.6298	0.8396	0.1493	-0.3301	-1.3872	0.4770
8	-1.5196	1.6762	0.1221	-0.7639	-1.5177	-0.5809
9	0.5430	1.8147	-0.6484	1.9040	-1.1908	0.6599
10	0.3697	-1.5878	0.3650	-1.1258	0.3740	2.6072

Figure 5.4 shows the predicting capability of the proposed IRI prediction model for Terai region with high traffic. The R^2 value of the model is 0.73 which is relatively less than that of other models that may be due to the relatively less number of data records used for development of the model. However, the value is still in range strong enough to show model's good fit to the data.

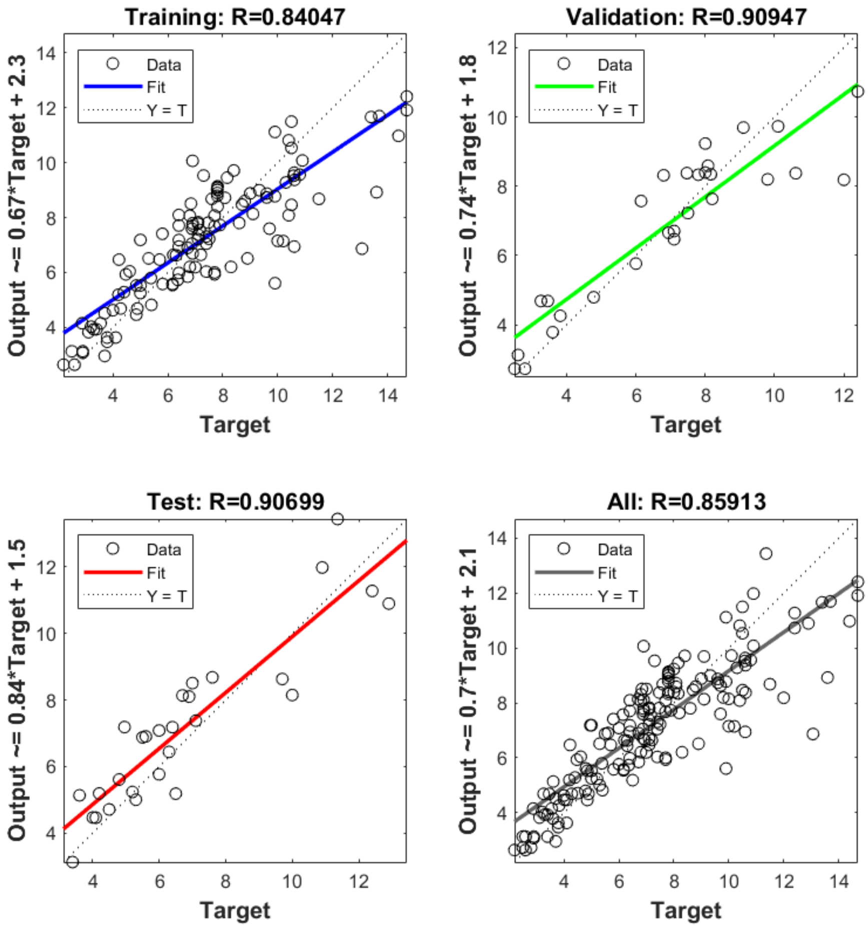

Figure 5.4 Goodness-of-fit of the IRI prediction model for Terai region with high traffic

5.6 IRI Prediction Model for Hilly Region with Low Traffic

There are 1300 data records under this category. Of this data records, 70% were used for training, 15% were used for validation and the rest 15% were used for testing. Equation (5.13) shows the IRI prediction model for hilly region with low traffic. The *F* values can be calculated using tansig function as given in Equation (5.14) based on the E_i values calculated from Equation (5.15) using weight and bias values given in Table 5.5.

$$IRI = -0.112\,F_1 - 0.155\,F_2 - 0.258\,F_3 + 0.239\,F_4 + 0.105\,F_5 - 0.128\,F_6 + 0.079\,F_7 + 0.381\,F_8 - 8.198\,F_9 - 1.272\,F_{10} - 7.558 \tag{5.13}$$

$$F_i = \left\{\frac{2}{1 + e^{-2E_i}} - 1\right\} \tag{5.14}$$

$$E_i = W_{1i}\,IRI_0 + W_{2i}\,R + W_{3i}\,TD_l + W_{4i}\,TD_h + W_{5i}\,CV + B_{1i} \tag{5.15}$$

Table 5.5 Weight and bias values for IRI prediction in Hilly region with low traffic

i	W_{1i}	W_{2i}	W_{3i}	W_{4i}	W_{5i}	B_{1i}
1	-9.6026	0.3170	-2.9812	2.6455	3.2377	-3.4666
2	-13.8676	39.3980	-12.8218	-11.8738	-13.4194	13.3522
3	1.1996	-4.2871	3.1719	1.0909	2.7475	-1.5735
4	0.1548	3.4319	-0.3528	1.1122	2.3819	3.0220
5	-13.1047	-2.3269	13.0432	-35.7248	-43.2009	-27.0615
6	12.3186	6.3884	-6.9926	3.8876	7.9839	3.8332
7	9.0458	-14.2337	-32.8027	-2.7509	8.6527	2.9985
8	2.5091	-0.9912	1.2144	-0.2168	0.1918	0.0596
9	0.0532	4.5032	-7.6358	2.5448	0.3119	-6.6261
10	-0.3250	-0.5914	1.4323	-1.1168	-0.3669	1.1929

Figure 5.5 shows the predicting capability of the proposed IRI prediction model for Hilly region with low traffic. More data are concentrated near the fit line and the R^2 value of the model is 0.86 showing a good fit to the data.

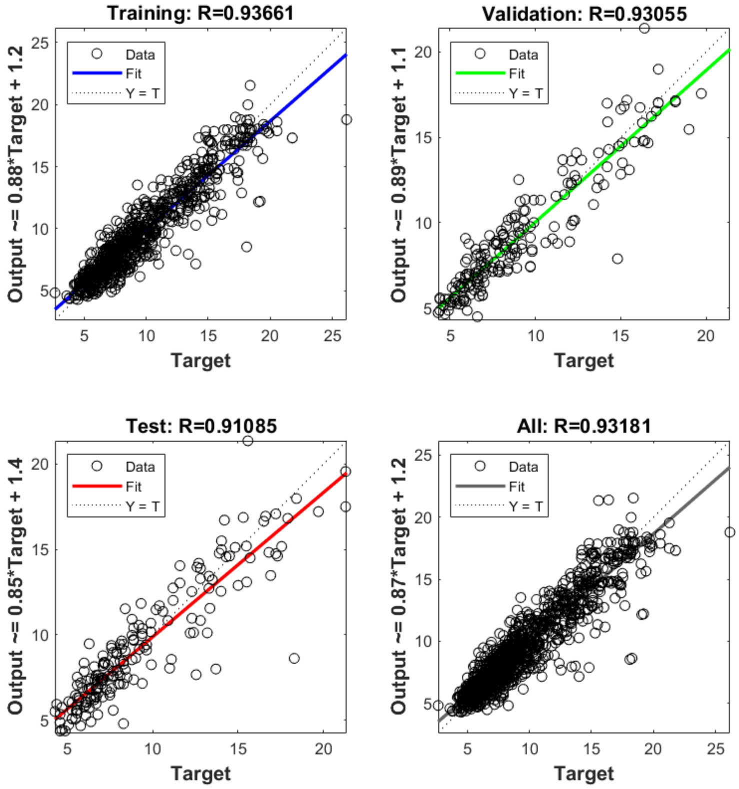

Figure 5.5 Goodness-of-fit of the IRI prediction model for Hilly region with low traffic

5.7 IRI Prediction Model for Hilly Region with High Traffic

There are 301 data records under this category. Of this data records, 70% were used for training, 15% were used for validation and the rest 15% were used for testing. Equation (5.16) shows the IRI prediction model for hilly region with high traffic. The *F* values can be calculated using tansig function as given in Equation (5.17) based on the E_i values calculated from Equation (5.18) using weight and bias values given in Table 5.6.

