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Comparative Study of Utilising Neural Network and Response Surface Methodology for Flexible Pavement Maintenance Treatments

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Abstract

The use of Artificial Intelligence (AI) for the prediction of flexible pavement maintenance that is caused by distressing on the surface layer is crucial in the effort to increase the service life span of pavements as well as reduce government expenses. This study aimed to predict flexible pavement maintenance in tropical regions by using an Artificial Neural Network (ANN) and the Response Surface Methodology (RSM) for predicting models for pavement maintenance in the tropical region. However, to predict the performance of the treatment techniques for flexible pavements, we used critical criteria to choose our date from different sources to represent the situation of the current pavement. The effect of the distress condition on the flexible pavement surface performance was one of the criteria considered in our study. The data were chosen in this study for 288 sets of treatment techniques for flexible pavements. The input parameters used for the prediction were severity, density, road function, and Average Daily Traffic (ADT). The finding of regression models in (R^2) values for the ANN prediction model is 0.93, while the (R^2) values are (RSM) prediction model dependent on the full quadratic is 0.85. The results of two methods were compared for their predictive capabilities in terms of the coefficient of determination (R^2), the Mean Squared Error (MSE), and the Root Mean Square Error (RMSE), based on the dataset. The results showed that the prediction made utilizing ANN was very relevant to the goal in contrast to that made using the statistical program RSM based on different types of mathematical methods such as full quadratic, pure quadratic, interactions, and linear regression.

Keywords: ANN; RSM; Prediction, Treatment Techniques; Flexible Pavement; Correlation Coefficient.

1. Introduction

Pavements are among the highest assets of a nation, and a considerable investment to provide a sustainable maintenance service for them is becoming a priority. This comes with the shared goal of reducing the environmental impacts caused by maintenance treatments. Flexible pavement deterioration is a complicated process that involves not only structural damage but also numerous functional distresses on the asphalt pavement. It is a result of the climate, materials used and the quality of maintenance [1, 2]. However, the maintenance and rehabilitation of these pavements for the required serviceability is a routine problem faced by highway engineers and organizations. Therefore, the performance of correct maintenance is the best approximate predictor of normal conditions caused by the significant complexity of the pavement surface deterioration process [3, 4].

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The performance assessment of road pavements includes uncertain data, and the expert's views are considered in the linguistic language. Thus, the diagnosis of pavement distress requires a considerable amount of engineering judgment, and this skill is scarce, particularly for the maintenance of flexible pavements in Malaysia and other tropical regions [5, 6]. The performance of mechanistic-based pavement structures is dependent on the precision of the used mechanistic variables [7, 8]. Experience in treatment maintenance differs substantially among highways agencies all over the world [9]. To select suitable types of maintenance actions for the pavement section, accurate and appropriate information is needed for these sections. Hence, for the estimation of the maintenance cost, substitution decisions are occasionally required along with the relevant information and engineering decisions [10-12].

In this study, Artificial Intelligence (AI) was adopted to build regression models by selecting ANN and RSM. Firstly, the ANN is currently being used in various fields of studies, including transportation and highways engineering fields, and has an impact on achievements [13-15]. ANN has been effectively used in the past to make decisions on the infrastructure of the pavement condition; researchers have stated that ANN gives acceptable predictions [16, 17]. However, several utilization of the ANN model for predicting the performance of the ride, cracking, rutting, and faulting indices on different pavement types [18-20]. In 2010, Kargah et al. utilized ANN design for improving the international roughness index (IRI) when using data from asphalt concrete rehabilitation research (SPS-5), which were obtained from LTPP [21]. The designed neural network systems with back-propagation for predicting the values of the Crack Index (CI) for a one-year period were tested on Florida's highway network [22]. Secondly, the RSM combines several different statistical methods with mathematical procedures to generate, enhance, and optimize several operations. In statistics, RSM explores the associations between several explanatory factors as well as single or results factors. However, they apply a second-degree polynomial technique considering that this type of system is simple to approximate or simple to be used irrespective of the approach of this method [23-25].

