ANN-Based Fatigue and Rutting Prediction Models versus Regression-Based Models for Flexible Pavements

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Abstract. Roads are exposed to continuous deterioration because of many factors such as traffic loads, climate and material characteristics. In Middle East countries, incredible investments have been made in constructing roads that necessitate conducting periodic evaluation and timely maintenance and rehabilitation (M&R) plan to keep the network operating under acceptable level of service. The M&R plan necessitates performance prediction models, which represent a key element in predicting pavement performance. Consequently, there is always a need to develop and update pavement performance prediction models specially for fatigue and rutting distresses, which are considered the most major distresses in asphalt pavement. On the other hand, Artificial Neural Network (ANN) is considered the best solution to developing such models with high accuracy due to its brilliant mechanism in training, testing and evaluating the data. In addition, the ANN approach has the flexibility to change many parameters such as number of neurons, hidden layers and function type to obtain more accurate predicted models. The scope of this paper is to develop ANN-based fatigue and rutting prediction models for asphalt roads. The ANN-based models were developed using MATLAB 2017b software based on actual field data obtained from Long-Term Pavement Performance (LTPP) database. The models were developed for both wet and dry non-freeze climatic zones. Results indicated that the ANN approach can be used in predicting both fatigue and rutting distresses with high accuracy as compared with the developed statistical models' approach, which were also developed in this study for both fatigue and rutting distresses.

Keywords: Prediction models · Distress models · LTPP · Neural network · Modelling · Climatic zone · Maintenance activities · ANN

1 Introduction

The Middle East countries are experiencing tremendous growth in infrastructure especially in constructing asphalt roads, which require periodic Maintenance and Rehabilitation (M&R) activities to preserve such investments. To identify M&R

S. Badawy and D.-H. Chen (Eds.): GeoMEast 2019, SUCI, pp. 117–133, 2020.
https://doi.org/10.1007/978-3-030-34196-1_9

activities based on yearly basis, future pavement condition should be predicted using pavement performance prediction models. This task should be implemented through application of well-designed Pavement Management System (PMS) (Haas and Zaniewski 1994; Hajek 2011; Zimmerman and Testa 2008). One of the main purposes of the PMS is to come up with the most cost-effectiveness policies for M&R activities. Pavement performance is predicted using distress/performance prediction models, which are considered the heart of the PMS system to quantify pavement deterioration rate and hence identifying M&R activities in a timely M&R plan supported by budget requirements (Zimmerman and Testa 2008; Naiel 2010).

Fatigue cracking and rutting or permanent deformation are considered two major distresses in asphalt pavements that cause structural failure in pavement layers. Horizontal tensile strain at the bottom of the asphalt layer(s) is the main cause for fatigue cracking; whereas rutting is produced due to vertical compressive strain on the top of subgrade layer due to weakness of foundation.

Consequently, there is always a need to develop and to update pavement performance prediction models embedded in PMS applications. Various performance prediction models had been introduced through the years, some of which are considered simple, while others are quite complex. There are two streams of pavement performance modelling, which are deterministic and stochastic approaches. The major differences between deterministic and stochastic performance prediction models are model development concepts, modelling processor formulation, and output format of the models. There are different types of deterministic models, such as mechanistic models, mechanistic-empirical models, and regression or empirical models. The mechanistic models draw the relationship between response parameters such as stress, strain, and deflection. The mechanistic-empirical models are oftentimes established in association with design systems and hence have not been broadly used in PMS but rather can possibly be applied at a network level. On the other hand, the regression models represent the link between the performance parameters such as pavement distresses and the forecasting parameters such as age, traffic loading, pavement material properties, and thickness (Abo-Hashema 2013; Mubaraki 2010; Radwan et al. 2019).

On the other hand, Artificial Neural Network have been effectively utilized for some errands including pattern recognition, optimization, function approximation, data retrieval, and predicting (Mubaraki 2010). ANN utilizes the mathematical emulation of genetic nervous systems in order to process acquired data and deduce predictive outputs after training the network suitably for pattern recognition (Thube 2012). A neural network comprises of various layers of parallel preparing component, or neurons. At least one hidden layer exists among an input layer and output one. The hidden layers neurons are associated with the neurons of a neighbouring layer through weighting factors which are adjustable via the training procedure of the model. The networks are structured according to training procedures for particular applications (Thube 2012).

This study focuses on developing ANN-based fatigue and rutting prediction models for asphalt roads located in both wet and dry non-freeze climatic zones, which represent most of the Middle East countries such as Egypt using data extracted from the Long-Term Pavement Performance (LTPP) database. Although, the ANN results were acceptable and more satisfied to predict Fatigue and Rutting distresses, the present study seeks for applying a comparison with another approach to show the powerful ability of ANN approach and to get the maximum benefit in forecasting fatigue and rutting distresses. Consequently, concerted efforts were also conducted in this study during another phase to develop regression prediction models through deterministic approach to predict fatigue and rutting distresses. Then, an interesting comparison was performed between results of the developed ANN-based fatigue and rutting models against similar developed models based on deterministic approach.

Based on the results, it was found that ANN-based models are appropriate to predict fatigue and rutting distresses with high accuracy due to its brilliant mechanism in testing and evaluating data. This study is considered as a crucial attempt to not only develop such models for the Middle East countries due to lack of resources led to unavailability of such models in most of Middle East countries, but also to compare between ANN-based and Regression-based fatigue and rutting prediction models.