$$IRI = 0.0992\,F_1 - 0.483\,F_2 + 0.1662\,F_3 - 0.7303\,F_4 - 0.58051\,F_5 + 0.04993\,F_6 + 0.0196\,F_7 - 0.7672\,F_8 - 0.696\,F_9 - 1.030\,F_{10} - 0.9023 \tag{5.16}$$

$$F_i = \left\{\frac{2}{1 + e^{-2E_i}} - 1\right\} \tag{5.17}$$

$$E_i = W_{1i}\,IRI_0 + W_{2i}\,RF + W_{3i}\,TD_l + W_{4i}\,TD_h + W_{5i}\,CV + B_{1i} \tag{5.18}$$

Table 5.6 Weight and bias values for IRI prediction in Hilly region with high traffic

i	W_{1i}	W_{2i}	W_{3i}	W_{4i}	W_{5i}	B_{1i}
1	1.9897	-0.7721	-1.2402	1.0188	-0.9066	-2.0444
2	0.0439	-1.8420	-1.5976	0.4617	-0.8740	-2.0502
3	2.6037	-1.1382	-0.8274	0.4212	-0.6094	-1.4443
4	-0.8791	-0.1628	-0.1928	0.2958	0.1453	0.6535
5	-1.0743	1.7092	0.5691	-1.1483	1.0521	-0.0963
6	-1.5242	-1.2675	-1.1906	-0.2142	-1.7018	1.6136
7	-1.0727	-2.9584	0.4703	-0.9503	-0.3034	-0.6902
8	1.3720	-0.8921	-2.1875	-1.1264	-1.8800	1.6442
9	-1.6287	-0.3585	0.4853	1.3505	-0.6247	-2.1304
10	-0.0707	0.2776	0.3799	-0.0831	-0.8893	-3.5736

Figure 5.6 shows the predicting capability of the proposed IRI prediction model for Hilly region with high traffic. As case with the model for Terai region with high traffic, the R^2 value of the model is slightly less 0.75 but still in a range well enough to show good fit of the model.

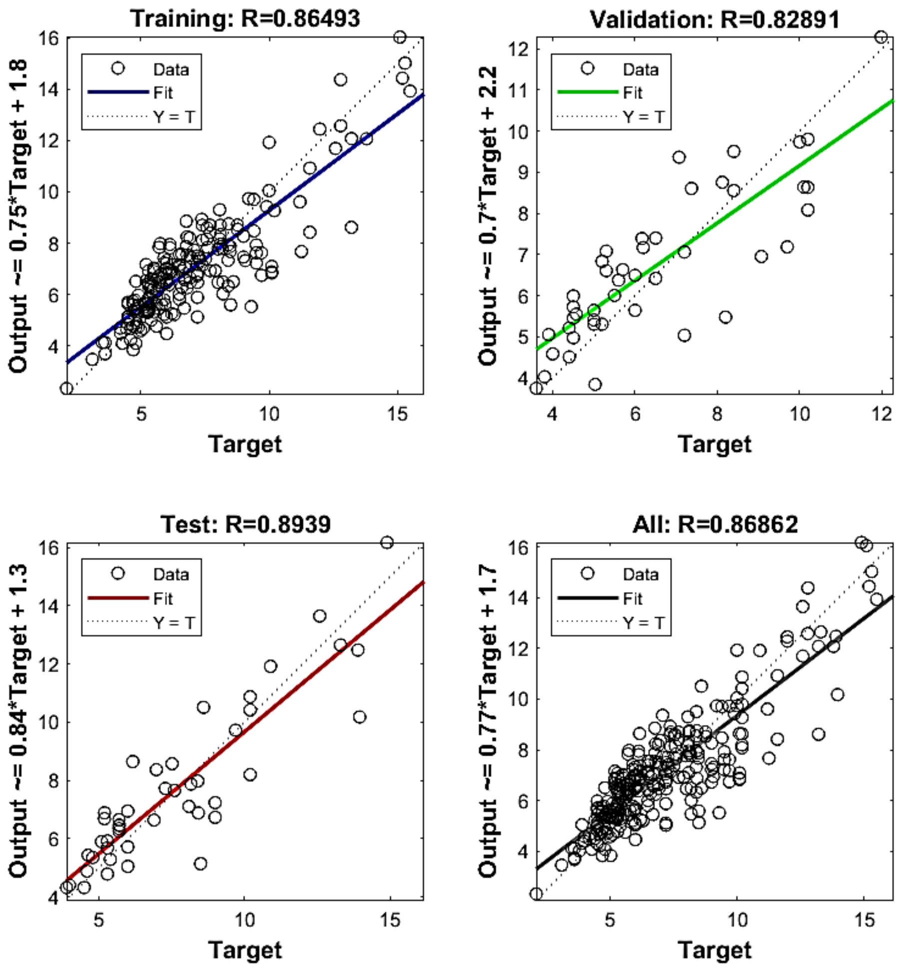

Figure 5.6 Goodness-of-fit of the IRI prediction model for Hilly region with high traffic

CHAPTER SIX: PERFORMANCE CURVE AND RECOMMENDATIONS FOR MAINTENANCE PLANNING

6.1 General

The ability of a pavement to serve traffic over time is termed as its performance. Conventionally, visual inspection and field experience was used to judge pavement's relative capacity to serve traffic. More recently, advanced tools and techniques are used to analyze pavement conditions and predict its performance. Prediction models of pavement performance indicators such as those developed in this study can be used to develop pavement performance curves from which appropriate maintenance cycles can be planned.

6.2 Pavement Performance Curve

As the pavement deteriorates due to traffic loads and environmental factors, the measured pavement roughness normally increases over time. Figure 6.1 depicts the expected International Roughness Index (IRI) trend of pavement sections of national highways in various zones of Nepal over time based on the IRI prediction models developed in Chapters 4 and 5. The terrain types and traffic number are used to divide the zones. It can be observed from the figure that the rate of IRI increment is higher for the pavement sections with high traffic in its initial period of up to two years. Following that, the rate of increase is gradual. However, for low traffic regions, the increase in IRI is gradual for the first two years and then increases rapidly. The trend of IRI progression is S- shape for all zones. Based on the performance curve, it can be said that in the early ages of pavement, traffic is a dominant factor that influence IRI while the influence of environmental factors appears to be dominant in the latter ages. Figure 6.1 also shows that the terminal IRI values for Hilly region is higher than that of Terai region.