A combination of layouts was selected for developing the second-order response surface model. This model is useful for applied initial designs for the most effective analysis. It includes layout factors with specific middle factors, which could be improved with some axial factors that enable the approximation of geometry. Nowadays, the RSM is implemented to evaluate the problems in a variety of fields in physical, chemical, engineering, clinical, and social sciences because of its efficiency and simplicity [26, 27]. In summary, the main goals of this study were as follows: (i) to present flexible pavement distress based on severity and density, road function, Average Daily Traffic (ADT), and treatment technique; (ii) to prepare the data for both training and testing the ANN model; (iii) to predict the pavement condition by using ANN and RSM models with different structures, and (iv) to evaluate the results by comparing the ANN model and make a recommendation concerning the RSM structure the provides the best prediction of the treatment technique. Moreover, this study was carried out to predict the treatment technique's action for flexible pavement maintenance by using two different approaches, namely ANN and RSM. Thus, the findings provide a broad understanding of new techniques for asphalt pavement maintenance.

Finally, the predictions of our study were made by comparing two regression models with ANN and RSM to be applied for flexible pavement maintenance. However, the ANN and RSM models were used for predicting the pavement maintenance for the treatment techniques. Section 2 describes the methodology used for developing an ANN and an RSM for creating the models. This section is subdivided into data acquisition, data preparation, ANN model, and RSM model. Section 3 describes the key results associated with the ANN and RSM models and their comparison. The conclusions are presented in Section 4.

2. Research Methodology

The methodology used for developing an ANN and an RSM consists of two steps. In the first step, the data collection and data sorting for maintenance flexible pavement prediction are determined. The second step involves the normalisation of the data from a category to the numerical form. Finally, the model development requires the collection of a considerable amount of data; in this study, we used multiple data sources and collected 288 sets of single and combined distress data.

Figure 1 illustrates the flowchart of the research methodology used in this study.

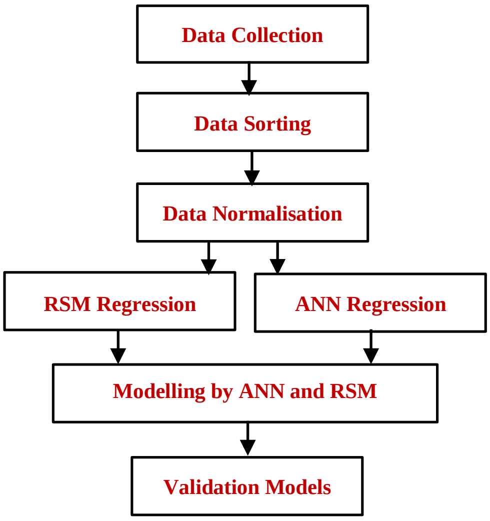

Figure 1. Research methodology flowchart

2.1. Data Acquisition

In general, traditional information collection solutions for pavement maintenance have several deficiencies such as low efficiency and poor performance. Therefore, the maintenance action may significantly change the shape of the performance models with no rehabilitation records. Knowledge Acquisition (KA) typically begins with the process of receiving or acquiring unique information from various sources and coding this information into the system. Domain skill depth and the type of experience in flexible pavement maintenance (theoretical, practical, or a combination of both) also need to be examined. In this study, the textual sources contain comprehensive information on flexible pavement maintenance and use a range of written sources, including manual guides, technical guides, and books [28–32]. Table 1 presents a sample of the obtained data. The first two columns show the result of the evaluation, i.e. severity and density, where severity ranges from low to medium to high, while density ranges from rare to intermittent to frequent to extensive. The third column presents the minor and major road functions. The fourth column presents the Average Daily Traffic (ADT) for vehicles, which ranges from less than 1000 to greater than 4000. The last column shows the treatment techniques of routing and seal > 6 mm, chip seal, and Cold In-Place Recycling (CIPR) reconstruction.