2 Overview of Pavement Distress Models

Several pavement distress prediction models had been introduced through the years. The models differ significantly in their generality, their capability to forecast pavement performance with acceptable accuracy, and requirements of input data. Many of these models are empirical and were produced for use under specific traffic and climatic environments. Some of the models are mechanistic-empirical in which the input parameters are estimated by mechanistic models.

Performance prediction model is defined as a mathematical formula to predict future pavement deterioration depending on the current pavement condition and other affecting factors (Mubaraki 2010). Historical database for measures of pavement condition, age and traffic are extremely important in fitting forecast pavement deterioration models. These models are the major input to the effective PMS (Mubaraki 2010).

On the other hand, pavement distress prediction models are exceptionally powerful for basic leadership process in setting up answers to the inquiries of what, where, when, concerning support maintenance needs. Additionally, these models are crucial in identifying a timely M&R plan and when the action plan should start to keep the road network under acceptable level of service (Vepa et al. 1996).

The factors that could affect fatigue prediction models include age, traffic loading, pavement condition data, climatic condition, material characteristics, and quality of construction and maintenance. On the other hand, the factors that could affect rut depth distress prediction models include internal factors, such as asphalt binder, air voids in total mix, layers thickness, voids in the mineral aggregate, Marshall stiffness, subgrade material stiffness, elastic modulus of asphalt layer; and external factors such as traffic loading and environmental related factors. The availability and accuracy of data definitely affect the confidence level of the prediction model.

3 Background of LTPP

The Long-Term Pavement Performance program (LTPP) is the largest pavement performance research program ever undertaken, gathering data from more than 2,000 pavement test sections over a 20-year test period. The single most significant product of the LTPP program is the pavement database - the largest and most comprehensive collection of research-quality performance data on in-service highway pavements ever assembled. LTPP is one of the significant research regions of the Strategic Highway Research Program (SHRP). Strategic Highway Research Program was the supportive for LTPP program for the first initial five years. The Federal Highway Administration (FHWA) had proceeded along with the administration and subsidizing of the program, since 1991. The LTPP program was overseen via the LTPP Team under the Office of Infrastructure Research and Development (Radwan et al. 2019; Abo-Hashema and Sharaf 2009; LTPP 2017; FHWA 2002).

There are two complementary experiments inside LTPP to achieve the objectives. First, the General Pavement Studies (GPS) utilize the originally constructed current pavements after the initial overlay and concentrate on the most frequently used pavement structural design. Specific Pavement Studies (SPS) is considered the second series of LTPP experiments whose test sections let the factors of critical design to be performed, controlled, and monitored from the construction date. The results will offer a preferable understanding of the way to select M&R and design factors which influence pavement performance. GPS and SPS sets comprise of more than 2,500 test segments situated on all through North America built in four climate zones: wet-non-freeze, wet-freeze, dry-non-freeze, and dry-freeze. The LTPP program screens and gathers asphalt execution information on every single dynamic site. The gathered information incorporates data to develop seven modules which are: Maintenance, Inventory, Rehabilitation, Monitoring (Distress, Deflection, and Profile), Traffic, Materials Testing, and Climatic. The LTPP Information Management System (IMS) is considered the focal database whereas the information gathered by the program of LTPP. This database is persistently being produced as more information is gathered and handled (Abo-Hashema 2013; Radwan et al. 2019).

4 Artificial Neural Networks

ANNs are later computational models characterized in similarity with the natural attributes to recreate the choice procedure in the cerebrum. They are helpful to inexact and estimate unknown functions relying upon different and various input esteems. One of the principle attributes of this methodology is that it speaks to an approach to solve very complicated and nonlinear issues utilizing only very modest mathematical process. Specifically, ANN can be considered as a "black-box" method, since the outcomes are created without any respects to the causal connections among input and output. The strategy probability is completely misused when embraced for big data analysis and it very well may be utilized to create generalized solutions for issues utilizing big series of data. Like the cerebrum, the ANN is comprised of different interconnected neurons, which get input, process the data, and produce output for other connected neurons (Sollazzo et al. 2017).

In this study, MATLAB software, version 2014b, was used as a tool in developing a neural network. A multilayer feed-forward backprop ANN model is considered the most widely used neural network. The system incorporates input layer, at least one hidden layer and the output layer. Each artificial neuron gets and process data entering from different neurons and after that hand-off the signs to other neurons. Figure 1 shows Typical structures of ANN (Sollazzo et al. 2017; Abo-Hashema 2013).

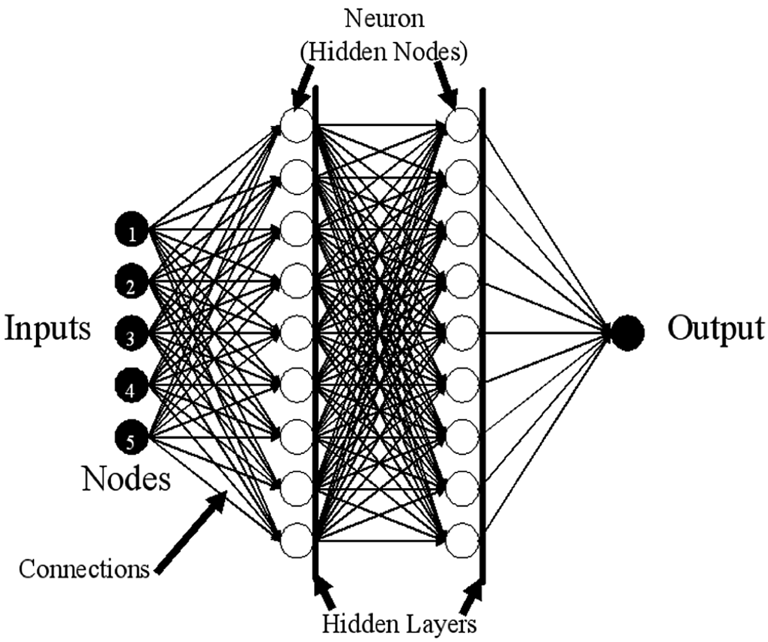

Fig. 1. Typical structure of ANN approach

A lot of papers discussed many applications of ANN on pavement Engineering such as developed an ANN for pavement condition evaluation, predicting present serviceability index (PSI), forecasting pavement performance using International Roughness Index (IRI), deducing of cracking progression, and studying of the variables affecting the compaction stage.

