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Pavement Performance Models For the Ethiopian Pavement Management System

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Abstract
Performance/condition prediction is a critical element in decision making tools including Pavement Management System (PMS), Asset Management Systems, and Design Systems. PMS is a system involving the identification of optimum strategies at various management levels and maintains pavements at an adequate level of serviceability. Most performance models developed to date have had limited success outside the location they were developed. This paper deals with the development of flexible pavement roughness progression models, expressed in terms of International Roughness Index, from PMS data of the Ethiopian road network, using Multi-Linear Regression (MLR) and Artificial Neural Network (ANN) techniques. The possible use of Light Weight Deflectometer's 'surface deflection modulus' variable in the models is investigated and verified. A comparative study was also made between the MLR and ANN models, and the results from this research effort demonstrated that the ANN models outperform the MLR models.

Keywords
Pavement management system, Deterioration models, Artificial neural networks, International roughness index, Light weight deflectometer.

1. Introduction

Due to the increasing challenges in pavement maintenance and rehabilitation, a Pavement Management System (PMS) has become a very beneficial management tool for highway agencies. PMS is a system involving the identification of optimum strategies at various management levels and maintains pavements at an adequate level of serviceability. These include, but are not limited to, systematic procedures for scheduling maintenance and rehabilitation activities based on optimization of benefits and minimization of costs. Quality pavement performance models have been recognized to be critical for successful application of a PMS around the world. As a result, an increasing research interest thrives in improving performance of pavement deterioration models. The inventory database established in the initial stage of a PMS provides researchers an indispensable data resource for the development of the quality pavement performance models (Yang, 2004). In this study pavement roughness models for the Ethiopian road network, expressed in terms of the International Roughness Index (IRI) are developed, using statistical Multi-Linear Regressions (MLR) and Artificial Neural Network (ANN) techniques. The models relate IRI with traffic loading, pavement age, thicknesses, climatic condition and pavement strength. The first four variables are easily found in the PMS database, while pavement strength in this research is determined using Light Weight Deflectometer (LWD). LWD is nondestructive testing equipment which is increasingly being used to routinely assess the strength (modulus) of pavement layers or overall pavement condition (surface deflection modulus). LWD is selected for use because it is easy to use and maintain, and affordable by highway agencies in developing countries than the highly sophisticated and expensive Falling Weight Deflectometer. A preliminary study on selected Norwegian roads showed rather promising results with regard to relating LWD 'surface deflection modulus' (LWD_E) to overall pavement condition (Taddesse, 2007). As part of a work to develop deterioration models for Ethiopian conditions, it was decided to carry out LWD measurements on selected roads included in the Ethiopian PMS database, where variables as traffic, environment, layer thicknesses etc. were known, and with more or less complete time series of IRI measurements. The hypothesis was that the 'surface deflection modulus' derived from the LWD measurements would significantly enhance the prediction of IRI on these roads.

2. Pavement Roughness and Variables

From literature review, it is evident that pavement deterioration over time mainly depends on five variables, i.e. traffic loading, pavement age, thicknesses, climatic condition and strength. These variables help to define the pavement roughness progression. *Roughness* is a measure of the ride quality of pavements, expressed in terms of International Roughness Index, which is the outcome of a World Bank's experiment in Brazil in 1982 (Paterson, 1987). *Pavement age* is considered in the developed model, because pavements deteriorate with time. Variation in *pavement layer thickness* can result in variations in the structural characteristics and in-service performance of pavements (Attoh-Okine and Roddis, 1994). Hence, the top two layers in the pavement structure are considered in the model, i.e. AC thickness and base course thickness. *Pavement strength* is mainly evaluated by nondestructive testing methods such as Falling Weight Deflectometer, Light Weight Deflectometer, Benkelman beam etc. complemented with other evaluation techniques. In the Ethiopian road databank no such data is found, hence, LWD tests were conducted on selected roads, and the 'surface deflection modulus' values determined are used in the model development. *Traffic loading* and *Environmental factors* are also considered in the models.

