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Research article

Road roughness modelling with clustered data using ANN approach

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ABSTRACT

It is a well established fact that the roughness is manifested as an effect of different individual pavement deterioration parameters. Several studies have been oriented in the direction of establishing the models capable of predicting the roughness. However, it was felt essential to develop a model explaining the dynamics of different pavement deterioration parameters on the roughness. In view of very limited studies reported in this direction, the present study is carried out, first by grouping available data into homogeneous clusters and then model them using Feed Forward Back Propagation Artificial Neural Network algorithm. K- Means partitional clustering algorithm has been adopted for clustering the data. A new mathematical algorithm has been proposed and used for optimizing the number of clusters, which is further verified with the available standard validity indices. The present modeling attempt has indicated strong correlation between the road roughness and the deterioration parameters *viz* cracking, raveling, potholes, patching and rutting. The models developed for all the clusters have shown decent statistical acceptability.

Keywords: Roughness modeling, International roughness index, Data Clustering techniques, Cluster validity techniques, K-Means partition clustering algorithm, Optimum number of clusters.

1. Introduction

Pavement roughness is an overall indicator of the quality of a pavement and it adversely affects not only the vehicle ride quality but also the road user costs. Universally, roughness is expressed as International Roughness Index (IRI) and it is usually manifested as a combined effect of different individual pavement deterioration parameters such as cracking, potholes, raveling and rutting (Rohde et al., 1999). It is a well established fact that the individual pavement distress parameters and the roughness complement each other (Al-Omari and Darter, 1995; Hassan et al., 1999). That is to say that the increase in individual deterioration parameters result in increasing roughness, which once again act as a catalyst in further deterioration of the pavement.

Though it looks like a simple excise to express the road roughness as a factor of these individual parameters, it is not that easy, though not impossible, to find all the contributory parameters to express road roughness as a simple sum of all these parameters. A majority of the modeling attempts have been observed to be made in the direction of roughness prediction rather than expressing the roughness as a function of individual deterioration parameters. Since roughness represents the overall condition of a pavement at any given point of time, in the present study, an attempt has been made to develop a model representing the roughness as a function of different deterioration parameters.

It is a well established fact that the models generated from data, pretreated to remove any distortions, will be qualitative. It is unavoidable to use number of enumerators during the data collection process. Consequently, data so collected, will suffer from unavoidable variability and hence non-homogeneity. To make such non-homogeneous data suitable for modeling excise, it is necessary to regroup the data into different homogeneous groups. Literature has shown that the clustering techniques are quite useful in organizing the data into different uniform groups, which can be modeled with better acceptability. In the present study of roughness modeling, such a pretreatment is required since the data in its raw form is non-homogeneous. Another important issue of deciding the optimum number of clusters has to be resolved. Hence, in the present study attempts are also being made to divide the data into different clusters using the best available clustering techniques and at the same time limit the number of clusters to an optimum number based on an intuitively developed mathematical algorithm.

Artificial Neural Networks (ANN) have been proved to be powerful and efficient computational tools in handling complicated and resource intensive problem situations. In particular, the modeling as well as forecasting problems have been dealt by several researchers (Jae-ho et al., 2004; Kaseko et al., 1994) in a better manner by using ANN tools in comparison with the other mathematical / statistical tools like regression. Hence, in this study, with the objectives mentioned below, Feed Forward Back Propagation (FFBP) algorithms have been used to model the clustered data sets for predicting the road roughness.

2. Study objectives

The present study has been carried out with the following objectives to arrive at a representative model expressing the road roughness as a function of different deterioration parameters considered during the study:

1. Critical analyzing the existing roughness models with a view to identify the various parameters influencing roughness.
2. Collecting roughness and other distress parameters
3. Data clustering and grouping using standard statistical clustering tools.
4. Establishing methodology to optimize the number of clusters to be taken for further analysis using logical interventions.
5. Developing roughness model as a function of different distress parameters for all the individual data clusters.

3. Review of literature

Detailed literature survey has been made with regard to the roughness models, clustering techniques and ANN as a part of this research study, the details of which have been summarized in the following sections.

3.1 Roughness models

Though number of works has been reported in the direction of development of roughness models, majority of these works have concentrated on the roughness progression modeling. Notable among these works are the world Banks HDM-III study, where the roughness progression is shown as a factor of four components *viz* cracking, raveling, potholes and rutting (Rohde et al., 1999). Further, the above equation has been modified by the World Bank during its HDM-IV study (Odoki and Henry, 2001) by incorporating the environmental parameters in addition to the parameters considered during HDM – III study. Majority of the other research studies have more or less followed the similar directions as that of World Banks HDM studies. In India, Central Road Research Institute(CRRI) has conducted numerous field investigations and developed the roughness progression as a factor of initial values of potholes, depressions, cracking, patchwork and raveling and the incremental values of these parameters observed over a period of time along with the traffic characteristics observed over the period of study (CRRI, 1993). Roughness progression model has also developed as a factor of the Benkelman Beam Deflection (BBD) and traffic (Reddy, 1996).