5 ANN-Based Fatigue and Rutting Prediction Models

5.1 Methodology

Figure 2 depicts the methodology adopted in developing the required distress prediction models for fatigue and rutting distresses based on ANN approach using MATLAB software version 2014b. The first crucial step is to create a database including all required data related to the required distresses. The database was created using LTPP sites located in wet and dry non-freeze climatic zones. Two database sets were created, one for training procedure and other for testing procedure. Sensitivity analysis using different numbers of hidden nodes and layers was also conducted on the trained ANN.

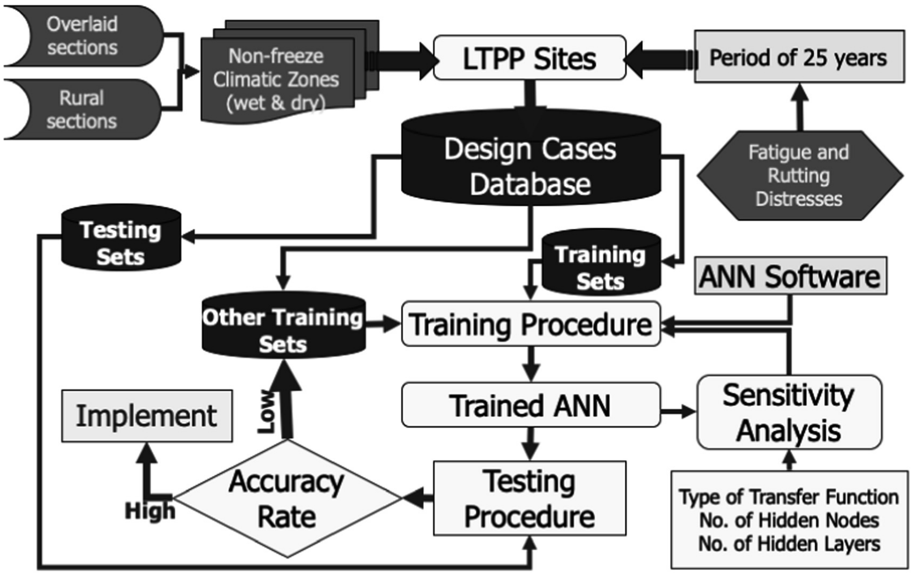

Fig. 2. Methodology implemented in this study

5.2 Design Cases Database

LTPP was the main source of data. Therefore, LTPP sites were selected to obtain the required data according to specific criteria as follows:

- Sites located in wet and dry non-Freeze climatic zones
- Only overlaid sections were chosen to simulate newly constructed pavement.
- Rural sections were selected represented main roads.
- Design period or data range was selected for 25 years, starting from 1991

Accordingly, 43 and 57 LTPP sites were selected for wet and dry non-freeze climatic zones, respectively. Data collection step was then started for the following data that related to Fatigue and Rutting distresses:

- Air temperature (Ta)
- Pavement age since overlay (PA)
- Traffic loading represented by Equivalent Single Axle Load (ESAL)
- Annual Precipitation
- Available pavement distresses
- Asphalt pavement thickness (T)

- Material characteristics:
  - Resilient modulus of subgrade soil (Mr)
  - % Passing the #200 sieve (0.075 mm) of subgrade soil (P_{200}),
  - % Air voids of asphalt mix (V_a),
  - % asphalt content in the mix (P_b)
  - Moisture content of base/subbase courses (MC_b),
  - Moisture content of subgrade soil (MC_S), and
  - Plasticity index of subgrade soil (PI)

All data were collected on different dates during the 25-year data range. The collected data have been filtered through a screening process to come up with feasible data that could be used to develop the required ANN models. The criteria for screening process are selected as follows:

1. Unavailability and/or insufficient of some distresses data
2. Absence of material characteristics data
3. Illogical data patterns, e.g. distress density should be increased with time not decreased

Consequently, 42 LTPP sites out of 43 were selected for wet non-freeze climatic zone; and 34 LTPP sites out of 57 were selected for dry non-freeze climatic zone, as shown in Table 1. The unit of distress data recorded in the LTPP database is based on the distress types. The unit of area is accounted for fatigue; on the other hand, the unit of length or depth is accounted for rutting distress. In addition to the collected distress data, distress density was calculated by dividing the length or area of distress by the area of examined section based on the PAVER system (Shahin and Kohn 1981).

For ANN-based fatigue and rutting prediction models, different inputs parameters are selected, and one output is required, which is fatigue distress density or rut depth. Sample of collected data is shown in Tables 2 and 3 for wet- and dry-non-freeze climatic zones, respectively (Radwan et al. 2019).

Two database sets were created, which are training and testing database. Other training database set was also created and could be used in case of low accuracy rate based on testing procedure.