3. Data Collection and Field Testing

Data was collected from many sources including Ethiopian Roads Authority (ERA) Pavement Management Branch, which runs the PMS, Environmental data from the Ethiopian Meteorological Agency and field tests using LWD. The Ethiopian road network consists of about 36500 km of Federal and Regional roads (from which about 5000 km are asphalt roads) and 30000 km of unclassified roads. The PMS was established in 1997 with the assistance of the World Bank (BCEOM, 1997).

After a thorough study of the whole database, six AC paved roads are selected for the model development. IRI should steadily increase with time unless there is some external interference. This rationale was used to check any abnormal breaks in the time sequence of the IRI data. Using this criterion, 322 sections with complete time series of IRI measurements are selected from these six roads. From the 322 sections, 73 sections are randomly selected for LWD measurements.

4. Model Development

In order to test the hypothesis that the LWD_E enhances the models predictions, the following cases are considered:

Case 1 – model without LWD_E (73 sections, 291 entries)
Case 2 – model with LWD_E (73 sections, 291 entries)
Case 3 – model using the whole dataset (no LWD_E; 322 sections, 1239 entries)

Statistical MLR and ANN methods are used for the model development, and a comparison between them is also made.

4.1 Statistical Multi-Linear Regression Analysis

Results from MLR analysis using SPSS software are explained here. Table 1 shows the coefficients of the regression models for each case together with the models summary results. It reports the strength of the relationship in the variables. R, the multiple correlation coefficient, is the linear correlation between the observed and model-predicted IRI values. Its large value of above 0.74 in all the models indicates a strong relationship. The ANOVA (Analysis of Variance) table tests the acceptability of the model from a statistical perspective (Table 2). The regression and residual sums of squares and R Square, the coefficient of determination, show that 58.4%, 62.6% and 61.3% of the variation in IRI is explained by the models in cases 1, 2 and 3, respectively..

Table 1: MLR Model Coefficients and Model Summary

Variable	Case 1	Case 2	Case 3
(Constant)	2.422	1.811	2.291
Age (years)	.445	.443	.384
AC thickness (cm)	-.056	-.130	-.105
ESAL (msa)	.014	.013	.019
Max temp (^{o}c)	.018	.029	.020
Precip (mm)	.001	.002	9.3E-4
Base thickness (cm)	-.055	-0.45	-.019
LWD_E (MPa)	-	-6.35E-4	-
R	.764	.791	.742
R Square	.584	.626	.613

Table 2: ANOVA – Sum of Squares Error

	Case 1	Case 2	Case 3
Regression	173.568	186.100	637.222
Residual	123.875	111.342	519.363
Total	297.442	297.442	1156.585

4.2 Artificial Neural Networks

4.2.1 Background

Neural Networks (NN) are named after the cells in the human brain that perform intelligent operations. They are recently becoming the preferred tool for many predictive applications because of their power, flexibility and ease of use. They are particularly useful in applications where the underlying process is complex, like in pavement deterioration.

An Artificial Neural Network (ANN) consists of three key components, the Architecture, the Neuron Activation Function and the Learning Algorithm which should be determined before solving any particular problem. A typical three layered neural network with one output neuron is shown in Figure 1. *Neural Activation Function* is known to be of the kind “distributed parallel computation” algorithm because of the independence property of neurons (Fausett 1994). A typical neuron (PE) on a hidden layer is shown in Figure 2. As can be noticed, the processing of each neuron simply involves a weighted summation (Linear Map) given by:

$$net_j = \sum_{i=1}^{n} x_i w_{ij} \qquad\qquad net_k = \sum_{j=1}^{m} y_j w_{jk} \tag{1}$$

In addition, it involves an instantaneous nonlinear map that transforms the weighted summation values (*net_j and net_k*) to the output variable (y_j or o_k), given by:

$$y_j = f(net_j) = f\left(\sum_{i=1}^{n} x_i w_{ij}\right) \qquad\qquad o_k = f(net_k) = f\left(\sum_{j=1}^{m} y_j w_{jk}\right) \tag{2}$$

where, i= number of units in the input layer *(i=1 … n)*, j= number of units in the hidden layer *(j=1 … m)*, k= number of units in the output layer *(k= 1 … l)*, x_i = i^{th} element in the input vector, and, w_{ij} = weight for the i^{th} input to the j^{th} unit in the hidden layer, y_j = j^{th} neuron output in the hidden layer, o_k= k^{th} neuron output in the output layer, $net_{j\ or\ k}$= input to the transfer functions.