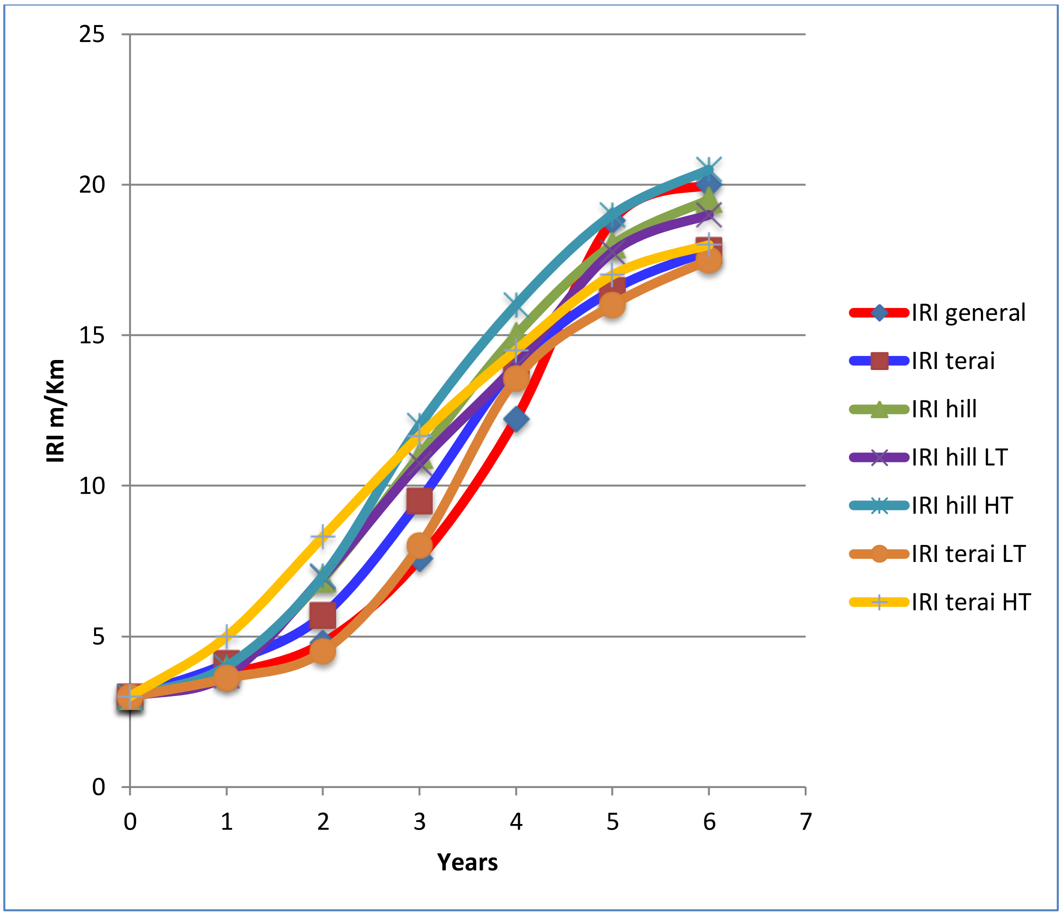

Figure 6.1 Performance curve for pavement section in different zone

6.3 Recommendation for Pavement Maintenance Planning

Based on the pavement curves in Figure 6.1 obtained using the developed IRI prediction models in this study, pavement maintenance cycles of 2 to 4 years is recommended in order to maintain the threshold IRI value of 8 m/km. For the qualitative validation of the models, this recommended maintenance cycle is compared with the DoR nominated maintenance cycle given in Table 6.1. DoR's maintenance cycle is provided on the basis of traffic and terrain type. In the present context, procedure and guidelines on periodic maintenance planning developed by Strengthen Maintenance Division Program is followed. The project selection is mainly carried out based on Traffic Group Index, Road Condition Index and Strategic Importance Indices. As the table shows, at present state maintenance cycles of 5 to 7 years has been recommended which is comparatively more than the periods obtained in this study. One of the reason behind the use of longer periods in DoR’s case could be due to the use of Surface Distress Index (SDI) as the Road Condition Index value which is a subjective rating. Moreover, the data records used in this study shows IRI of some sections exceeded the threshold value 8m/km within the four periods. This also justifies the need to shorten the currently in use maintenance cycle of 5 to 7 years cycles. The study also shows that the initial IRI is highly sensitive parameter for IRI progression and flexible pavements in Nepal are mostly in rougher condition. Therefore, slightly longer period of maintenance cycle can be achieved provided the initial IRI of the pavements are improved.

Table 6.1: DoR's nominated maintenance cycle and predicted maintenance cycle.

Traffic	Low and Moderate Traffic up to 1500vpd		High Traffic > 1500vpd	
Terrain	Maintenance Cycle	Predicted Age	Maintenance Cycle	Predicted Age
Plains	7	3-4	6	2-3
Hill	6	3-4	5	2-3

CHAPTER SEVEN: CONCLUSIONS AND DIRECTIONS FOR FUTURE WORK

7.1 Conclusions

International Roughness Index (IRI) considers the interaction between pavement and vehicles, and is a globally accepted pavement performance indicator. IRI is often modeled by considering combinations of pavement distress data, pavement structural design data, material properties data, environmental data and traffic data. Collection of distress data is labor intensive and time consuming. Pavement structural design data needs sophisticated equipment such as Falling Weight Deflectometer, Benkalmen Beam etc. and sometimes even requires core sampling destructive tests. Design data is one of the most important parameters for evaluating the structural performance of the pavement but literature shows functional performance of pavement is not significantly affected by design data. This study developed IRI prediction models for flexible pavements of national highways in Nepal based on traffic (number of commercial vehicle), and environmental factors (temperature and rainfall) utilizing the IRI database for national highways in Nepal. Previous study in context of Nepal had been carried out to model Surface Distress Index (SDI) as pavement performance indicator using time as independent variable. To the knowledge of authors, no IRI prediction model has been developed in context to Nepal. Therefore, the model has potential to facilitate pavement maintenance planning in Nepal.

IRI prediction models were developed using both Artificial Neural Network technique and multiple linear regression approach to identify the model that provides best fit to the data. Both generalized and regional IRI prediction models were then developed that can be used for predicting pavement roughness of flexible pavements of highways of Nepal at national and regional levels. The pavement performance prediction curves were developed based on the developed models and recommendations for maintenance planning are provided. Following concludes the findings of the study:

- The ANN-based IRI prediction model outperforms the regression-based model. For the generalized model, R^2 value for former was obtained to be 0.82 while that for later was obtained to be 0.76.
- The IRI value is most sensitive to initial IRI and is least sensitive to the low temperature days.
- The R^2 values of regional models are in a range 0.73 to 0.86 showing good fit to the data. The values for high traffic cases are slightly lower (0.73 to 0.75) compare to that with low traffic cases (0.79 to 0.86) which could be due to lesser number of data records available for the later cases.
- The general trend of IRI over time for national highways in Nepal is S- shape. In the early years, the effect of traffic variables on IRI seems to outweigh the combined effects of environmental factors. The performance prediction curve shows maintenance cycle of 2 to 4 years as appropriate periods to maintain the threshold IRI values of 6 - 8 m/km suggested by Department of Roads (DoR).

7.2 Future Work Directions

For future works, following recommendations appears to be appropriate to enhance the model predicting capability and practical application of the developed models:

- Due to ambiguity axle loading pattern of vehicle classes in the database and time constraint to conduct sample axle distribution survey, this study uses number of commercial vehicles and do not consider their differences in axle load distributions. Therefore, future studies can be conducted to more appropriately represent the effect of commercial vehicle traffic by considering the axle load distributions of the vehicle types. The predictability of the model can be further enhanced using pavement design data and material properties along with the climatic and traffic data.
- The models appropriateness directly depends on the quality of database used in model development. Therefore, it is recommended to maintain a consistency in measurement of IRI and other traffic and environmental information and to keep a record of database of high accuracy.