All sets of training data were utilized to estimate error gradient and update weights and biases of the network. Moreover, the validation set error was monitored through the training procedure. In case of increasing the validation error, training had to be stopped.

5.3 Training Procedure

To develop performance prediction models for Fatigue and Rutting distresses based on ANN approach, the ANN network should be trained well using training database. The training database consists of 206 design cases for both fatigue and rutting distresses. The process was conducted using MATLAB software. It is noteworthy that MATLAB software divided the training dataset into two sets for training and validation.

Table 1. Selected non-freeze LTPP sites.

Site ID	State	Site ID	State
Wet-Non-Freeze Climatic Zone			
12-3997	Florida (FL)	28-2807	Mississippi (MS)
12-3996	***Florida (FL)***	28-3081	Mississippi (MS)
12-4106	Florida (FL)	37-1024	North Carolina (NC)
12-4107	Florida (FL)	37-1030	North Carolina (NC)
12-4108	***Florida (FL)***	37-1802	North Carolina (NC)
12-4097	Florida (FL)	40-1017	Oklahoma (OK)
12-9054	Florida (FL)	40-4163	Oklahoma (OK)
13-4096	Georgia (GA)	40-4087	Oklahoma (OK)
13-4112	Georgia (GA)	40-4161	Oklahoma (OK)
13-4113	Georgia (GA)	40-4165	Oklahoma (OK)
13-4111	***Georgia (GA)***	45-1025	South Carolina (SC)
13-4420	Georgia (GA)	5-3048	Arkansas
1-1021	Alabama (AL)	**48-3729**	**Texas (TX)**
1-4126	Alabama (AL)	**48-1113**	**Texas (TX)**
1-4129	Alabama (AL)	**48-1116**	**Texas (TX)**
1-1001	Alabama (AL)	**48-1093**	**Texas (TX)**
1-1019	Alabama (AL)	48-1068	Texas (TX)
24-1632	**Maryland (MD)**	48-1060	Texas (TX)
28-1001	Mississippi (MS)	48-3609	Texas (TX)
28-3028	Mississippi (MS)	**51-1023**	**Virginia (VA)**
28-3091	**Mississippi (MS)**	51-2021	Virginia (VA)
Dry-Non-Freeze Climatic Zone			
4-1002	Arizona (AZ)	**35-0108**	**New Mexico (NM)**
4-1003	Arizona (AZ)	35-0103	New Mexico (NM)
4-1006	Arizona (AZ)	**35-0104**	**New Mexico (NM)**
4-1007	Arizona (AZ)	35-0106	New Mexico (NM)
4-1015	Arizona (AZ)	35-0105	New Mexico (NM)
4-1017	Arizona (AZ)	**35-1112**	**New Mexico (NM)**
4-1021	Arizona (AZ)	35-0107	New Mexico (NM)
4-1024	Arizona (AZ)	35-0109	New Mexico (NM)
4-1025	Arizona (AZ)	35-0110	New Mexico (NM)
4-0113	**Arizona (AZ)**	35-0112	New Mexico (NM)
4-1062	Arizona (AZ)	**35-0101**	**New Mexico (NM)**
4-0160	Arizona (AZ)	48-1111	Texas (TX)
4-1065	Arizona (AZ)	48-1061	Texas (TX)
4-6055	Arizona (AZ)	48-1076	Texas (TX)
6-8151	California (CA)	48-3769	Texas (TX)
6-2004	California (CA)	48-6060	Texas (TX)
35-0101	New Mexico (NM)	**48-1048**	**Texas (TX)**
Sites to be selected for validation process			

Table 2. Sample of collected data for wet-non-freeze LTPP site.

%Density	Ta, °C	PA, Years	Mr, MPa	P_{200}	%Va	$\%MC_b$	$\%MC_S$	PI
Fatigue cracking model								
0	24.30	4	114	–	–	4	7	–
6.67	19.40	14	73	3.50	–	4	7	2
16.67	21.90	16.16	65	9.40	–	3	15	–

Rut depth mm	Ta, °C	PA, Years	ESAL	Annual precipitation	%Va
Rutting model					
6	15.89	5.92	711	1778.5	7.091
8	16.89	15.3	59	1679.30	5.823
10	15.60	12	40	1290.30	7.09
15	19.79	9.66	106	1418.59	3.993

Table 3. Sample of collected data for dry-non-freeze LTPP sites.

%Density	Ta, °C	PA, Years	Mr, MPa	P_{200}	%Va	T, mm	$\%MC_b$	$\%MC_S$	PI
Fatigue cracking model									
11.8	17.6	15.5	87	–	–	221	5	11	30
36.67	19.1	15.58	37	–	–	53.3	3	7	0
37.7	18.5	17.41	114	–	–	63.5	2	9	9

Rut depth mm	Ta, °C	PA, Years	ESAL	Annual precipitation	%Va
Rutting model					
11	22.70	18.25	925	121.9	16.3
7	23.10	16.58	768	41	16.3
5	17.70	15.5	4	343.4	6.12
4	16.10	8.416	12	294.6	6.12

5.4 Sensitivity Analysis

The aim of this step is to evaluate the fitness of the developed neural networks as an efficient way in predicting fatigue and rutting distresses with the most achievable accuracy that can be obtained. The neural networks are impressed by numerous parameters that can ensure the greatest possible accuracy such as transfer functions, number of nodes or neurons, and number of hidden layers.