A close look at the above case studies indicate that these works are oriented in the direction of developing a model, capable of predicting the roughness as a progressive parameter. However, much light was not thrown in the direction of developing the roughness models capable of expressing the roughness at a given point of time as a function of noticeable deterioration parameters. Such a model, if developed, would help in identifying one or two major contributing parameters causing road roughness. This intern would enable the agency looking after pavement management in planning the maintenance activities in an appropriate manner by according the higher priorities for correcting the identified major contributory failure patterns that cause the roughness.

3.2 Clustering techniques

Clustering is a division of data into groups of similar objects. Each group, called a cluster, consists of objects that are similar among themselves and dissimilar to objects of the other groups (Jain et al., 1999). This is an important process in pattern recognition and machine learning (Hamerly and Elkan, 2002[(1)]). Literature indicates that the clustering algorithms can be effectively used for Data compression and Data mining (Hamerly, 2003). Many diverse techniques have been developed in order to discover similar groups in large datasets, out of which, Hierarchical and Partitional techniques are being widely used (Han and Kamber, 2001). Hierarchical algorithms create a hierarchical decomposition of the objects into either agglomerative (bottom-up) or divisive (top-down). On one hand, agglomerative algorithms start with each object being a separate cluster by itself and successively merge groups according to a distance measure. The clustering may stop when all objects are in a single group or at any other point the user wants. On the other hand, divisive algorithms follow the opposite strategy. They start with one group of all objects and successively split groups into smaller ones, until each object falls into one cluster, or as desired. The hierarchical algorithms are highly user friendly in the sense that there is no need to specify the number of clusters at the beginning. However, it suffers with major limitations of being static in nature i.e, not being accommodative in moving a pattern assigned from one cluster to another. In addition, it is also computationally complicated (Mahamed, 2004; Turi, 2001).

Partitional clustering algorithm constructs partitions of the data, where each cluster optimizes a clustering criterion such as the minimization of the sum of squared distance from the mean within each cluster. The distance measure usually employed is the Euclidean distance. A close look into the hierarchical and partitional algorithms indicate very clearly that the limitations of one technique are being explained by other technique. However, the partitional clustering algorithm needs the number of clusters to be specified at the beginning itself unlike in the hierarchical algorithm (Mahamed, 2004). Though it looks to be a limitation, the flexibility offered by partitional algorithm in moving a given pattern from one cluster to other cluster in a dynamically iterative manner. Due to this dynamism, this has been the preferred choice by various researchers for variety of application (Jain et al., 1999). The limitation of not being accommodative in fixing the number of clusters can be easily overcome mathematically. In addition partitional algorithms are being observed to be very accurate in comparison with hierarchical techniques especially in the pattern recognition (Jain et al., 1999). It is with this background that these techniques have been used in the present research activity.

Though number of specific techniques have been developed within the domain of partitional clustering algorithm, K-Means technique has been the preferred choice because of its simplicity in usage and the efficiency (Mahamed, 2004; Turi, 2001). Hence, in the present study, K- Means algorithm has been adopted for clustering the observed data. For ready reference, a few salient features of this technique have been presented in the following paragraphs.

3.2.1 The K-means algorithm

jK-Means is one of the simplest partitional algorithms that solve the well known clustering problem (Hamerly, 2003). The objective of the K-means is to find the partition of the data, which minimize the squared-error or the sum of the squared distances between all the points and their respective cluster centers. In other words, K- Means minimize the intra cluster distance. The algorithm is composed of the following steps (Jain et al., 1999; Turi, 2001)

1. Choose K initial cluster centers
2. Assign each data point to the group that has the closest center by calculating the distance between all the centers and the data points.
3. After assigning all the data points, recalculate the positions of the K centers.
4. Repeat second and third steps until the K centers no longer move.

3.3 Artificial neural networks

ANN find wide applications in traffic planning, control, operation and pavement engineering especially when it is required to develop a cause-effect relationship or a forecasting relationship. Several studies (Eldin and Senouci, 1995; Mehmet and Serdal, 2003; Abdullah and Ali, 1998; Jae-ho et al., 2004) have indicated the effective usage of ANN for pavement maintenance, back calculation of pavement layer module, developing roughness progression models etc. Basically ANN consists of input, hidden and output layers. Each of these layers includes an array of processing elements called neurons. These neurons will have interconnectivity amongst themselves between different layers.