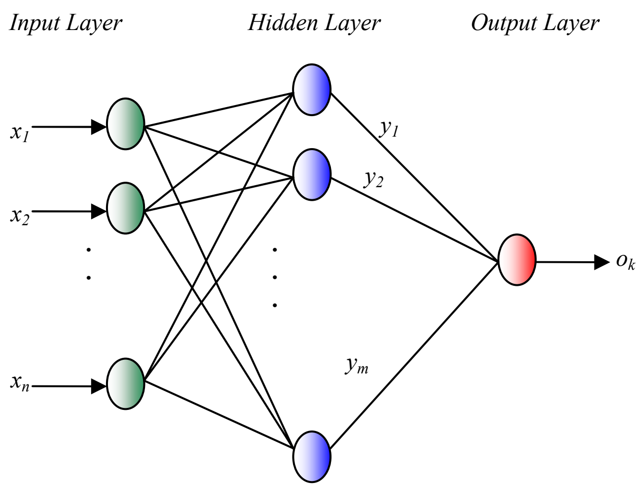

Figure 1: A Typical Three Layered Feed-Forward Neural Network

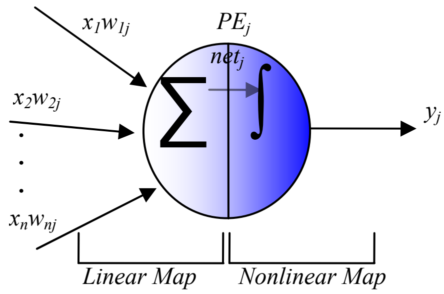

Figure 2: Typical Artificial Neuron (PE) on Hidden Layer

Learning Algorithms give ANN the capability to learn by adjusting the signs and magnitudes of their weights according to learning rules that seek to minimize a cost or error function. During the training of the neural network, two error types (Sum of Squares and Relative Error) are calculated, which are the measures that the neural network tries to minimize to acceptable levels by iterations. The Sum of Squares error is calculated using the formula:

$$E_T(w) = \sum_{r=1}^{s} E_r(w) \quad ; \quad E_r(w) = \frac{1}{2}\sum_{k=1}^{l}\left(T_k^{(r)} - o_k^{(r)}\right)^2 \tag{3}$$

Where $E_T(w)$= sum of squares of the output error for all training cases, $E_r(w)$ = square of output error for a single input case, s = number of cases in the data sample, l = number of neurons in the output layer; $T_k^{(r)}$ = target value of neuron k for case r; and $o_k^{(r)}$ = output of neuron k for case r

The Relative Error (RE) is computed using the formula:

$$RE = \frac{\sum_{r=1}^{s}\sum_{k=1}^{l}\left(T_k^{(r)} - o_k^{(r)}\right)^2}{\sum_{r=1}^{s}\sum_{k=1}^{l}\left(T_k^{(r)} - \bar{o}_k\right)^2} \tag{4}$$

Where $\bar{o}_k$ is the mean of $o_k^{(r)}$ over all cases (patterns).

4.2.2 ANN modeling

In building ANNs, it is not clear as to how many hidden layers and nodes are needed, however it was proved from several studies that one hidden layer with sufficient nodes is capable of representing any mapping (Choi *et al*., 2004). The SPSS Neural Network software is adopted for the ANN model development (SPSS 2007). For all our modeling cases, all possible combinations of activation functions between hidden and output layers were tested, and the hyperbolic tangent function for hidden layer neurons and the sigmoid function for the output layer neuron give the least amount of errors. After choosing the activation functions, the optimum number of units in the hidden layer was found by simply running the NN training program varying the number of units in the hidden layer from one to 20. The results of this task are depicted in figures 3, 4 and 5. As can be noticed, the errors and goodness-of-fit values after 9 units (neurons) in the hidden layers show very little difference. Hence the following architectures are selected for the respective cases: Case 1: 6-14-1, Case 2: 6-12-1 and Case 3: 6-13-1. In this research, a random selection of 70% of the dataset is used for training, 20% for testing and 10% for validation.