A multilayer feed-forward backprop ANN model and TANSIG transfer function are developed to predict pavement fatigue and rutting distresses. The mean square error (MSE) and the coefficient of determination (R^2) were utilized to set the goodness or performance of models. The R^2 is defined as the proportion of the variance in the dependent variable that is predictable from the independent variable(s). A higher estimation of R^2 and lower MSE esteem guarantee a superior execution of the model and are increasingly valuable for forecast (Shafabakhsh et al. 2015).

The model precision of ANN relies upon the network architecture. Choosing quantity of the neurons in hidden layer doesn't have any broad guideline (Shafabakhsh et al. 2015). Distinctive ANN structures had attempted as far as cycles and hidden layer numbers. Rutting-Dry Neural Network model was considered as an example for showing graphs due to massive number of graphs in the study.

Figure 3 depicts the MSE estimations of networks against different neurons in hidden layer for Rutting-Dry Neural Network model. As shown in Fig. 3, the ANN with 8, 8, 18 and 20 neurons of hidden layer provided an impression of being the most ideal structure for predicting fatigue and rutting (Wet and Dry) distresses, respectively.

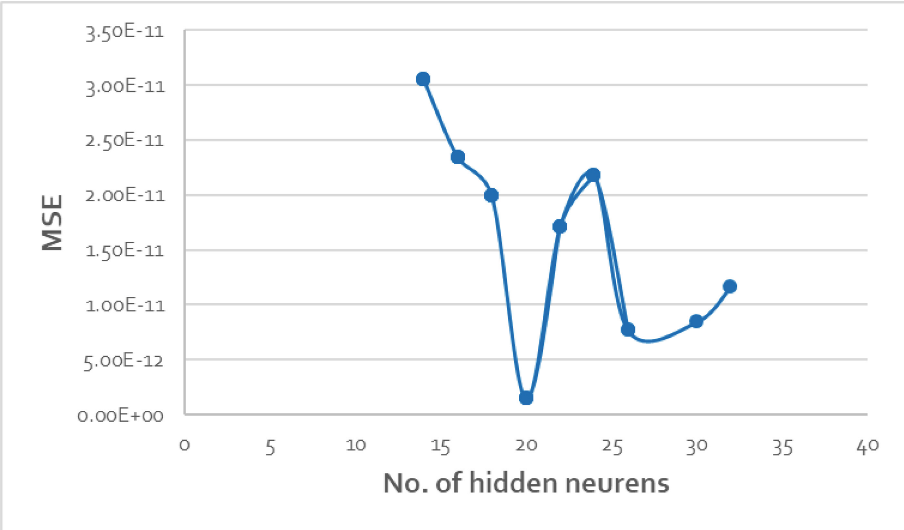

Fig. 3. Performance of rutting-dry ANN model under different No. of neurons

As shown in Fig. 3, Dry ANN model with 20 neurons has the lower MSE. Therefore, it is considered the most appropriate model for forecasting Rutting-Dry ANN model.

5.5 Testing Procedure

After the network was trained, testing procedure should begin using testing database extracted from the main developed database. The testing dataset have to be different from the data used in the training procedure.

The fitting graph between predicted and measured values utilizing the created Rutting-Dry Neural Network is shown in Fig. 4. As shown, the predicted values are close to measured values. This shows a solid relationship among the input parameters of the ANN model and the outputs.

As shown in Fig. 4, R^2 of data training, validation and testing values are 0.8183, 0.9199, and 0.8026, individually. Consequently, R^2 values achieved through ANN modelling method in the study are more than 0.8223 for all sets. The results revealed