A detailed review of literature has indicated that it is not essentially decipherable as how many hidden layers need to be considered and also that how many neurons need to be taken in each of these hidden layers for a given problem situation. Usually an optimum number of neurons will be determined on trial and error basis (Rao, S.G., 2002; Trefor, P.W. and Nenad, G., 1995). Almost all the studies which have been reviewed indicate that one hidden layer with sufficient neurons can handle any kind of network (Haykin, 1999; Lou et al., 2000).

The success of any given neural network algorithm depends upon the efficiency of data training mechanism available. Majority of literature (Meier et al., 1997; Abdullah and Ali, 1998; Haykin, 1999) indicated that the Feed Forward and Back Propagation (FFBP) algorithm have performed better than the other alternatives available. Hence in the present study, the FFBP algorithm has been used while the number of hidden layers and number of neurons in each of the hidden layers are being fixed in an iterative manner.

4. Study methodology and details of work carried-out

The present work has been primarily carried out in 4 phases, which are pictorially depicted in Figure 1.

4.1 Phase-I: data collection

The following deterioration parameters have been identified as the candidates influencing the road roughness.

1. Cracking, 2) Potholes, 3) Patching, 4) Raveling, 5) Rutting

On a few National Highways (NH) and State Highways (SH) in India, totaling a length of 617Km, the above listed deterioration parameters along with the roughness, determined using Road Measurement Data Acquisition System (ROMDAS), for every km have been collected. A sample of the collected data has been presented in Table 1, for reference.

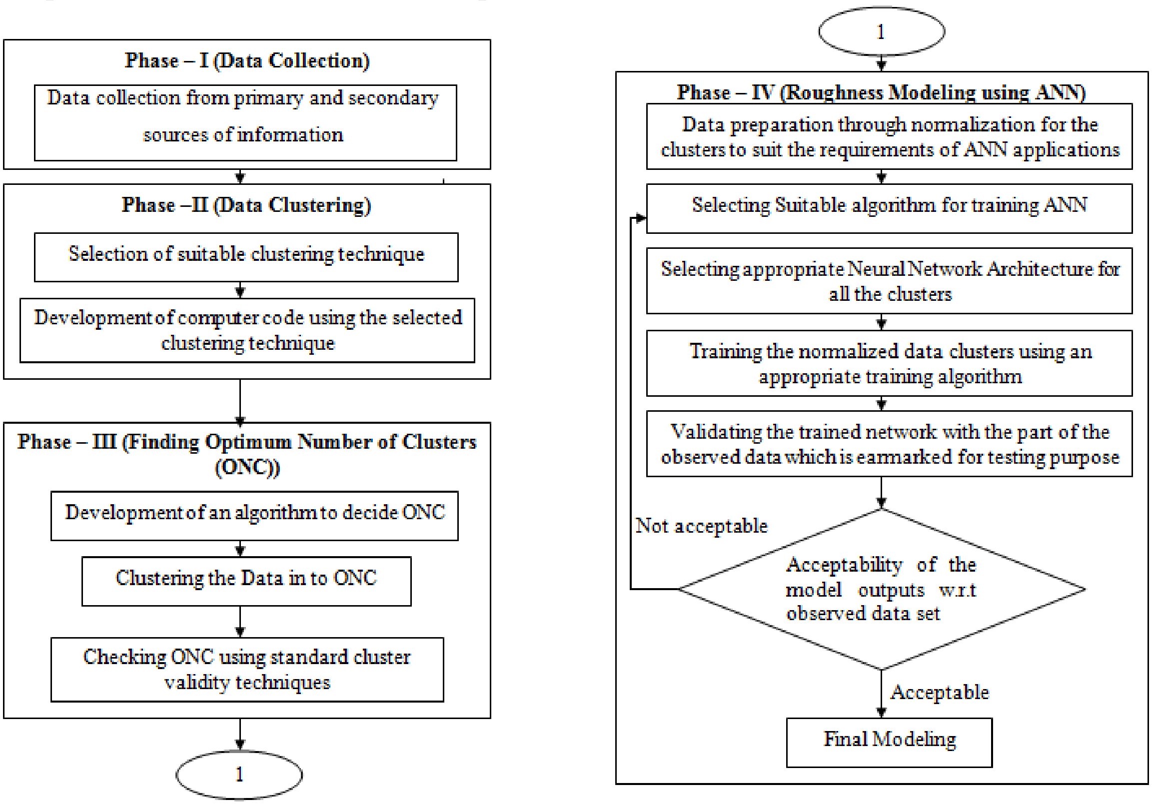

Figure 1: Phases in development of roughness model

Table 1: Sample of road deterioration data

S.No	Cracking (%)	Potholes (No's)	Patching (%)	Raveling (%)	Rutting (mm)	Roughness (m/km)
1	17.00	0	1	10	0	2.29
2	19.40	0	0	5.6	5	1.39
3	26.40	2	2	9	4	2.25
4	29.40	0	9.6	9	7	1.97
5	17.00	4	6	11	0	4.92
6	10.00	5	10	20	12	5.19
7	14.00	3	10	16	8	3.18
:	:	:	:	:	:	:
:	:	:	:	:	:	:
616	32.00	2	8.4	8.80	11	3.65
617	44	0	0	5.00	8	1.17