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APPENDIX 1: MATLAB GENERATED ANN CODE FOR IRI PREDICTION

```
function [Y,Xf,Af] = myNeuralNetworkFunction(X,~,~)
%MYNEURALNETWORKFUNCTION neural network simulation function.
%
% Auto-generated by MATLAB, 17-Aug-2021 18:22:53.
%
% [Y] = myNeuralNetworkFunction(X,~,~) takes these arguments:
%
%   X = 1xTS cell, 1 inputs over TS timesteps
%   Each X{1,ts} = Qx5 matrix, input #1 at timestep ts.
%
% and returns:
%   Y = 1xTS cell of 1 outputs over TS timesteps.
%   Each Y{1,ts} = Qx1 matrix, output #1 at timestep ts.
%
% where Q is number of samples (or series) and TS is the number of
timesteps.

%#ok<*RPMT0>

% ===== NEURAL NETWORK CONSTANTS =====

% Input 1
x1_step1.xoffset = [1;242.4;1941;0;49];
x1_step1.gain =
[0.121951219512195;0.000171802118320119;0.000189771325552709;0.000112
771356075557;0.000174687745654642];
x1_step1.ymin = -1;

% Layer 1
b1 = [-2.8054455701089779929;1.6627686065209419386;-
0.60837438535551757735;-0.24601610174208804471;-
1.9712867604042805247;-0.65082572880924727254;-
5.0607245082493834687;-
3.4506936468313602617;2.3789863308556915555;3.2505390902846515999];
IW1_1 = [1.7416755998290294194 -5.0980412260186938056 -
4.122690977713715732 -2.0075938665072561307 -1.1176486552643474237;-
1.4770407834914802692 -1.354402044320427434 -0.62206743131823927229
1.0234642614889839507 -0.60719451338602203894;0.15472320905973083183
3.6867553464900160165 -1.0984482591079745006 -2.6295553849347794717 -
0.7121462823255101382;-0.0025769005322018589954 4.2609554723482974126
-1.3096335782019739025 -2.7920240045022857167 -
0.47803136489353681426;2.2512117933962603189 -1.224481301120222243
4.2426250141076184974 3.0379619952250678239 0.88151210514408506747;-
0.72099212412476343381 0.14834307668325655283 0.095984374936324404204
0.020560046887230225277 -0.051616311418635221764;-
4.5367729684115003508 3.8406270732182350436 -0.25606661036832151224 -
1.2355848722685764951 -3.039231862380462168;-4.8560141080210073028 -
3.9733052908163957184 -1.255620548037434725 1.3021408277039570045 -
0.65421637544335431436;-1.3258430795763347376 -2.1231923713080251837
-0.078241069968292276116 2.9912647951954944858
2.5782063379982549378;-0.18550623125952350745 2.0969024354990017933
5.1102882811586551881 1.3086475924689513484 -1.6366093944779649405];

% Layer 2
b2 = -0.99359341918893495649;
LW2_1 = [-0.044950105886140179212 0.15788743743632419059 -
1.7590573224423065035 1.4822742619445703482 0.086348537979075837279 -
```

```
1.6339570579071696077 0.31985411204849012456 -0.059568531908364932836
-0.15155751720341581468 0.10067041760551770357];

% Output 1
y1_step1.ymin = -1;
y1_step1.gain = 0.0831255195344971;
y1_step1.xoffset = 2.1;

% ===== SIMULATION ========

% Format Input Arguments
isCellX = iscell(X);
if ~isCellX
    X = {X};
end

% Dimensions
TS = size(X,2); % timesteps
if ~isempty(X)
    Q = size(X{1},1); % samples/series
else
    Q = 0;
end

% Allocate Outputs
Y = cell(1,TS);

% Time loop
for ts=1:TS

    % Input 1
    X{1,ts} = X{1,ts}';
    Xp1 = mapminmax_apply(X{1,ts},x1_step1);

    % Layer 1
    a1 = tansig_apply(repmat(b1,1,Q) + IW1_1*Xp1);

    % Layer 2
    a2 = repmat(b2,1,Q) + LW2_1*a1;

    % Output 1
    Y{1,ts} = mapminmax_reverse(a2,y1_step1);
    Y{1,ts} = Y{1,ts}';
end

% Final Delay States
Xf = cell(1,0);
Af = cell(2,0);

% Format Output Arguments
if ~isCellX
    Y = cell2mat(Y);
end
end

% ===== MODULE FUNCTIONS ========

% Map Minimum and Maximum Input Processing Function
function y = mapminmax_apply(x,settings)
y = bsxfun(@minus,x,settings.xoffset);
y = bsxfun(@times,y,settings.gain);
```

```
y = bsxfun(@plus,y,settings.ymin);
end

% Sigmoid Symmetric Transfer Function
function a = tansig_apply(n,~)
a = 2 ./ (1 + exp(-2*n)) - 1;
end

% Map Minimum and Maximum Output Reverse-Processing Function
function x = mapminmax_reverse(y,settings)
x = bsxfun(@minus,y,settings.ymin);
x = bsxfun(@rdivide,x,settings.gain);
x = bsxfun(@plus,x,settings.xoffset);
end
```