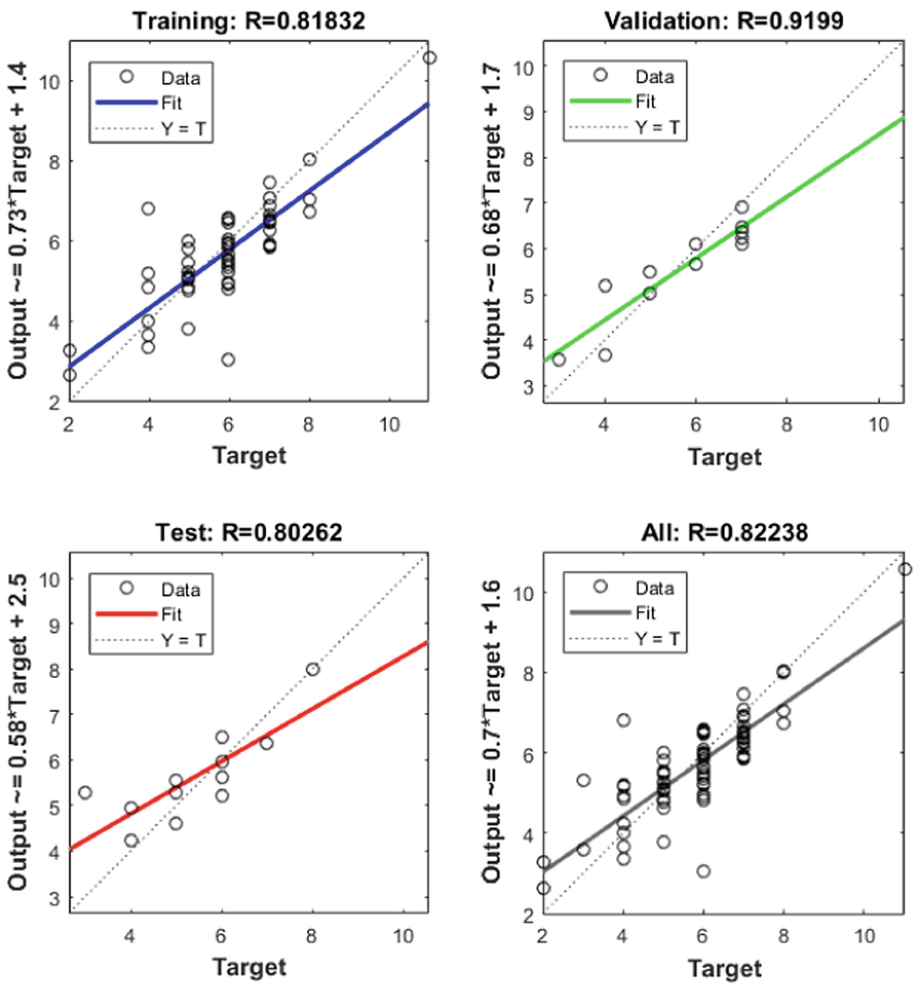

Fig. 4. Comparison between measured and predicted values for dry non-freeze rut depth by ANN for training data, validation data, testing data, and all data

that the established model has the capability to achieve at least 82% of the measured data for this model.

Figures 5 and 6 show Error in predicting rut depth for Dry Non-Freeze for training and testing Dataset, respectively. It can be seen from the figures that the predicted rut depth for Dry Non-Freeze accompanied with low errors, which are considered positive for forecasting rut depth values.

According to this, it tends to be reasoned that the suggested neural network can take in the connection among the distinctive input parameters and outputs. It creates the impression that established values from the ANN model considered genuinely near the actual values; also, they are equipped for propagating the input factors and outputs with high exactness of forecast.

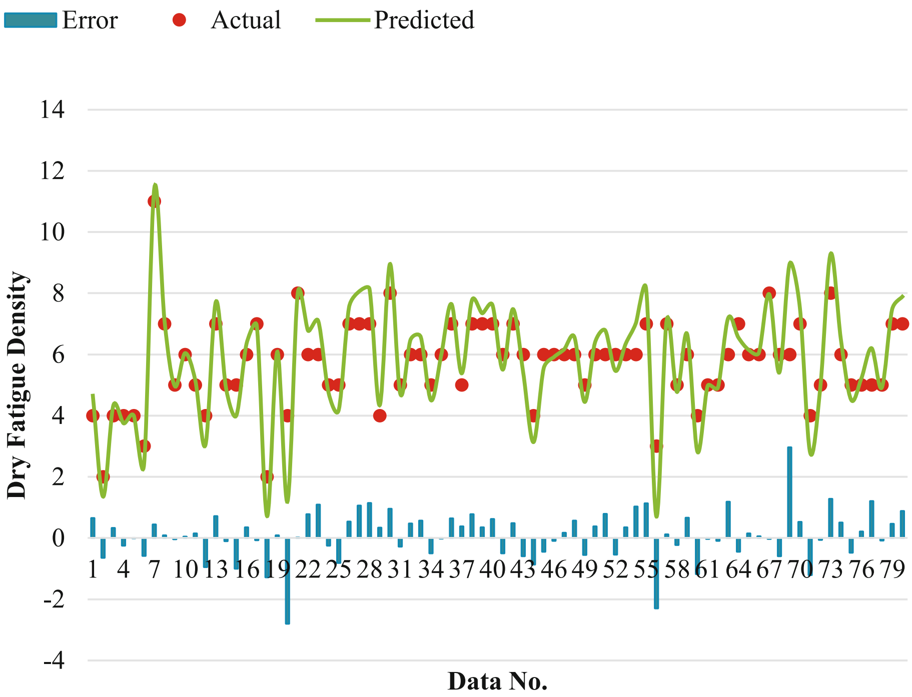

Fig. 5. Relationship between calculated and predicted rut depth in dry non-freeze zone for training set.

6 Development of Regression-Based Fatigue and Rutting Predictions Models

The main objective of the study is to develop pavement performance prediction models. The objective was achieved in many study phases. The first and second phases of this study were to develop regression-based pavement deterioration models for fatigue, rutting, bleeding, ravelling, longitudinal, and transverse distresses. The third phase of this study was to develop ANN-based fatigue and rutting prediction models and to compare with regression-based models, which is the subject of this paper. Other phases are related to comparison between developed models and available published models; in addition to implementation of the developed models in Egypt roads network, which necessitates performance data in a yearly basis.

A comparison between the ANN-based fatigue and rutting prediction models with similar ones developed by regression models to examine the suitability of using such models. Therefore, regression-based fatigue and rutting prediction models, which were developed during the first and second phases of this study, were used in this comparison (Radwan et al. 2019).

Stepwise regression test was performed within 95% confidence interval to come up with the most effective factors that could affect fatigue cracking and rutting distresses.