Table 1. Criteria for the maintenance of transverse cracking (categorical data)

Evaluation		Road Function	Average Daily Traffic	Treatment Technique
Severity	**Density**			
Low	Rare	Minor	<1000	Routing and seal > 6 mm
Low	Rare	Major	>4000	Routing and seal > 6 mm
Low	Intermittent	Minor	<1000	Routing and seal > 6 mm
Low	Intermittent	Major	>4000	Routing and seal > 6 mm
Low	Frequent	Minor	<1000	Routing and seal > 6 mm
Low	Frequent	Major	>4000	Routing and seal > 6 mm
Low	Extensive	Minor	<1000	Routing and seal > 6 mm
Low	Extensive	Major	>4000	Routing and seal > 6 mm
Medium	Rare	Minor	<1000	Routing and seal > 6 mm
Medium	Rare	Major	>4000	Routing and seal > 6 mm
Medium	Intermittent	Minor	<1000	Routing and seal > 6 mm
Medium	Intermittent	Major	>4000	Routing and seal > 6 mm
Medium	Frequent	Minor	<1000	Chip seal
Medium	Frequent	Major	>4000	Chip seal
Medium	Extensive	Minor	<1000	Reconstruction (CIPR)
Medium	Extensive	Major	>4000	Reconstruction (CIPR)
High	Rare	Minor	<1000	Crack fill
High	Rare	Major	>4000	Crack fill
High	Intermittent	Minor	<1000	Chip seal
High	Intermittent	Major	>4000	Chip seal
High	Frequent	Minor	<1000	Reconstruction (CIPR)
High	Frequent	Major	>4000	Reconstruction (CIPR)
High	Extensive	Minor	<1000	Reconstruction (CIPR)
High	Extensive	Major	>4000	Reconstruction (CIPR)

2.2. Data Preparation

In this study, the parameters used in the prediction analysis with the ANN and RSM models were divided into two parts: input dataset and target dataset. In all, 288 datasets was used. The four input datasets were as follows: severity (low, medium, or high), density (rare, intermittent, frequent, or extensive), road function (minor or major), and average daily traffic (<1000 or >4000 vehicles). The target was the treatment techniques (routing and seal > 6 mm, chip seal, reconstruction (CIPR), crack fill, clean and seal, coarse and seal, fog seal, spray patching, micro-surfacing, thin hot mix overlay, cold mix patching, or spray injection patching). Both the ANN and the RSM models required the predictors to be numerically encoded. Hence, all the gathered categorical datasets were encoded into numerals between zero and one. Table 2 shows how the categorical dataset in Table 1 was encoded into numerical values.

Table 2. Encoding categorical dataset to numeric form

Evaluation		Road Function	Average Daily Traffic	Treatment Technique
Severity	Density			
0.1	0.19	0.32	0.24	0.12
0.1	0.19	0.3	0.18	0.12
0.1	0.22	0.32	0.24	0.12
0.1	0.22	0.3	0.18	0.12
0.1	0.25	0.32	0.24	0.12
0.1	0.25	0.3	0.18	0.12
0.1	0.28	0.32	0.24	0.12
0.1	0.28	0.3	0.18	0.12
0.13	0.19	0.32	0.24	0.12
0.13	0.19	0.3	0.18	0.12
0.13	0.22	0.32	0.24	0.12
0.13	0.22	0.3	0.18	0.12
0.13	0.25	0.32	0.24	0.15
0.13	0.25	0.3	0.18	0.15
0.13	0.28	0.32	0.24	0.21
0.13	0.28	0.3	0.18	0.21
0.16	0.19	0.32	0.24	0.27
0.16	0.19	0.3	0.18	0.27
0.16	0.22	0.32	0.24	0.15
0.16	0.22	0.3	0.18	0.15
0.16	0.25	0.32	0.24	0.21
0.16	0.25	0.3	0.18	0.21
0.16	0.28	0.32	0.24	0.21
0.16	0.28	0.3	0.18	0.21

2.3. ANN Model

ANN was selected as one of the modelling applications for this study because of its ability to achieve different training algorithms. The neural networks were developed with a many-layer structure as well as by applying back-propagation rules for training. The model development required the training of the neural system, which depended on the training for data collection. In order to estimate the performance of the ANN model, the coefficient of selection, R^2, and the Mean Square of Error (MSE) were used for the analysis [33]. The accuracy of the predicted treatment techniques was determined using the following Equations 1 and 2.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{Y}i - Yi)^2 \tag{1}$$

$$R^2 = \frac{\sum_{i=1}^{n}(Yi - \bar{Y}i)^2 - \sum_{i=1}^{n}(Yi - \hat{Y}i)^2}{\sum_{i=1}^{n}(Yi - \hat{Y}i)^2} \tag{2}$$