4.2 Phase-II: Data clustering

The initial attempt to model the data in its raw form has failed to produce the acceptable outcome. This is due to the unavoidable and obvious noise dominating the raw data. In similar situations, researchers (Jain et al., 1999; Hamerly, 2003) have found the clustering techniques being very handy. Hence, in the present study, a detailed review of different clustering techniques has been made and consequently, K- Means clustering algorithm (Hamerly, 2003) has been chosen for clustering. A suitable code has been developed and used in MATLAB computer package for clustering the data collected.

4.3 Phase-III: Methodology to find the Optimum Number of Clusters (ONC)

Most of the clustering algorithms require the user to specify the number of clusters in advance (Hamerly and Elkan, 2002[(2)]); Lee and Antonsson, 2000). Finding the optimum number of clusters is often an *ad hoc* decision based on prior knowledge, assumptions, and practical experience (Hamerly and Elkan, 2002[(2)]). The problem of finding optimum number of clusters in a data set has been the subject of research (Halkidi, et al., 2001). However, the outcome is still unsatisfactory in this area (Rosenberger and Chehdi, 2002).

Since it is not possible to fix the number of clusters for any given data set for obvious reasons, it is necessary to try iteratively, different number of clusters till the ONC is identified. In the present study, an iterative algorithm has been developed to find the number of clusters, as detailed below:

Step 1: Using the code developed in MATLAB for K-Means clustering technique, the data points (cracking, potholes, patching, raveling and rutting data) were clustered into groups and the roughness is assigned to corresponding data points.

Step 2: Cluster centroid was calculated using the Equation 1

$$\overline{x_j} = \sum_{i=1}^{n} x_{ij} / n \quad \forall \ \text{j} = 1, \ldots, 5 \tag{1}$$

Where j is the number of variables in one data point
n is the number of data points in a cluster
$\overline{x_j}$ is the j^{th} column centroid
x_{ij} is the data point in i^{th} row and j^{th} column
$\forall$ represents for all

Step 3: For all the individual clusters in a cluster group, the distance between data points and its cluster centroid (also known as intra cluster distance) was computed using Equation 2

$$D_i = \sqrt{\sum_{i=1}^{n} (x_{ij} - \overline{x}_j)^2} \quad \forall \ \text{i} = 1, \ldots, \text{n and} \ \forall \ \text{j} = 1, \ldots, 5 \tag{2}$$

Where D_i is the distance of i^{th} row in a cluster from its centroid and remaining parameters are as explained in Equation 1

Step 4: The Average of all the distances from each data point and its corresponding cluster centroid is computed for all the individual clusters in a chosen cluster group using Equation 3. Further, the Weighted Averages of the distances of the each cluster group are being calculated using Equation 4. The outcome of this exercise is being summarized and presented in Table 2.

$$\overline{D}_k = \frac{1}{n} \sum_{i=1}^{n} D_i \quad \forall \ \text{k} = 1, \ldots, \text{K and} \ \forall \ \text{n} = 1, \ldots, \text{K} \tag{3}$$

Where K is the total number of clusters in a cluster group
'k' is the individual cluster number in a cluster group
'n' is the total number of data points in individual cluster

$$K_{WA} = \frac{\sum_{k=1}^{K} \overline{D}_k * n_k}{\sum_{k=1}^{K} n_k} \tag{4}$$

Where K_{WA} is the weighted average distance of the cluster group

Step 5: A graph is plotted between weighted average distances of all cluster groups and number of clusters the respective cluster groups as presented in Figure 2. It has been observed that the weighted average distance decreases as the number of the clusters increases.

Hence, the optimum number of clusters is observed to be the point where the increase in the number of clusters does not result in any appreciable reduction in the distances. Hence, it can be easily deduced from the graph that the ONC is Eight.