APPENDIX 2: OBSERVED AND PREDICTED IRI FOR DIFFERENT REGIONS

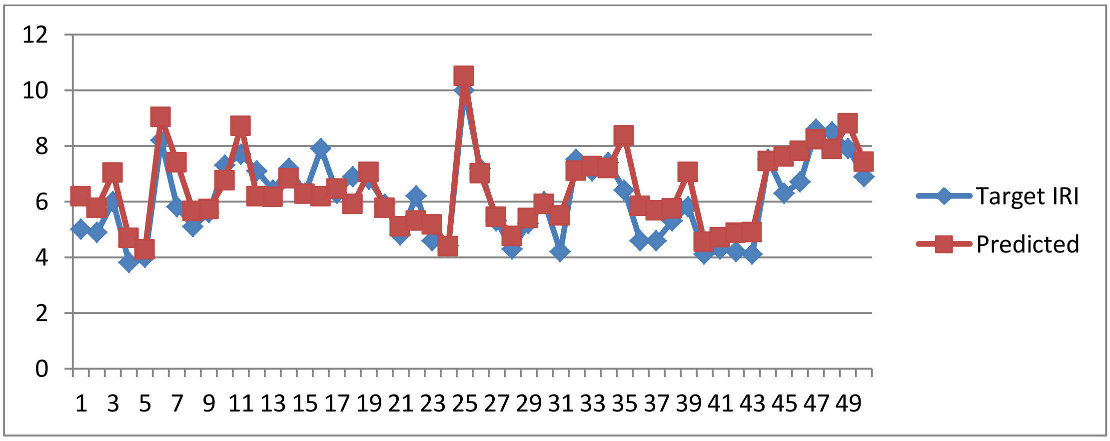

Figure A-2.1 Comparison of Observed IRI with Predicted IRI for Generalized Model

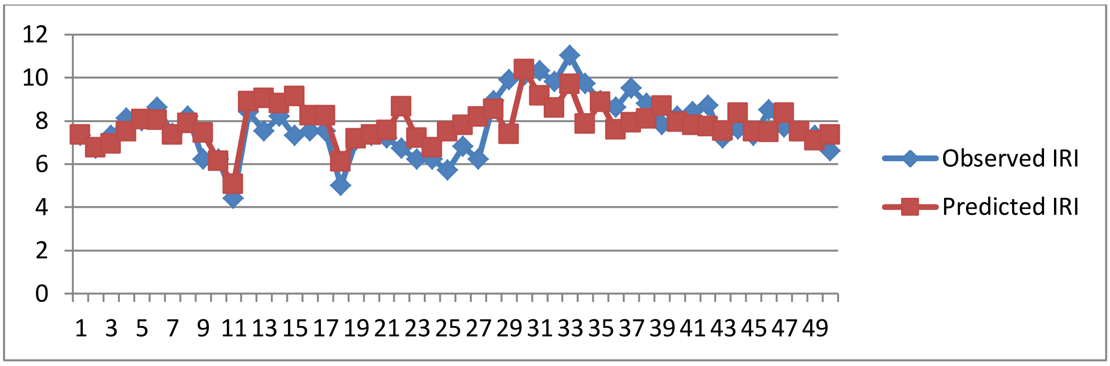

Figure A-2.2 Comparison of Observed IRI with Predicted IRI for Terai Region

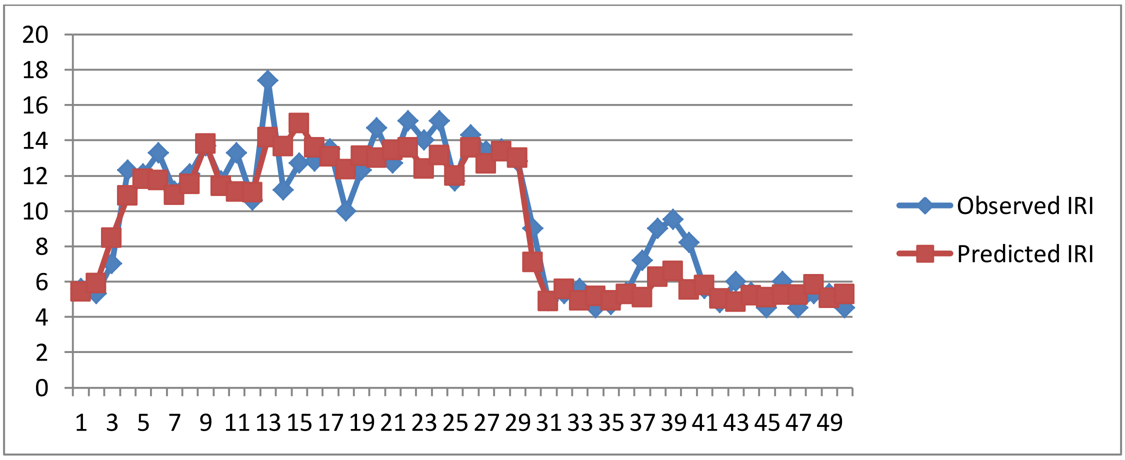

Figure A-2.3 Comparison of Observed IRI with Predicted IRI for Hill Region

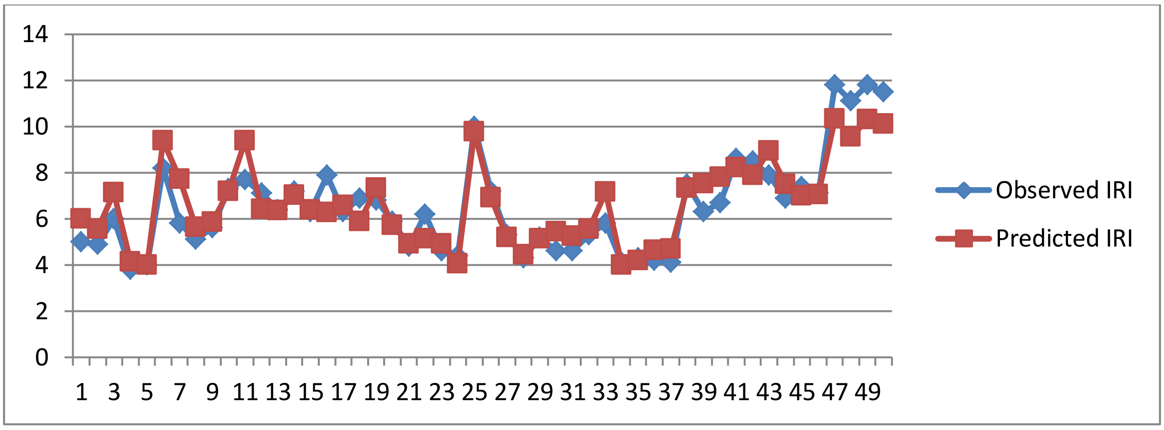

Figure A-2.4 Comparison of Observed IRI with Predicted IRI for Low Traffic Terai Region.

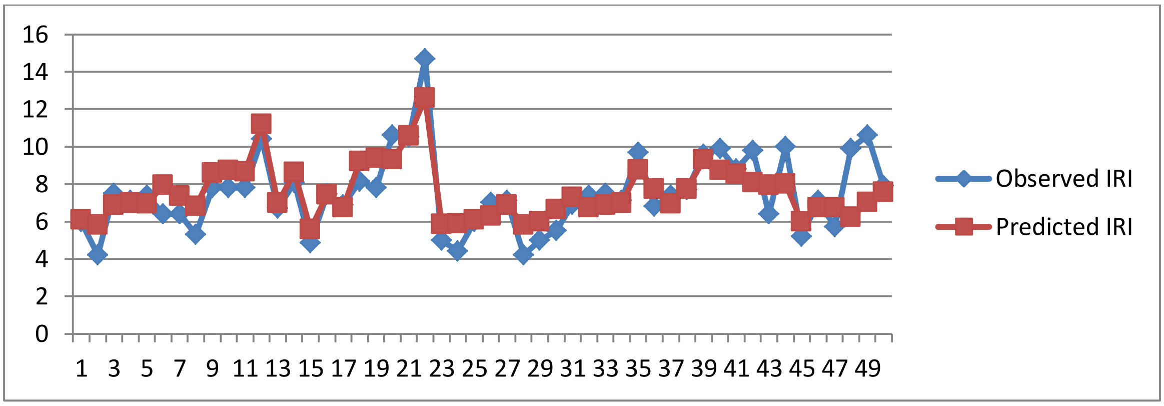

Figure A-2.5 Comparison of Observed IRI with Predicted IRI for High Traffic Terai Region.

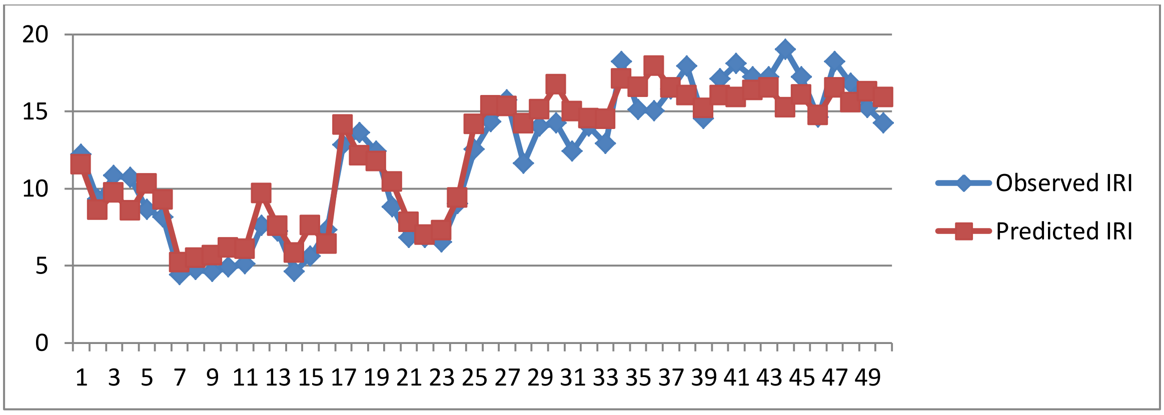

Figure A-2.6 Comparison of Observed IRI with Predicted IRI for Low Traffic Hill Region.

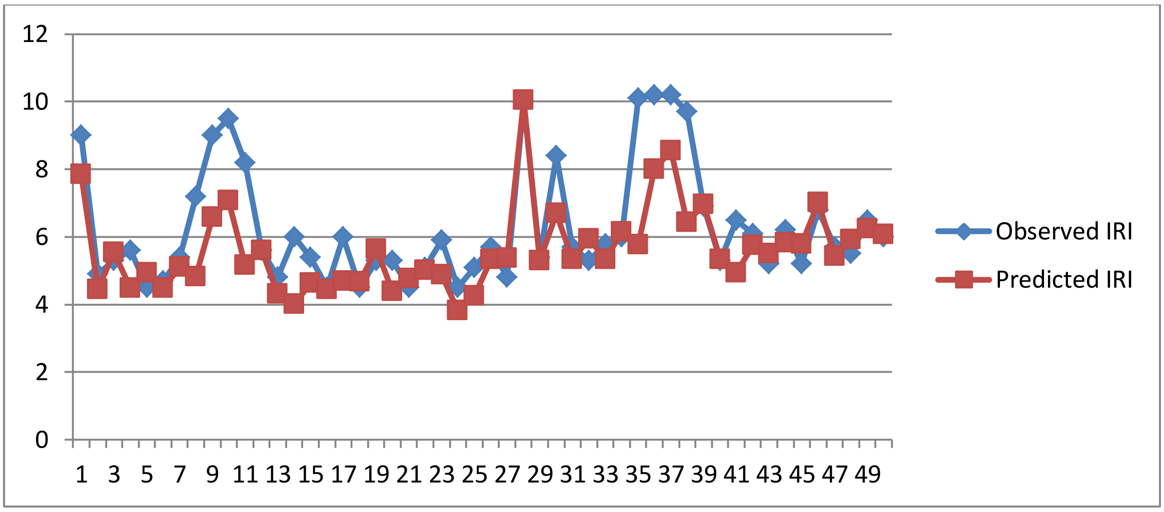

Figure A-2.7 Comparison of Observed IRI with Predicted IRI for High Traffic Hill Region.