Furthermore, testing with the chosen data for a test that presented the performance of the model was checked; the training was conducted with the validation dataset. From the collected data, 70% were randomly chosen to be used for training the neural system, 15% were used as the test data, and 15% were used to validate the capability of the system. In the development of the ANN system for predicting the treatment technique, the data chosen as the input parameters were severity, density, road function, and average daily traffic, while the treatment technique was chosen as the target parameter. The networking method utilised was a feed-forward with a tan sigmoid switch operation in the invisible layer and a linear switch function in the outcome layer. There were ten neurons in the invisible layer with four inputs to generate the result of the treatment technique. There were ten hidden layers and one output layer. Figure 2 shows the ANN model framework for the treatment technique prediction, while Figure 3 shows the structure of the ANN model used for making the predictions.

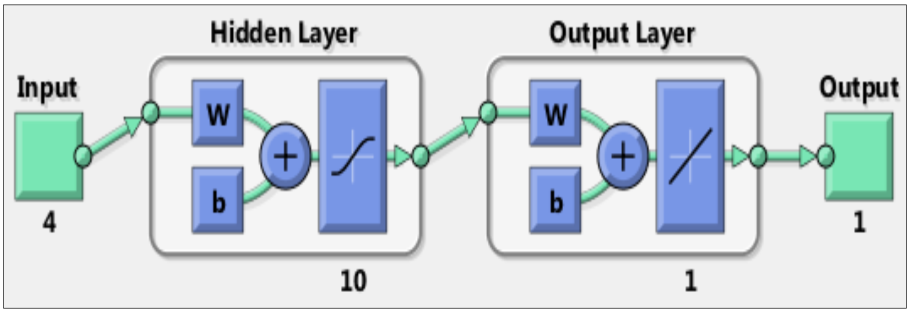

Figure 2. ANN model framework for treatment technique prediction

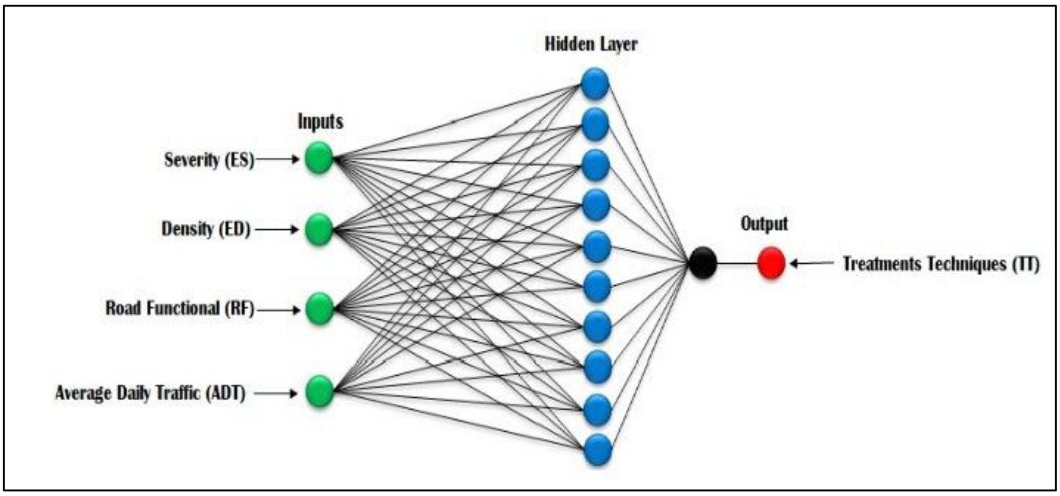

Figure 3. Typical ANN structure model used for making predictions

2.4. RSM Model

The optimisation method was performed by implementing the RSM to predict the treatment technique for flexible pavements; Figure 4 shows the structure of the RSM model used for making predictions. However, the multiple optimisation procedure was used for the optimisation of several different responses [34]. In Equation 3 indicates of most developed results.