Table 2: Distances and weighted average distances of different cluster group

Total number of data points: 617

	Number of data points in each cluster (Average of distances of the data points form their respective cluster centers)											
Number of cluster groups	1	2	3	4	5	6	7	8	9	10	11	**Weighted Average distance of cluster group**
1	617 (15.32)											15.32
2	158 (14.97)	459 (11.73)										12.559
3	393 (8.8)	102 (15.26)	122 (12.44)									10.587
4	363 (8.32)	61 (15.19)	83 (10.54)	110 (12.28)								10.00
5	68 (10.89)	40 (14.33)	91 (11.88)	115 (9.89)	303 (6.99)							9.157
6	139 (8.65)	272 (6.47)	63 (10.79)	30 (13.32)	52 (10.05)	61 (11.27)						8.511
7	138 (8.08)	64 (8.73)	34 (12.90)	39 (12.30)	53 (9.85)	247 (6.14)	42 (10.82)					8.241
8	235 (5.97)	29 (10.82)	40 (10.04)	26 (12.63)	46 (10.81)	128 (7.92)	71 (7.97)	42 (10.14)				8.021
9	51 (9.89)	29 (11.61)	20 (10.63)	61 (9.9)	64 (9.44)	105 (6.82)	9 (12.68)	18 (10.22)	260 (6.24)			7.93
10	30 (10.56)	114 (7.44)	9 (10.61)	23 (8.9)	63 (7.98)	19 (12.11)	61 (8.79)	43 (10.77)	29 (9.18)	226 (5.76)		7.72
11	29 (10.89)	222 (5.52)	7 (10.18)	87 (6.32)	17 (9.95)	6 (13.46)	96 (8.8)	23 (9.04)	54 (9.07)	49 (8.65)	27 (10.42)	7.55

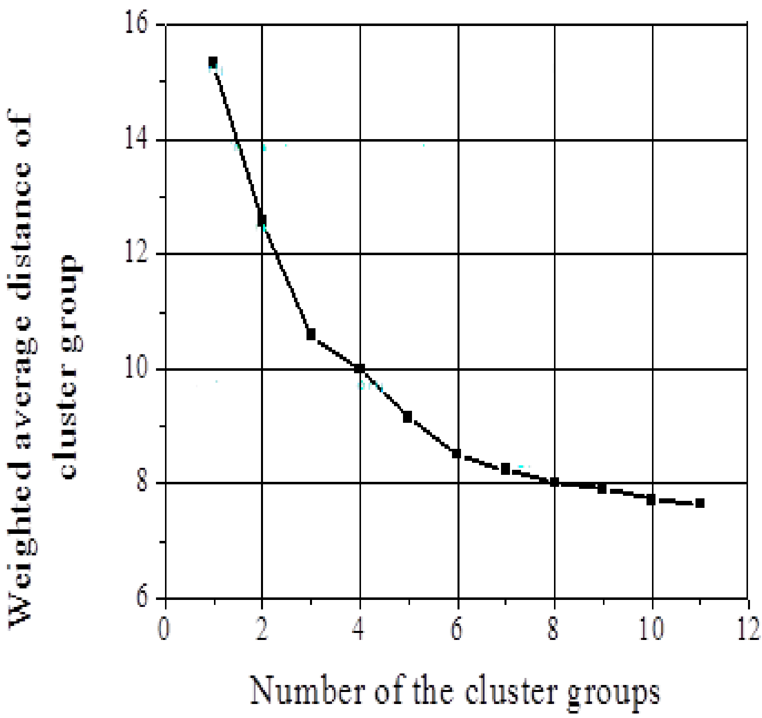

Figure 2: Plot between number of cluster group and weighted average distance of cluster group.

4.3.1 Cluster validity techniques

Though an algorithm has been developed and presented for ONC, it was decided to cross check its acceptability through the existing cluster validity techniques. Popular techniques *viz.* Dunn's and Davies-Bouldin Indices, as detailed in the following paragraphs, have been chosen for further examination.

4.3.1.1 Dunn's validity index

This technique (Dunn, 1974; Mahamed, 2004) is based on the idea of identifying the cluster sets that are compact and well separated. The main goal of Dunn's validity index is to maximize the inter-cluster distances (i.e separation) while minimizing intra-cluster distances (i.e increase compactness). The Dunn's validation index (*DV)*, can be computed with using Equation 5. The number of clusters, which maximizes the *DV* is consider as the ONC.

$$DV = \min_{k=1,....,K}\left\{\min_{l=k+1,....K}\left\{\frac{d(c_k, c_l)}{\max_{a=1,...,K}\{d'(c_a)\}}\right\}\right\} \quad (5)$$

Where

d (ck, cl) is the distance between clusters *ck* and *cl* in the cluster group

d'(ca) is diameter of the clusters in the cluster group 'a'

K is the number of clusters in a group.

4.3.1.2 Davies-Bouldin validity index

This index (Davies and Bouldin, 1979; Mahamed, 2004) is a function of the ratio of the sum of intra-cluster scatter to inter-cluster separation. The ratio is small if the clusters are compact and far from each other. Consequently, Davies-Bouldin index (DB) will have a small value for ONC. The DB index can be computed using Equation 6.

$$DB = \frac{1}{K}\sum_{k=1}^{K}\max_{\substack{l=1,....,K \\ k\neq l}}\left(\frac{d'(c_k)+d'(c_l)}{d(c_k, c_l)}\right) \quad (6)$$

All the parameters are as explained for equation 5.