APPENDIX 3: NEURAL NETWORK TRAINING, VALIDATION AND TESTING DATA SAMPLE FOR IRI MODELING

SN	Roughness Value				Rainfall			Temperature						CV		
								Minimum			Maximum					
	2013/14	2014	2015	2016	2014	2014+15	2014+15+16	2014	2014+15	2014+15+16	2014	2014+15	2014+15+16	14	14+15	14+15+16
1	4.87	5	5.5	5.84	2075	4154.9	6683.9	3093	6604	10162	5526	11198	16961	556	1510	2352
2	4.66	4.9	6.4	6.72	1399.3	3232.4	6113.8	3093	6604	10162	5526	11198	16961	1231	2440	5038
3	5.61	6	6.1	8.08	1695.8	3727.1	6084.2	3093	6604	10162	5526	11198	16961	1231	2440	5038
4	3.74	3.8	4	4.85	1695.8	3727.1	6084.2	3093	6604	10162	5526	11198	16961	1231	2440	5038
5	3.29	4	4.3	4.64	1096.4	2172.7	3764.9	4007	7492	11044	5798	11285	16865	658	1139	3024
6	7.03	8.2	9.1	9.11	1391.6	2820.9	4531.6	4007	7492	11044	5798	11285	16865	760	1441	2116
7	5.75	5.8	6.7	7.6	1391.6	2820.9	4531.6	4007	7492	11044	5798	11285	16865	760	1441	2116
8	4.41	5.1	6.3	8.01	1391.6	2820.9	4531.6	4007	7492	11044	5798	11285	16865	760	1441	2116
9	4.54	5.6	7	7.69	1691.4	3346.9	5050.5	3659	7304	10928	5511	11067	16662	972	1837	3704
10	5.37	7.3	8.2	8.35	1691.4	3346.9	5050.5	3659	7304	10928	5511	11067	16662	972	1837	3704
11	6.92	7.7	9.7	10.3	1859.9	3439.4	5022.7	3659	7304	10928	5511	11067	16662	972	1837	3704
12	4.89	7.1	8.4	9.07	1859.9	3439.4	5022.7	3659	7304	10928	5511	11067	16662	972	1837	3704
13	4.87	6.4	7	8.6	1859.9	3439.4	5022.7	3659	7304	10928	5511	11067	16662	972	1837	3704
14	5.4	7.2	9.9	10.3	1859.9	3439.4	5022.7	3659	7304	10928	5511	11067	16662	714	1704	3532
15	4.97	6.3	7.4	10.3	1859.9	3439.4	5022.7	3659	7304	10928	5511	11067	16662	714	1704	3532
16	4.9	7.9	9.9	11.2	1859.9	3439.4	5022.7	3659	7304	10928	5511	11067	16662	714	1704	3532
17	5.11	6.3	8.1	8.42	1859.9	3439.4	5022.7	3659	7304	10928	5511	11067	16662	714	1704	3532

SN	Roughness Value				Rainfall			Temperature						CV		
								Minimum			Maximum					
	2013/14	2014	2015	2016	2014	2014+15	2014+15+16	2014	2014+15	2014+15+16	2014	2014+15	2014+15+16	14	14+15	14+15+16
19	5.59	6.8	7.9	7.92	1859.9	3439.4	5022.7	3659	7304	10928	5511	11067	16662	714	1704	3532
20	4.55	5.9	6.3	8.81	1859.9	3439.4	5022.7	3659	7304	10928	5511	11067	16662	714	1704	3532
21	3.98	4.8	5.7	7.85	1859.9	3439.4	5022.7	3659	7304	10928	5511	11067	16662	714	1704	3532
22	4.15	6.2	6.3	8.93	1859.9	3439.4	5022.7	3659	7304	10928	5511	11067	16662	714	1704	3532
23	3.91	4.6	4.9	5.7	242.4	525.9	856	3659	7304	10928	5511	11067	16662	714	1704	3532
24	3.35	4.4	4.9	7.62	242.4	525.9	856	3659	7304	10928	5511	11067	16662	714	1704	3532
25	7.78	10	10.5	10.9	242.4	525.9	856	3659	7304	10928	5511	11067	16662	714	1704	3532
26	5.19	7.2	9	9.82	242.4	525.9	856	3659	7304	10928	5511	11067	16662	714	1704	3532
27	4.09	5.3	6.3	7.36	242.4	525.9	856	3659	7304	10928	5511	11067	16662	714	1704	3532
28	3.61	4.3	4.6	5.74	242.4	525.9	856	3659	7304	10928	5511	11067	16662	714	1704	3532
29	4.06	5.2	6	6.42	242.4	525.9	856	3659	7304	10928	5511	11067	16662	714	1704	3532
30	4.23	6	6.4	7.47	1642	3103.6	3609.4	3126	6297	9215	5325	10601	15972	2828	4638	7278
31	3.9	4.2	5.3	6.88	1642	3103.6	3609.4	3126	6297	9215	5325	10601	15972	2828	4638	7278
32	5.22	7.5	7.8	8.16	1642	3103.6	3609.4	3126	6297	9215	5325	10601	15972	2828	4638	7278
33	5.35	7.1	7.8	7.81	1642	3103.6	3609.4	3126	6297	9215	5325	10601	15972	2828	4638	7278
34	5.29	7.4	7.8	10.6	1642	3103.6	3609.4	3126	6297	9215	5325	10601	15972	2828	4638	7278
35	6.06	6.4	10.4	10.5	2143.5	4071.9	6155.5	3126	6297	9215	5325	10601	15972	2828	4638	7278
36	4.52	4.6	5.1	6.17	2198.5	4307.7	6831.2	2619	5264	8712	5498	11619	17735	822	1815	4158
37	4.38	4.6	5.3	5.81	2198.5	4307.7	6831.2	2619	5264	8712	5498	11619	17735	822	1815	4158
38	4.58	5.3	5.8	6.84	1934	3408.2	5715.9	2619	5264	8712	5498	11619	17735	822	1815	4158
39	5.62	5.8	8.8	10.6	1934	3408.2	5715.9	2619	5264	8712	5498	11619	17735	822	1815	4158

SN	Roughness Value				Rainfall			Temperature						CV		
								Minimum			Maximum					
	2013/14	2014	2015	2016	2014	2014+15	2014+15+16	2014	2014+15	2014+15+16	2014	2014+15	2014+15+16	14	14+15	14+15+16
40	3.72	4.1	4.6	5	1502.8	2863.3	4640.1	2619	5264	8712	5498	11619	17735	1092	2157	4178
41	3.85	4.3	5.2	6.15	1502.8	2863.3	4640.1	2619	5264	8712	5498	11619	17735	1092	2157	4178
42	3.99	4.2	4.8	4.86	1502.8	2863.3	4640.1	2619	5264	8712	5498	11619	17735	917	1774	3128
43	4.02	4.1	4.6	4.89	1502.8	2863.3	4640.1	2619	5264	8712	5498	11619	17735	917	1774	3128
44	5.96	7.5	8	11.7	1342	2383.1	3962.8	2619	5264	8712	5498	11619	17735	1167	2058	3295
45	6.1	6.3	6.9	7.36	1342	2383.1	3962.8	2619	5264	8712	5498	11619	17735	1167	2058	3295
46	6.2	6.7	7.5	8.03	1941.5	3466.5	5159.4	2619	5264	8712	5498	11619	17735	441	859	2117
47	6.52	8.6	10.3	12.3	1941.5	3466.5	5159.4	2619	5264	8712	5498	11619	17735	441	859	2117
48	6.26	8.5	8.6	9.31	1941.5	3466.5	5159.4	2619	5264	8712	5498	11619	17735	441	859	2117
49	6.98	7.9	8.9	11.5	1941.5	3466.5	5159.4	2619	5264	8712	5498	11619	17735	1062	1786	2725
50	5.9	6.9	9	10.6	1941.5	3466.5	5159.4	2619	5264	8712	5498	11619	17735	1062	1786	2725
51	5.58	7.4	7.9	9.7	1941.5	3466.5	5159.4	2619	5264	8712	5498	11619	17735	586	1264	1883
52	5.62	7.1	8.3	13.6	1941.5	3466.5	5159.4	2619	5264	8712	5498	11619	17735	586	1264	1883
53	8.5	11.8	12.5	14.2	870.5	1704.2	2931.3	2619	5264	8712	5498	11619	17735	586	1264	1883
54	7.56	11.1	11.7	17.9	870.5	1704.2	2931.3	2619	5264	8712	5498	11619	17735	586	1264	1883
55	8.46	11.8	13.3	16.2	870.5	1704.2	2931.3	2619	5264	8712	5498	11619	17735	586	1264	1883
56	8.23	11.5	13.3	13.8	870.5	1704.2	2931.3	2619	5264	8712	5498	11619	17735	586	1264	1883
57	8.36	11.1	14.1	14.4	870.5	1704.2	2931.3	2619	5264	8712	5498	11619	17735	586	1264	1883
58	5.8	10.1	11.4	12.5	870.5	1704.2	2931.3	2619	5264	8712	5498	11619	17735	586	1264	1883
59	7.91	9.1	10	12.1	870.5	1704.2	2931.3	3576	7157	10299	5579	11162	16901	586	1264	1883
60	4.97	7.9	9	13.7	870.5	1704.2	2931.3	3576	7157	10299	5579	11162	16901	679	1279	2243