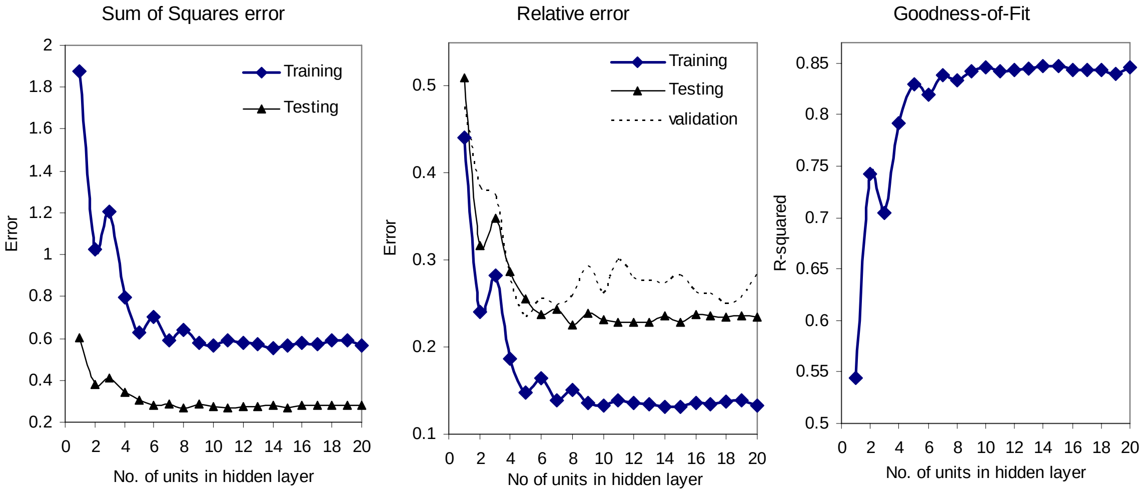

Figure 3: Plots of Errors and Goodness-of-Fit, versus No. of Units on Hidden Layer for Case 1

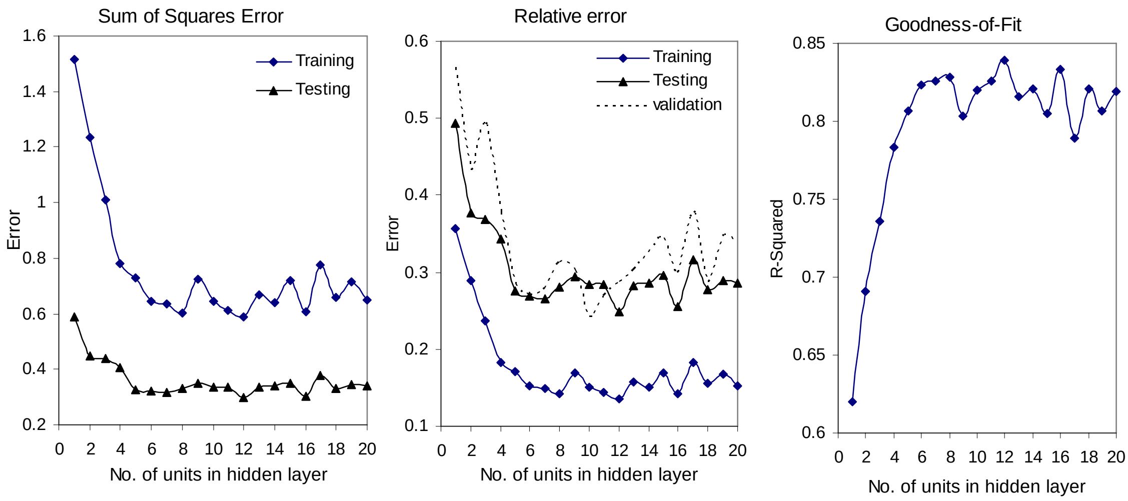

Figure 4: Plots of Errors and Goodness-of-Fit, versus No. of Units on Hidden Layer for Case 2