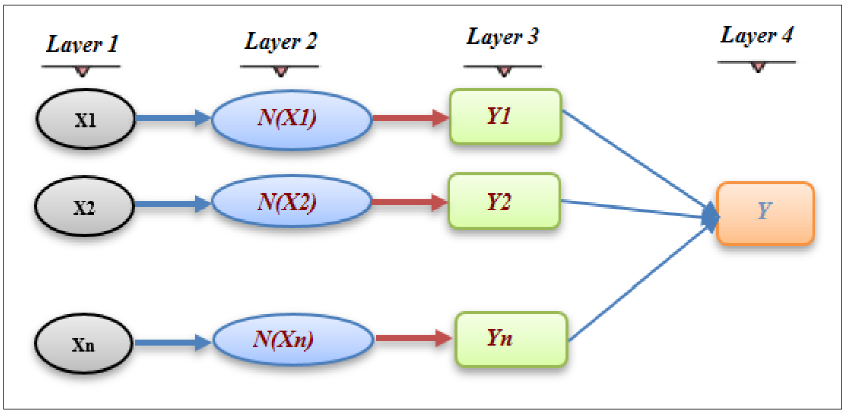

Figure 4. Framework of RSM for treatment technique prediction

$$D = (d_1 * d_1 * d_1 * d_1 \ldots .* d_1) = \left(\prod_{i=1}^{n} d_i\right)^{1/n} \tag{3}$$

Where n denotes the responses in the evaluation [40]. This technique takes advantage of the desirability functions. RSM prediction was carried out by applying four numerical systems, namely interactions, full quadratic, pure quadratic, and linear. The expressions for the numerical selections are given in Equations 4-7.

Linear:

$$y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 \tag{4}$$

Pure Quadratic

$$y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_1^2 + \beta_6 x_2^2 + \beta_7 x_3^2 + \beta_8 x_4^2 \tag{5}$$

Interaction

$$y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_1 x_2 + \beta_6 x_1 x_3 + \beta_7 x_1 x_4 + \beta_8 x_2 x_3 + \beta_9 x_2 x_4 + \beta_{10} x_3 x_4 \tag{6}$$

Full Quadratic

$$y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_1 x_2 + \beta_6 x_1 x_3 + \beta_7 x_1 x_4 + \beta_8 x_2 x_3 + \beta_9 x_2 x_4 + \beta_{10} x_3 x_4 + \beta_{11} x_1^2 + \beta_{12} x_2^2 + \beta_{13} x_3^2 + \beta_{14} x_4^2 \tag{7}$$

Where y_i is the predicted value of the treatment technique for severity, density, road function, and average daily traffic. x_1 denotes the severity; x_2, the density; x_3, the road function, and x_4, the average daily traffic. y_i and x_1, x_2, x_3, x_4 represent the utilised data, whereas β_0 to β_{14} are values generated by the RSM model.

3. Results and Discussions

3.1. Development of ANN Model

The prediction for the ANN model designed for treatment techniques is shown in Figure 5. The green line with a triangle form in the figure represents the target data that are relevant to the treatment techniques. The red line with a square form represents the predicted values by the ANN model. The x-axis shows the number and the order of the dataset. At the same time, the y-axis represents the target and the predicted output values. The capability method of the ANN model was used to measure the efficient prediction of the treatment technique values using R^2, which was the determination coefficient. The ANN training model had high accuracy with R^2 of 0.94, and ANN tested the model with the R^2 value of 0.92. Furthermore, the value of R^2 for the validating dataset was used to prove that the effect of predicting the ability of the ANN model was 0.93. The RMSE values for the training, testing, and validation of the ANN model were 0.037, 0.0602, and 0.0821, respectively. The values of R^2 were more significant than 0.8 for all the models of training, testing, and validation; these outputs indicated that the proposed ANN model had achieved a useful dataset. Figure 6 shows the overall coefficient of determination (R^2) for the predicted output values of the ANN model as well as the linear equation between the dependent values (predicted output values for ANN) and the independent value (the target value for the treatment techniques).