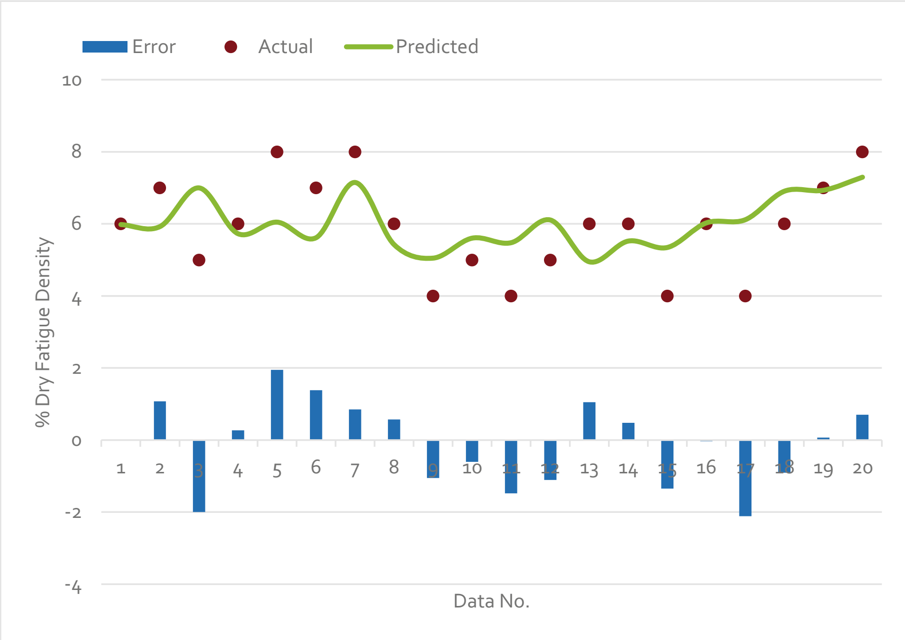

Fig. 6. Relationship between calculated and predicted for rut depth in dry non-freeze for testing set.

Hence, multiple regression analysis technique was applied to develop fatigue cracking and rut depth prediction models for wet and dry non-freeze climatic zones using SPSS software. Several trials were made to develop the required models that best represents the relation between the distresses with related factors. Therefore, the proposed distress models of fatigue cracking and rut Depth could be written as follows (Radwan et al. 2019):

Wet-non-freeze zone:

$$\%Fatigue\ Cracking = e^{(-10.356 + 1.936x\sqrt{PA} + 1.422x\sqrt{MC_S})} \tag{1}$$

$$Rut\ Depth = 10.097 - 0.987\,x\,Ln(ESAL) + 0.478xV_a \tag{2}$$

Dry-non-freeze Zone:

$$\%Fatigue\ Cracking = e^{\left(-45.28 + 9.26\sqrt{PA} + 2.1\sqrt{PI}\right)} + 6.14\cos Ta \tag{3}$$

$$Rut\ depth = 21.39 + 0.009xESAL - 1.05 * Ta + 0.255xV_a \tag{4}$$

The study of statistical analysis approach showed that goodness of developed models was found to have bad fit with the same data trends with insufficient accuracy, which strengthen applying ANN approach in forecasting fatigue and rutting prediction models (Radwan et al. 2019).

7 Comparison Between ANN-Based and Regression-Based Prediction Models

Table 4 presents a comparison between developed ANN-based and Regression-based models for prediction of fatigue and rutting distresses. The comparison is made to show the fitness of each approach in the light of goodness of models which include R^2, MSE values and percent of error.

Table 4. Comparison between ANN and Regression Approaches for both R^2 and MSE values

Distress model	Climate	Statistical regression approach		ANN approach	
		R^2	MSE	R^2	MSE
Fatigue cracking	Wet	0.544	488.633	0.999	$1.23e^{-12}$
	Dry	0.465	482.729	0.937	$8.23e^{-13}$
Rut depth	Wet	0.233	693.294	0.977	$2.8e^{-11}$
	Dry	0.479	411.999	0.822	$1.42e^{-12}$

It was shown from Table 4 that R^2 value of most developed models for ANN approach is approximately twice of that R^2 value of the same developed models by statistical regression approach. Also, MSE of all developed models by ANN approach reached approximately to zero. Generally, R^2 value for all developed models by ANN approach is not less than 0.822, which confirms that ANN approach is the intelligent solution to predict fatigue and rutting models in both wet and dry non-freeze zones.

Figures 7, 8, 9 and 10 depict comparison between ANN-based and Regression-based prediction models through the difference in %error for predicted pavement distress fatigue and rutting (Wet and Dry), respectively. It was clear from graphs that the average of %error value for fatigue and rutting (Wet and Dry) by statistical approach is 4 times the value of the average %error for the same models by ANN approach, which strongly confirms that ANN approach is the magic technique for predicting fatigue and rutting (Wet and Dry) models.

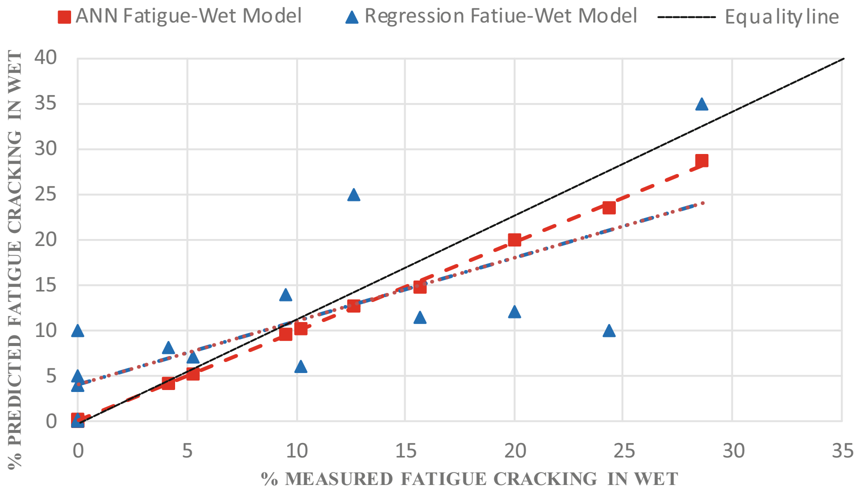

Fig. 7. Measured vs. predicted values for ANN-based and regression-based fatigue wet models