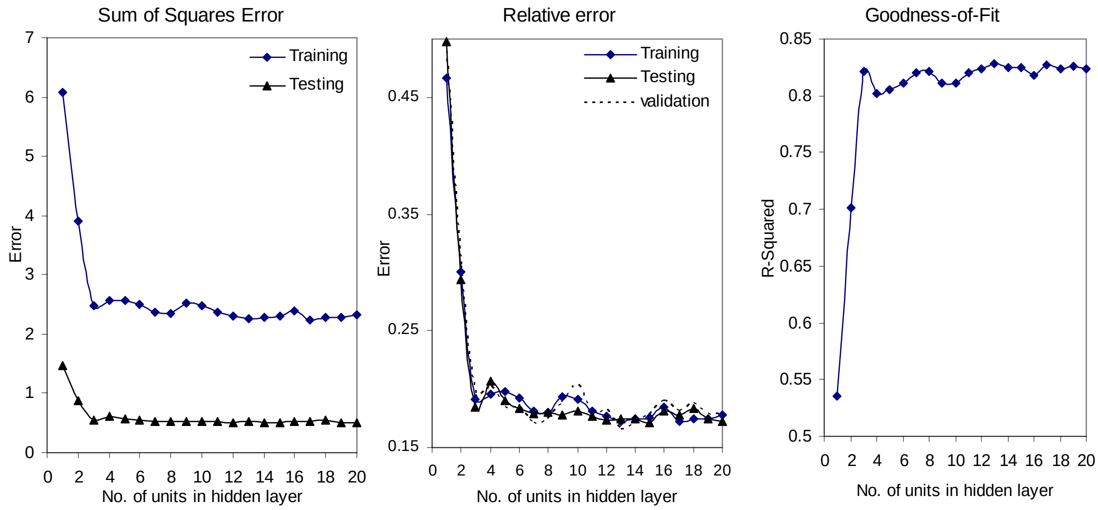

Figure 5: Plots of Errors and Goodness-of-Fit, versus No. of Units on Hidden Layer for Case 3

4.2.3 Validation of the ANN models

After training and testing the ANN, the last step is to verify the performance of the network with an out-of-sample dataset. For this purpose a validation dataset of 10%, as explained in the previous paragraph, was set aside during the training and testing phases. IRI predictions were carried out using this dataset, the results of which are depicted in Figure 6 for cases 1, 2 and 3. It can easily be seen that the ANN models predictions correlate very well with the actual measurements.

4.3 Discussion of Results

The first two cases were meant to investigate how the LWD_E values enhance the model prediction capabilities. This replacement enhances the prediction in the regression models, where the R-squared value increased from 0.584 to 0.626 (cases 1 and 2), refer Figure 7a) and Figure 8a). However, in the ANN models they are almost equal (0.847 and 0.846), as shown in Figure 7b) and Figure 8b).

Figures 7, 8 and 9 show scatterplots of actual versus predicted IRI values using regression and ANN models for the three cases. Evidently, the ANN models have produced results that are much better than those from MLR. The coefficients of correlation indicate that the ANN models have better generalization capability than the MLR (R-squared for case 1, 2 and 3 using MLR are 0.584, 0.626 and 0.613, and using ANNs they are 0.847, 0.846 and 0.821, respectively). The results clearly show that the ANN models outperform the MLR models.

5. Summary and Conclusion

Pavement deterioration models are crucial components of Pavement Management System (PMS). Flexible pavement deterioration models, expressed in terms of IRI, were developed from PMS data of the Ethiopian road network, using Multi-linear Regression (MLR) and Artificial Neural network (ANN) techniques. Neural networks are recently becoming the preferred tool for many predictive applications because of their power, flexibility, and ease of use. They are particularly useful in applications where the underlying process is complex, like in pavement deterioration. The widely accepted global variables on which pavement deterioration mainly depends are included in the model, i.e. traffic, pavement age, thicknesses, climatic condition and structural capacity. Comparison of the results between the developed MLR & ANN models showed that the ANN models produced results that are much better than the results from MLR models. The coefficients of correlation indicate that the ANN models have better generalization capability than the MLR (for three different cases of modeling, R-squared using MLR are around 0.6, and using ANNs are more than 0.8). This clearly shows that, in this research, the ANN models outperform the regression models. From this research it is shown that the inclusion of Light Weight Deflectometer's 'surface deflection modulus' variable significantly enhances the prediction of IRI from the performance models. This is a great advantage in managing roads especially in developing countries that do not have the financial resources and expertise in the use of the more expensive and sophisticated Falling Weight Deflectometers (FWD).