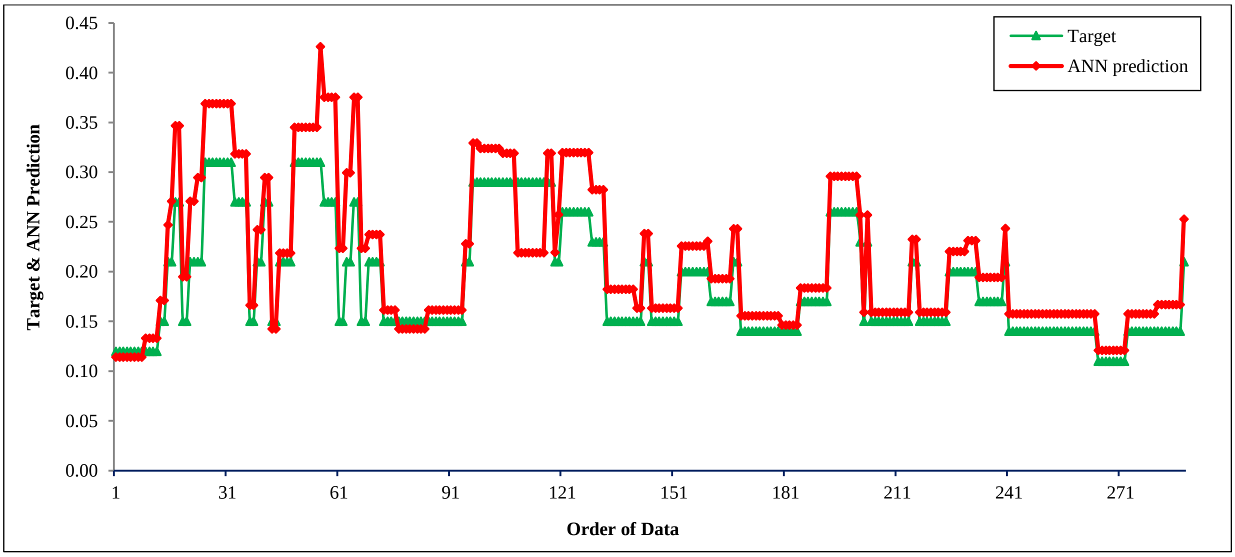

Figure 5. ANN prediction output for treatment technique

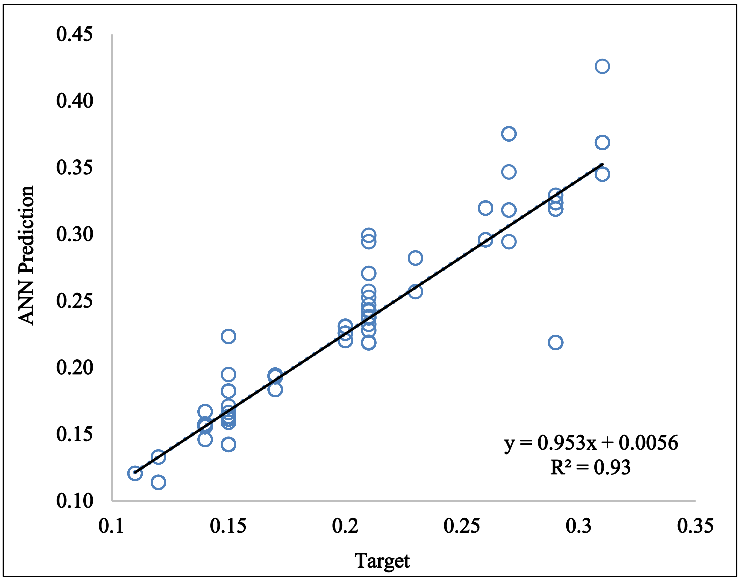

Figure 6. Coefficient of determination (R^2) for the ANN model

$$y = 0.953x + 0.0056 \tag{8}$$

Where y is the dependent value (the predicted output value for ANN) and x is the independent value (the target value for the treatment technique).

3.2. Development of RSM Model

In the current study, optimisation was performed by choosing RSM to predict the treatment technique. Equation 7 presents the perfect numerical model (full quadratic) for predicting the treatment technique using the RSM model. Figure 7 shows a comparison between the target values and the predicted output. The green line with a triangle shape represents the target data, or treatment technique, while the red line with a square shape represents the values predicted by the RMS model. The x-axis shows the number and the order of the dataset, while the y-axis represents the target and the predicted output values. The capability of the RSM prediction models was measured using multiple determination values (R^2). The R^2 for the full quadratic mathematical model was 0.85, as shown in Figure 8. Table 3 indicates that the full quadratic mathematical model was a better statistical method for any of the factors of y_i for the RMSE of the best value irrespective of the other selections that provided efficient predictions. RMSE is a method used for calculating the extent of the mathematical numerical model around the target data. The extensive data of RMSE indicate the system is far away from the target data. An RMSE of zero indicates that the system can correctly predict most of the target data. In this study, the process of decision-making as a useful approach was conducted by utilising the RSM to predict treatment techniques. Equation 9 shows a better mathematical model (full quadratic) for treatment technique prediction by utilising the RSM model. Figure 6 shows the difference between the predicted outputs and the target values. The green line with a triangle form represents the target data or treatment technique.