SN	Roughness Value				Rainfall			Temperature						CV		
								Minimum			Maximum					
	2013/14	2014	2015	2016	2014	2014+15	2014+15+16	2014	2014+15	2014+15+16	2014	2014+15	2014+15+16	14	14+15	14+15+16
61	6.74	9	10.3	15.2	870.5	1704.2	2931.3	3576	7157	10299	5579	11162	16901	679	1279	2243
62	6.55	8.7	9.5	15.1	870.5	1704.2	2931.3	3576	7157	10299	5579	11162	16901	679	1279	2243
63	6.84	9.3	10.1	10.5	870.5	1704.2	2931.3	3576	7157	10299	5579	11162	16901	679	1279	2243
64	6.15	9.1	9.8	11.3	870.5	1704.2	2931.3	3576	7157	10299	5579	11162	16901	679	1279	2243
65	6.63	8.7	9.9	11.4	1398.4	2206.5	3217.4	3576	7157	10299	5579	11162	16901	679	1279	2243
66	6.47	8.3	10	10.1	1398.4	2206.5	3217.4	3576	7157	10299	5579	11162	16901	679	1279	2243
67	5.78	8.3	8.6	10.7	1384.8	2732.6	4124.9	3576	7157	10299	5579	11162	16901	526	949	1689
68	5.85	7.6	8.1	11.3	1384.8	2732.6	4124.9	3576	7157	10299	5579	11162	16901	526	949	1689
69	5.86	8.3	8.7	10.5	1384.8	2732.6	4124.9	3576	7157	10299	5579	11162	16901	526	949	1689
70	5.88	8.9	9.5	10.6	1384.8	2732.6	4124.9	3576	7157	10299	5579	11162	16901	526	949	1689
71	8.22	10.6	10.8	12.4	1384.8	2732.6	4124.9	3576	7157	10299	5579	11162	16901	526	949	1689
72	6.78	8.6	8.8	11.3	1610.7	3077.7	4589	3576	7157	10299	5579	11162	16901	526	949	1689
73	5.59	8.6	9.6	10.6	1610.7	3077.7	4589	3576	7157	10299	5579	11162	16901	526	949	1689
74	5.27	6.8	7.2	8.59	1610.7	3077.7	4589	3576	7157	10299	5579	11162	16901	526	949	1689
75	5.69	7	7.9	8.87	1610.7	3077.7	4589	3576	7157	10299	5579	11162	16901	526	949	1689
76	6.01	7.6	8.8	9.18	1610.7	3077.7	4589	3576	7157	10299	5579	11162	16901	526	949	1689
77	5.11	5.4	6.1	9.3	1610.7	3077.7	4589	3576	7157	10299	5579	11162	16901	562	1027	1940
78	3.98	4.7	6	9.28	1610.7	3077.7	4589	3576	7157	10299	5579	11162	16901	562	1027	1940
79	3.77	4	5	5.82	1610.7	3077.7	4589	3576	7157	10299	5579	11162	16901	562	1027	1940
80	4.46	4.7	4.9	6.14	1610.7	3077.7	4589	3576	7157	10299	5579	11162	16901	562	1027	1940
81	3.35	3.8	4.3	4.48	1610.7	3077.7	4589	3576	7157	10299	5579	11162	16901	562	1027	1940