Using Equations 5and6, DV value and DB value have been calculated for different number of clusters and presented in Table 3. From this Table, it can be observed very clearly that the Dunn's Index is gives maximum value at Seven number of clusters while the DB index, which works based on minimization criteria, provides the ONC as Nine. It can be recalled here that the ONC obtained from the algorithm presented in the paper as Eight, which is very close to the values obtained by Dunn's and DB index. Hence, it was decided that the optimum number of clusters for the data considered as 'Eight' and the technique proposed to find the ONC being acceptable.

Table 3: Dunn's and DB validity indices

No of clusters	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
DV Value	0.57	0.68	0.51	0.52	0.62	**0.7**	0.61	0.65	0.65	0.64
DB Value	3.11	2.28	2.38	2.17	1.96	2.019	2.031	**1.82**	1.92	1.96

4.4 Phase-IV: Neural network construction and model development

A program has been developed in MATLAB to train the clustered data sets, developed in article 4.2 and 4.3 using FFBP Artificial Neural Network algorithm. Non linear sigmoid transfer function is being used to for training because it is bounded and simple derivative (Mehmet et al., 2000). For validation purpose 10% to 20% of the data depending on the data in each cluster has been kept aside and the remaining data has been used for the training. As suggested in earlier studies mentioned in literature review, one hidden layer with sufficient number of neurons is being selected in addition to an input layer consisting of five deterioration parameters and the sole output neuron i.e roughness. This system as been pictorially presented in Figure 3, where it was shown that the hidden layer may have any number of neurons between 1 and 20. All the cluster data sets have been trained with FFBP neural network algorithm with varying the number of neurons from 1 to 20 in the hidden layer.

The MSE between the actual observations being used as test data sets and the modeled outputs obtained for all the 20 alternative trials with the varying neuron in the hidden layer for all the 8 clusters have been computed. One typical network structure is being picked up based on the MSE criteria for all the 8 clusters and the selected network structures have been summarized and presented in Table 4.

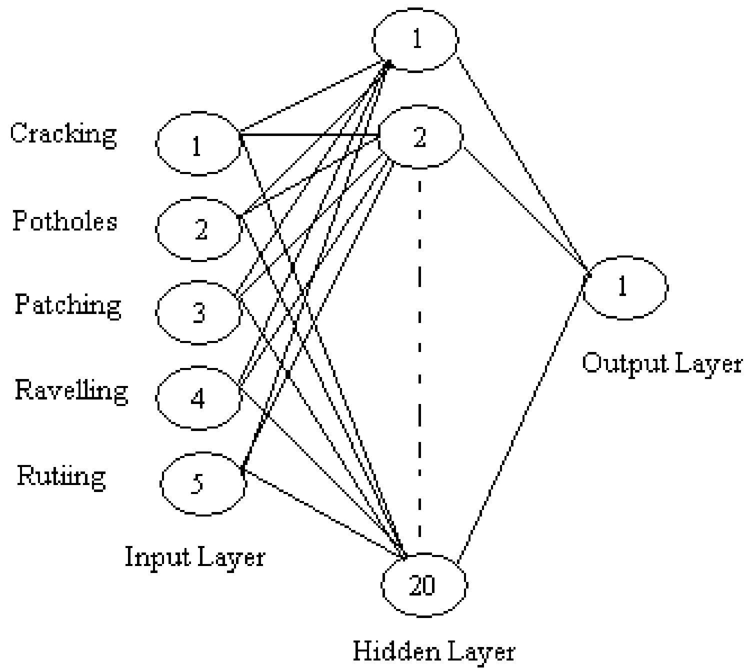

Figure 3: Neural Network Architecture

It is to be noted here that the first numeral represents the number of neurons in input layer, second numeral represents number of neurons in the hidden layer and the third numeral represents neurons in output layer.

Table 4: Selected artificial neural network structures for different clusters

Cluster No	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Network Structure	5-08-1	5-07-1	5-03-1	5-12-1	5-15-1	5-03-1	5-15-1	5-02-1

4.4.1 Model validation

The ANN models, developed for all the eight data clusters, have been used to estimate the dependable variable, road roughness. These values have been observed with the test data set which is not being used during the training process. With a view to validate the estimated values, plots are being drawn between estimated roughness values on ordinates and the observed roughness values on abscissa as shown through Figures 4 to 11. A 45^0 line has been drawn and it was visualized that for almost all the models considered in the present study, the plotted points are scattered more or less equally on either side of this ideal line. Further, it was also observed that the amount of scatter is also not excessively high. This indicates that the fitted models are acceptable with confidence for further use. However, it can be expected to get better models with large number of data sets.