In contrast, the red line with a square form represents the outputs predicted by the RMS model. The x-axis shows the number and the order of the dataset. At the same time, the y-axis represents the target and the predicted output values. The capability of the RSM prediction models was assessed using several determination values (R^2). The R^2 for the full quadratic mathematical model was 0.85, as shown in Figure 8. Table 3 shows that the full quadratic mathematical model was a good system for any value of y_i that was used in RMSE for most cases, while the other numerical models could reach a perfect prediction. The evaluation method used to verify the numerical models in terms of the output values was an RMSE method. A significant value of RMSE indicated that the method was far away from the target value. In contrast, a value close to zero indicated that the model could accurately predict all the target data.

$$\begin{aligned} y_i = 3.95412 &- 0.14351x_1 - 0.05437x_2 - 0.07962x_3 - 0.08547x_4 - 0.00013x_1x_2 + 0.00248x_1x_3 \\ &+ 0.00547x_1x_4 + 0.00548x_2x_3 + 0.000104x_2x_4 + 0.00365x_3x_4 + 0.0681x_1^2 \\ &+ 0.00175x_2^2 + 0.000109x_3^2 + 0.04521x_4^2 \end{aligned} \tag{9}$$

Where y_i is the predicted value (treatment technique) and x_1, x_2, x_3, x_4 are the input values, i.e. severity, density, road function, and average daily traffic.

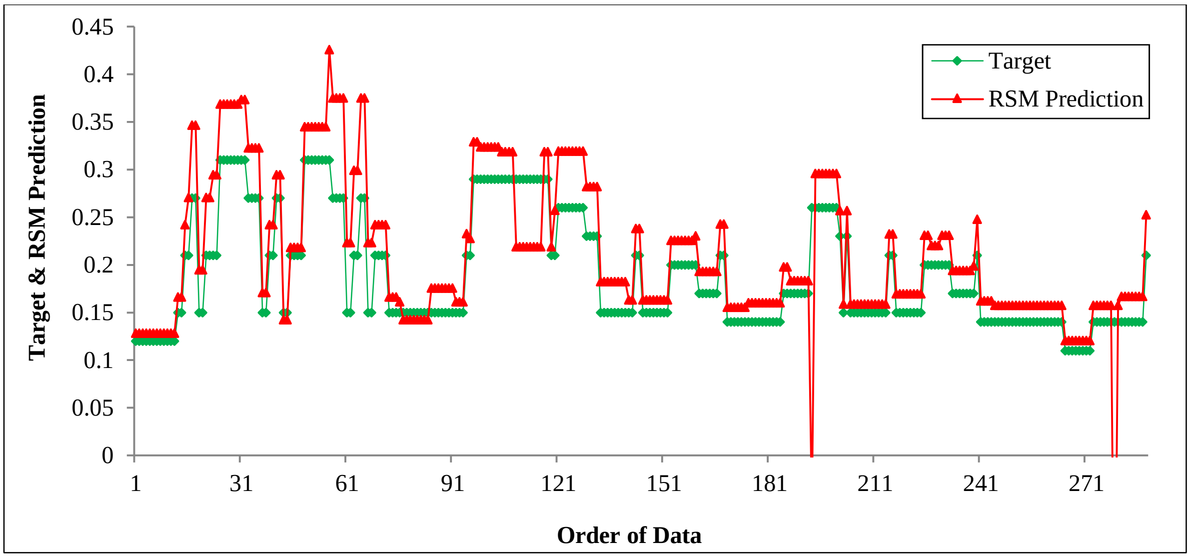

Figure 7. Target and predicted output values generated by the RSM full quadratic model