APPENDIX 4: MAINTENANCE RECORD SAMPLE FROM ROADS BOARD NEPAL

Road Register 2074/075

Road Ref No	Link Code	Link Name	Link From	Link To	Link Length	BT	GR	ER	UC	PL	Terrain	Link Section	Section From	Section To	Section Length	Pavement Type	Pavement Width	Year of Last Resurfacing	Surface Distress Index SDI	Surface Distress Index SDI Class	International Roughness Index IRI (m/Km)	International Roughness Index IRI Class	Traffic Volume AADT	Traffic Class	Project Name
[illegible]	H1004	Mahendranagar-Chisapani Khola	24.10	28.20	4.10	4.10	0.00	0.00	0.00	0.00	H	H1004-A	24.10	27.10	3.00	STGB	21.00	2014	2.20	Fair	9.78	Bad	2,989	High	
			0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		H1004-B	27.10	28.20	1.10	STGB	6.00	2014	2.20	Fair	9.78	Bad	2,989	High	RSDPAF 2012-13 1YPM Completed
H17	H1722	Narayanchok - Parasi (Postal)	439.00	453.00	14.00	0.00	12.00	2.00	0.00	0.00	P	H1722-A	439.00	451.00	12.00	GR	4.00	9999	-1.00	No Survey	-1.00	No Survey	1,053	Moderate	Postal : PHP II
			0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		H1722-B	451.00	453.00	2.00	ER	4.50	9999	-1.00	No Survey	-1.00	No Survey	1,053	Moderate	Postal : PHP II
	Total		0.00	0.00	567.98	356.44	40.54	152.00	0.00	19.00			0.00	0.00	0.00		0.00		0.00		0.00		-		
[illegible]																									
F06	F00601	Nawalpur-Malangwa municipality boundary	0.00	22.02	22.02	0.00	22.02	0.00	0.00	0.00	P	F00601-A	0.00	22.02	22.02	GR	5.33	9999	5.00	Poor	11.62	Bad	2,146	High	PHP-1 On going Project
F06	F00602	Malangwa municipality boundary-Malangwa	22.02	26.63	4.61	0.00	4.61	0.00	0.00	0.00	P	F00602-A	22.02	26.63	4.61	GR	6.11	9999	5.00	Poor	12.55	Bad	2,146	High	PHP-1 On going project
F06	F00603	Malangwa-Sanhara (IB)	26.63	29.19	2.56	2.56	0.00	0.00	0.00	0.00	P	F00603-A	26.63	27.99	1.36	STGB	6.00	2016	5.00	Poor	8.25	Bad	2,146	High	RBN 2016 April (7th year from 2.2 billion)
			0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		F00603-B	27.99	29.19	1.20	STGB	5.20	2005	4.98	Poor	-1.00	No Survey	2,146	High	
F07	F00701	Chandranigahpur-Gaur municipality boundary	0.00	38.27	38.27	38.27	0.00	0.00	0.00	0.00	P	F00701-A	0.00	38.27	38.27	STGB	6.11	2012	1.05	Good	4.77	Fair	2,921	High	RIP to DRO for ARMP 071-72
F07	F00702	Gaur municipality boundary-Gaur	38.27	44.14	5.87	5.87	0.00	0.00	0.00	0.00	P	F00702-A	38.27	44.14	5.87	STGB	5.46	2012	0.83	Good	4.63	Fair	2,921	High	RIP to DRO for ARMP 071-72
F07	F00703	Gaur-Bairgania (IB)	44.14	45.44	1.30	1.30	0.00	0.00	0.00	0.00	P	F00703-A	44.14	45.44	1.30	STGB	7.00	2016	2.00	Fair	0.85	Good	2,921	High	RIP to DRO for ARMP 071-72,RBN 2015/016 (6th Yr)
F116	F11601	Phulter (MRM)-Bhelahi	0.00	22.00	22.00	0.00	22.00	0.00	0.00	0.00	P	F11601-A	0.00	22.00	22.00	GR	4.00	9999	-1.00	No Survey	-1.00	No Survey	300	Moderate	Postal : PHP II
F116	F11602	Bhelahi-Tribhuwannagar	22.00	24.00	2.00	0.00	0.00	0.00	0.00	2.00	P	F11602-A	22.00	24.00	2.00	PL	0.00	9999	-1.00	No Survey	-1.00	No Survey	1	No Survey	
F117	F11701	Naya Road (MRM)-Barahbhawa-Madhwapur	0.00	42.00	42.00	0.00	42.00	0.00	0.00	0.00	P	F11701-A	0.00	42.00	42.00	GR	4.00	9999	-1.00	No Survey	-1.00	No Survey	300	Moderate	PHP I on going project
F188	F18801	Sanke (MRM) - Sangrampur (IB)	0.00	22.00	22.00	0.00	12.00	10.00	0.00	0.00	P	F18801-A	0.00	12.00	12.00	GR	0.00	9999	-1.00	No Survey	-1.00	No Survey	100	Low	
			0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		F18801-B	12.00	22.00	10.00	ER	4.50	9999	-1.00	No Survey	-1.00	No Survey	100	Low	Postal : PHP II
F205	F20502	Chaira-Shaukpur-Pataura-Bankul-Gaur	8.00	56.00	48.00	0.00	33.00	0.00	0.00	15.00	P	F20502-A	41.00	56.00	15.00	PL	0.00	9999	-1.00	No Survey	-1.00	No Survey	1	No Survey	ACOMP PROJECT
			0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		F20502-B	8.00	41.00	33.00	GR	0.00	9999	-1.00	No Survey	-1.00	No Survey	1	No Survey	ACOMP PROJECT
F206	F20601	Gaur-Pipara-Sitarampur-Santapur-Nunther Road	0.00	38.00	38.00	0.00	0.50	0.00	0.00	38.00	P	F20601-A	0.00	38.00	38.00	PL	0.00	9999	-1.00	No Survey	-1.00	No Survey	1	No Survey	
F207	F20705	Bankul-Kerawa	74.50	80.00	5.50	0.00	0.00	0.00	0.00	5.50	P	F20705-A	74.50	80.00	5.50	PL	0.00	9999	-1.00	No Survey	-1.00	No Survey	1	No Survey	RIP III Study
H01	H0124	Banke-Nawalpur	283.30	300.18	16.88	16.88	0.00	0.00	0.00	0.00	P	H0124-A	283.30	287.00	3.70	STGB	6.15	2015	1.06	Good	6.33	Poor	4,748	High	RBN 2013/014 (4th Yr), RBN 2014/015 (5th Yr) Reseal Ongoing
			0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		H0124-B	287.00	300.18	13.18	STGB	6.15	2014	1.06	Good	6.33	Poor	4,748	High	RBN 2013/014 (4th Yr) Reseal Ongoing
H01	H0125	Nawalpur-Bhagaha	300.18	313.53	13.35	13.35	0.00	0.00	0.00	0.00	P	H0125-A	300.18	313.53	13.35	STGB	6.30	2014	1.29	Good	9.26	Bad	4,404	High	RBN 2013/014 (4th Yr) Reseal Ongoing
H01	H0126	Bhagaha-Chandranigahapur	313.53	327.24	13.71	13.71	0.00	0.00	0.00	0.00	P	H0126-A	313.53	327.24	13.71	STGB	6.40	2014	0.87	Good	7.71	Poor	4,404	High	RBN 2013/014 (4th Yr) Reseal Ongoing
H01	H0127	Chandranigahapur-Dhumar	327.24	339.92	12.68	12.68	0.00	0.00	0.00	0.00	P	H0127-A	327.24	339.92	12.68	STGB	6.48	2014	0.54	Good	2.70	Poor	4,404	High	RBN 2013/014 (4th Yr) Reseal Ongoing
H17	H1712	Hardi Khola (Sitapur)-Malangawa (Postal)	219.00	233.50	14.50	0.00	14.50	0.00	0.00	0.00	P	H1712-A	219.00	233.50	14.50	GR	4.09	9999	1.47	Good	-1.00	No Survey	322	Moderate	Postal : PHP II
H17	H1713	Malangawa-Kharahi (Postal)	233.50	252.00	18.50	0.00	15.50	3.00	0.00	0.00	P	H1713-A	233.50	249.00	15.50	GR	4.15	9999	1.52	Good	-1.00	No Survey	322	Moderate	Postal : PHP II
			0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		H1713-B	249.00	252.00	3.00	ER	4.50	9999	-1.00	No Survey	-1.00	No Survey	322	Moderate	Postal : PHP II
H17	H1714	Gadahiya (Bagamati River) (Postal)	252.00	260.00	8.00	0.00	0.00	3.00	0.50	4.50	P	H1714-A	252.00	255.00	3.00	ER	4.50	9999	-1.00	No Survey	-1.00	No Survey	322	Moderate	Postal : PHP II
			0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		H1714-B	255.00	255.50	0.50	UC	4.50	9999	-1.00	No Survey	-1.00	No Survey	322	Moderate	Postal : PHP II
			0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		H1714-C	255.50	260.00	4.50	PL	0.00	9999	-1.00	No Survey	-1.00	No Survey	1	No Survey	Postal : PHP II
H17	H1715	Gadahiya (Bagamati River)-Sarsiya (Postal)	260.00	266.00	6.00	0.00	0.00	0.00	0.00	6.00	P	H1715-A	260.00	266.00	6.00	PL	0.00	9999	-1.00	No Survey	-1.00	No Survey	1	No Survey	Postal : PHP II
H17	H1716	Sarsiya-Gaur (Postal)	266.00	269.00	3.00	0.00	3.00	0.00	0.00	0.00	P	H1716-A	266.00	269.00	3.00	GR	4.00	9999	-1.00	No Survey	-1.00	No Survey	438	Moderate	Postal : PHP II
H17	H1717	Gaur-Amwa river-Kachorwa (Postal)	269.00	293.00	24.00	0.00	6.00	7.00	11.00	0.00	P	H1717-A	269.00	275.00	6.00	GR	4.13	9999	1.73	Fair	-1.00	No Survey	438	Moderate	Postal : PHP II
			0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		H1717-B	275.00	282.00	7.00	ER	4.50	9999	-1.00	No Survey	-1.00	No Survey	438	Moderate	Postal : PHP II
			0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		H1717-C	282.00	293.00	11.00	UC	4.50	9999	-1.00	No Survey	-1.00	No Survey	438	Moderate	Postal : PHP II
	Total		0.00	0.00	384.73	102.62	174.63	23.00	11.50	71.00			0.00	0.00	0.00		0.00		0.00		0.00		-		
[illegible]																									
F026	F02604	Dhalkebar-Chiepur Junction To Sindhuli Access Road	25.43	35.85	10.42	10.42	0.00	0.00	0.00	0.00	H	F02604-A	25.43	35.85	10.42	STGB	4.50	2013	3.80	Poor	6.11	Poor	241	Low	RIP to DRO for ARMP 071-72
F026	F02605	Chiepur Junction To Sindhuli Access Road-Bhimsthan Junction To F031	35.85	48.45	12.60	12.60	0.00	0.00	0.00	0.00	H	F02605-A	35.85	48.45	12.60	STGB	4.50	2013	1.00	Good	-1.00	No Survey	185	Low	RIP to DRO for ARMP 071-72
F026	F02606	Bhimsthan Junction to F031-Chisapani	48.45	70.45	22.00	0.00	0.00	22.00	0.00	0.00	H	F02606-A	48.45	70.45	22.00	ER	4.50	9999	-1.00	No Survey	-1.00	No Survey	261	Moderate	
F030	F03002	Lalgadh Khola-Melamchi	10.66	22.50	11.84	11.84	0.00	0.00	0.00	0.00	H	F03002-A	10.66	22.50	11.84	STGB	4.68	2013	3.58	Poor	11.25	Bad	1,353	Moderate	Under Melamchi W/S Project
F030	F03003	Melamchi-Helambu	22.50	63.00	40.50	0.00	6.00	34.50	0.00	0.00	H	F03003-A	22.50	28.50	6.00	GR	4.76	9999	4.00	Poor	11.44	Bad	1,353	Moderate	Under Melamchi W/S Project
			0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		F03003-B	28.50	63.00	34.50	ER	4.50	9999	4.00	Poor	-1.00	No Survey	1,353	Moderate	Under Melamchi W/S Project
F031	F03101	Dolalghat-Chautara	0.00	25.11	25.11	25.11	0.00	0.00	0.00	0.00	H	F03101-A	0.00	25.11	25.11	STGB	3.98	2015	1.76	Fair	6.41	Poor	261	Moderate	RBN 2014/015 (5th Yr)
F032	F03201	Lamosangu-Ningalekdanda	0.00	28.27	28.27	28.27	0.00	0.00	0.00	0.00	H	F03201-A	0.00	28.27	28.27	STGB	3.01	2012	2.89	Fair	12.12	Bad	710	Moderate	RSDPAF 2011-12 5YPM Completed and ADB/Connectivity-S1 to DRO for ARMP 2071-72, RIP II From 2072
F032	F03202	Ningalekdanda-Charikot	28.27	53.72	25.45	25.45	0.00	0.00	0.00	0.00	H	F03202-A	28.27	53.72	25.45	STGB	3.00	2011	2.26	Fair	9.20	Bad	710	Moderate	RSDPAF 2011-12 5YPM Completed, RIP II From 2072