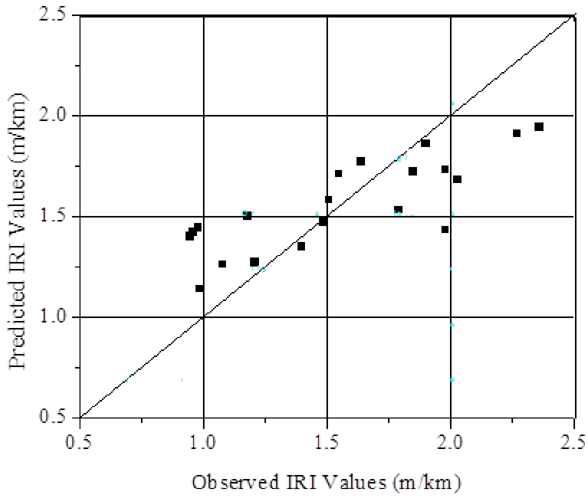

Figure 4: Observed values versus predicted values for cluster 1

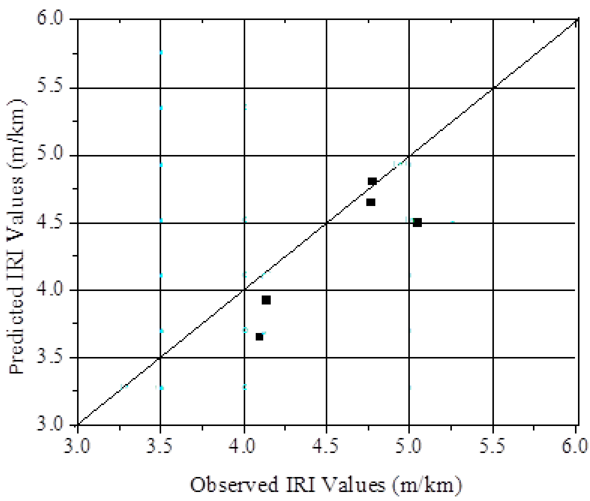

Figure 5: Observed values versus predicted values for cluster 2

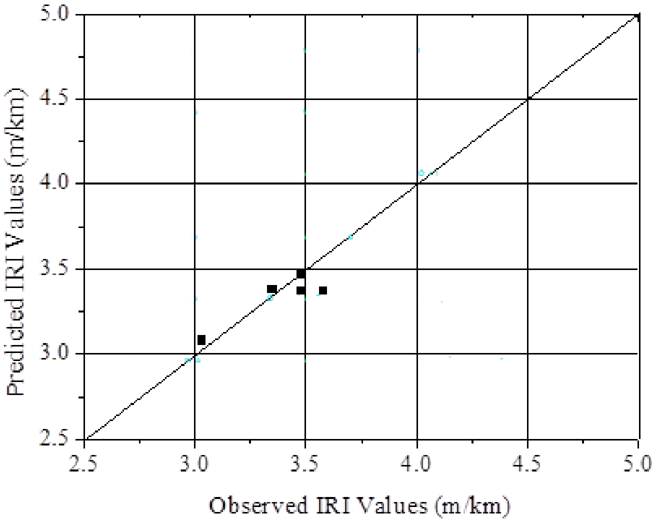

Figure 6: Observed values versus predicted values for cluster 3

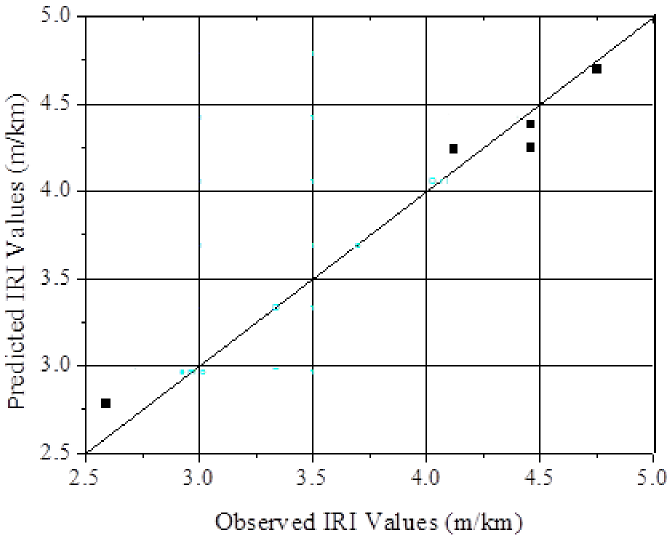

Figure 7: Observed values versus predicted values for cluster 4

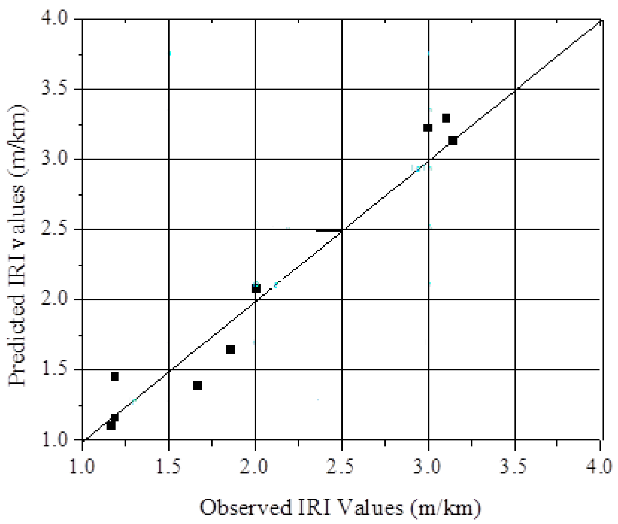

Figure 8: Observed values versus predicted values for cluster 5

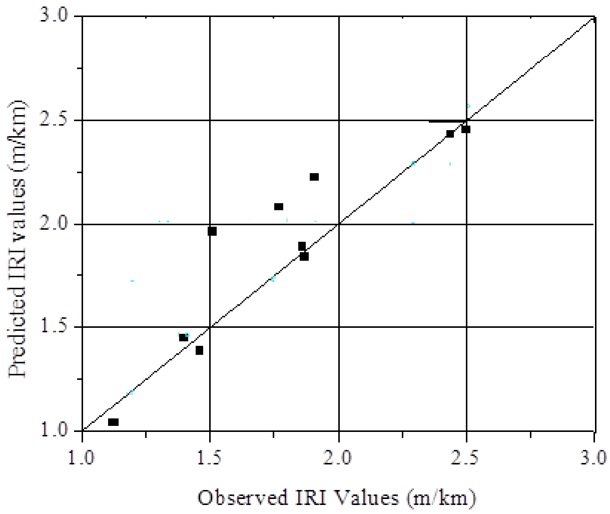

Figure 9: observed values versus predicted values for cluster 6

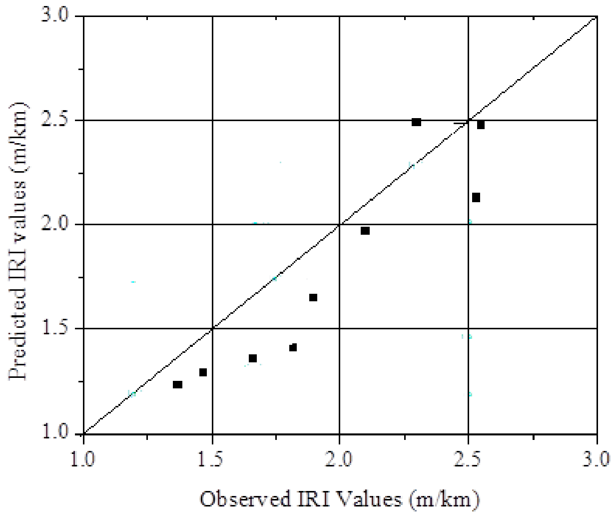

Figure 10: Observed values versus predicted values for cluster 7

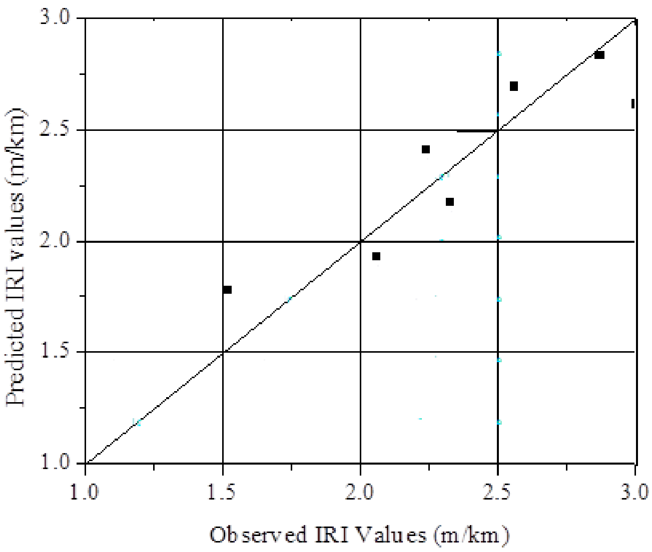

Figure 11: Observed values versus predicted values for cluster 8

5. Conclusions

From the study carried out the following conclusions have been arrived at.

1. K- Means Partition clustering algorithm was found to be quite effective in clustering the data used in the present research study.
2. The mathematical algorithm, developed for finding Optimum Number of Clusters, is observed to be performing well as it yielded the results matching with those obtained from the standard validity indices developed by Dunn's and Davies-Bouldin.
3. Dispersion around the 45^0 line for the graph plotted between predicted and observed IRI values indicates that a decent level of acceptability of the developed ANN models. However, these models can be expected to yield better results with a larger database.
4. It is to be noted that different data clusters, extracted from the same data source, required different ANN structures during the modeling phase.

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