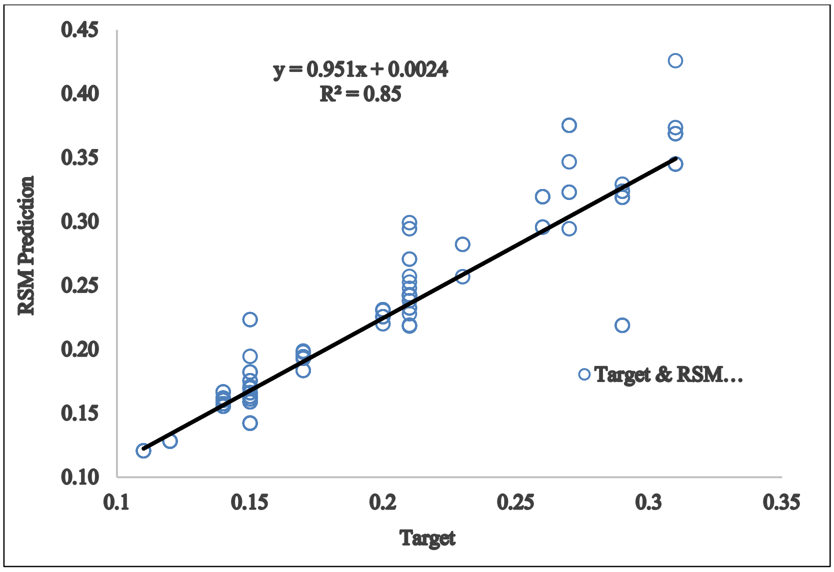

Figure 8. Coefficient of determination (R^2) for the RSM full quadratic model

Table 3. RMSE for RSM prediction models

Predicted Output	Linear	Pure Quadratic	Interaction	Full Quadratic
Treatment techniques	0.1206	0.0972	0.1072	0.0481

3.3. Comparison of ANN and RSM

A comparison of the results generated by the ANN and RSM models showed that both the models could produce an accurate prediction. Then, we compared the performance the RSM and ANN methodologies with their modelling, prediction, and generalisation capabilities using the experimental data. The ANN models were found to be accurate at improved predictions [35, 36]. In the present study, ANN and RSM methods were used to predict pavement maintenance with treatment techniques. The performance of the constructed ANN and RSM models was also statistically measured, and Table 4 shows a comparison of the ANN and RSM models in terms of the squared correlation coefficient (R^2), MSE, and RMSE. The table shows that the ANN and RSM models based on the full quadratic could successfully predict the treatment techniques with the ANN model showing superior performance to the RSM model. Furthermore, the residual variations in the cases of the ANN model were reasonably small and regular as compared to those in the case of the RSM model. Hence, the RSM model indicated a higher variance than the ANN model. Note that although RSM had the advantage of providing a predictive regression equation and showing the effect of the parameters and their interactions on a response as compared to ANN, ANN provided the ability to adapt the model to every treatment technique. The ANN approach was versatile and enabled us to incorporate new treatment technique data to create a trustable model; therefore, it was more logical and consistent to view the ANN architecture.

Table 4. R^2, MSE, and RMSE for ANN and RSM prediction models

Prediction Model	R^2	MSE	RMSE
ANN	0.93	0.00137	0.037
RSM (Full quadratic)	0.85	0.00230	0.048

4. Conclusion

The selection of optimal maintenance methods and materials for flexible pavement is a complex process that needs excellent skills and experience to cover all the relevant factors. In this study, the use of ANN and RSM for flexible pavement maintenance in the tropical regions was explored. This study aimed to find the optimal prediction for the treatment technique. It demonstrated that the forecast made using ANN was more accurate than that made using statistical methods and RSM based on mathematical models of linear methods for a rapid identification of pavement maintenance in certain regions. The results showed that the treatment techniques for flexible pavement could accurately be predicted by using statistical methods, namely RSM and ANN. An evaluation of the mathematical numerical methods showed that the full quadratic formula provided a more precise prediction than the other methods. The coefficient of determination (R^2) of each model dictated the model's ability to predict the treatment/techniques of output values correctly. A comparison of the developed ANN system with the RSM technique showed that the output produced by ANN was comparable to that of RSM. Finally, on the basis of the results obtained in this study, we concluded that the ANN and RSM models were a reasonable modelling tool for the prediction of pavement maintenance. Moreover, this study showed that flexible pavement distress could be effectively predicted using both of these models.

5. Acknowledgement

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6. Conflicts of Interest

The authors declare no conflict of interest.

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