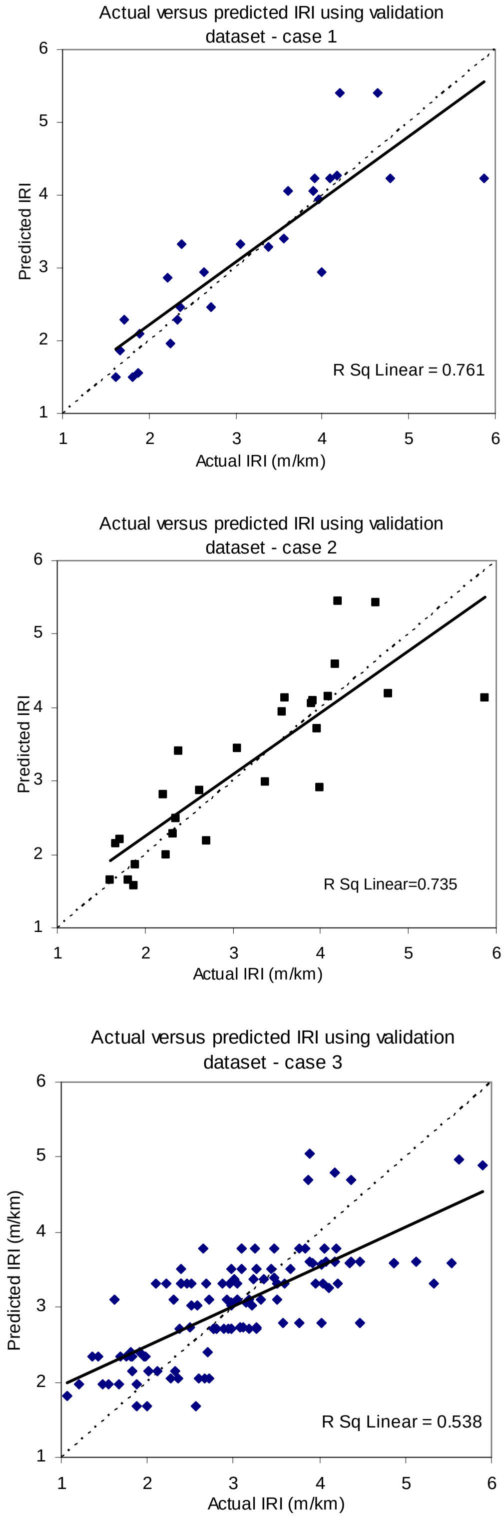

Figure 6: Actual versus Predicted IRI Using Validation Dataset

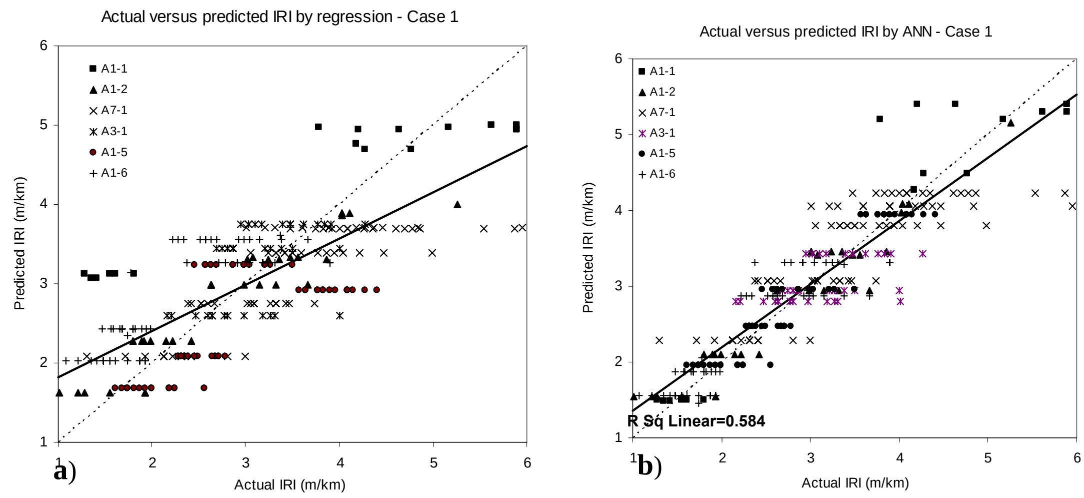

Figure 7: Plots of Actual versus Predicted IRI Values for Case 1; a) by Regression, b) by ANN

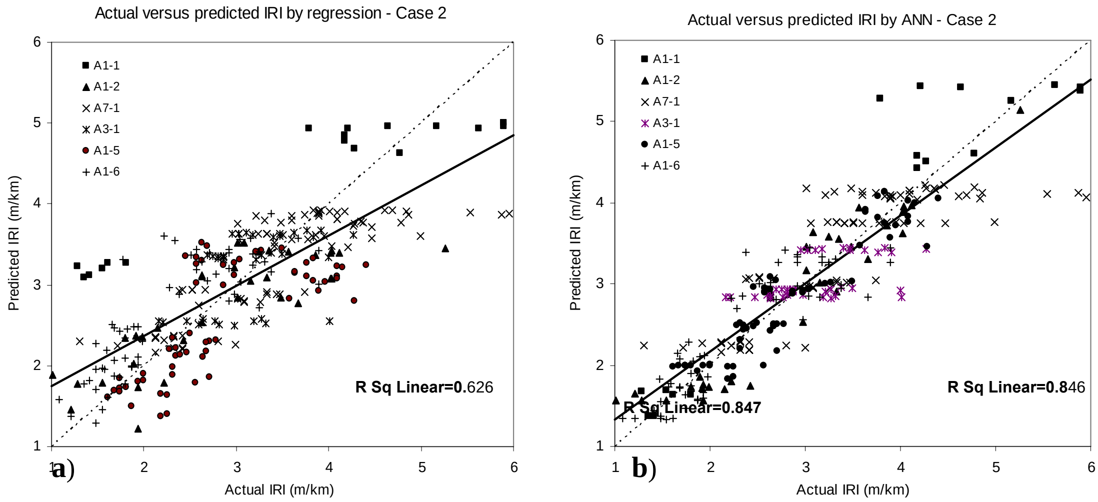

Figure 8: Plots of Actual versus Predicted IRI Values for Case 2; a) by Regression, b) by ANN

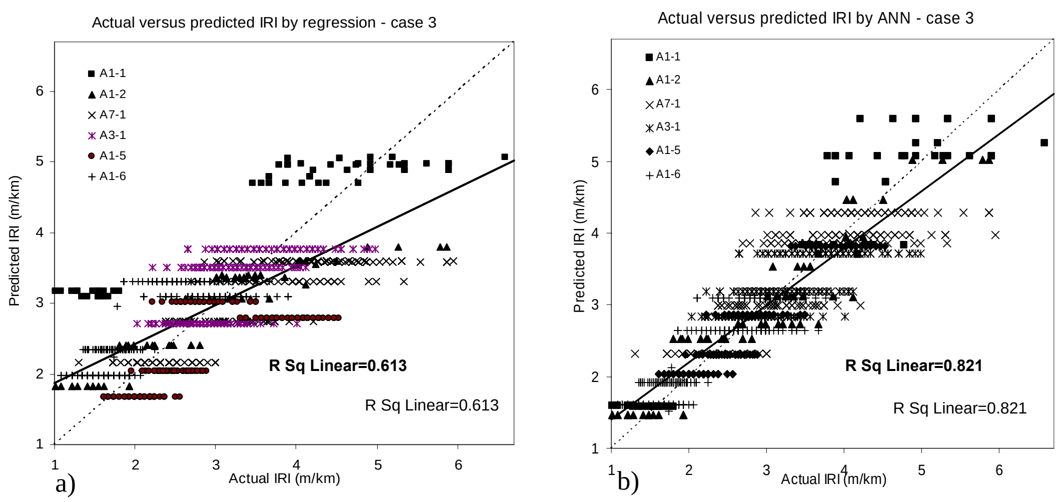

Figure 9: Plots of Actual versus Predicted IRI Values for Case 3; a) by Regression, b) by ANN

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