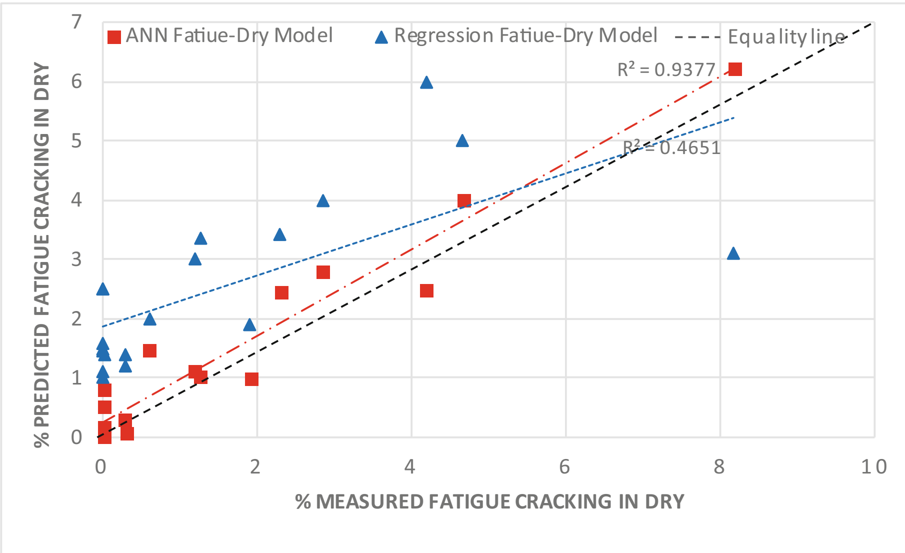

Fig. 8. Measured vs. predicted values for ANN-based and regression-based fatigue dry models

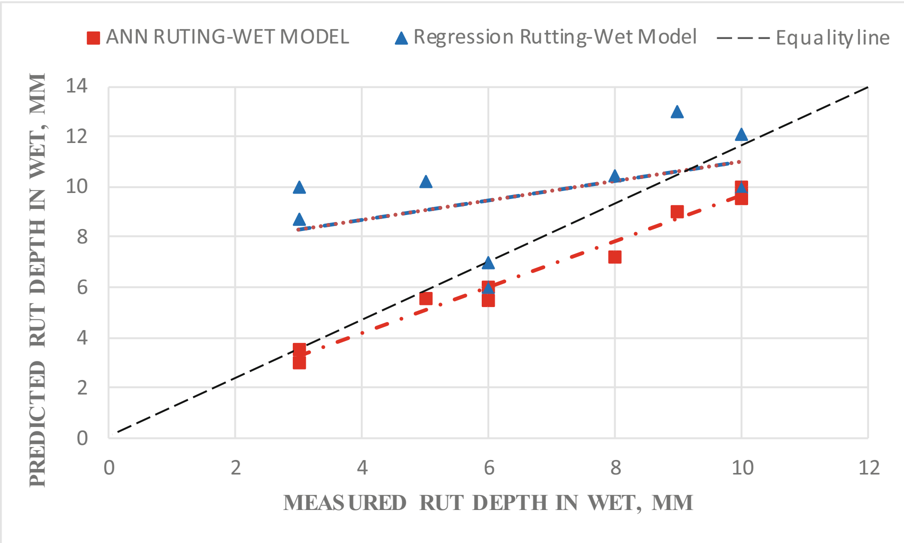

Fig. 9. Measured vs. predicted values for ANN-based and regression-based rut wet models

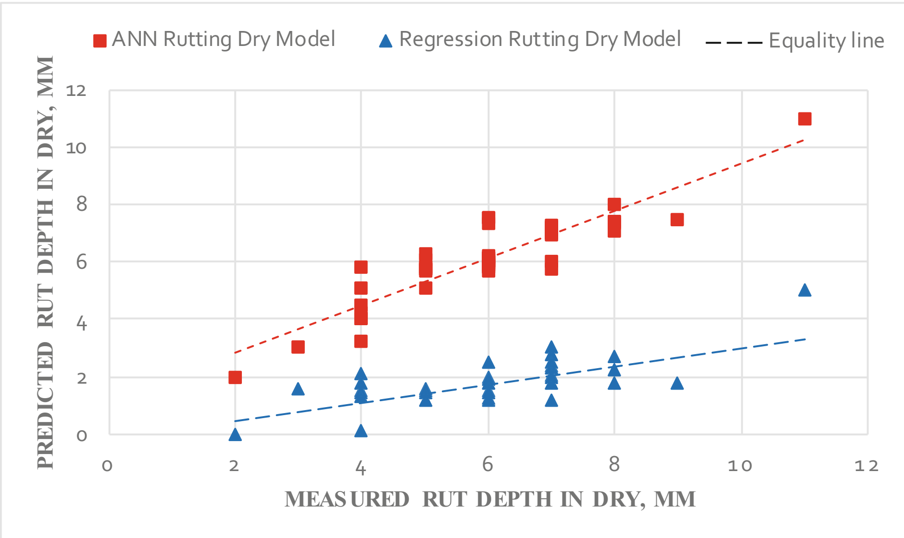

Fig. 10. Measured vs. predicted values for ANN-based and regression-based rut dry models

8 Conclusions

Two models were developed to forecast pavement fatigue and rutting distresses for both wet and dry non-freeze climatic zones using ANN approach. Furthermore, Regression-based models were also developed using the same data to predict fatigue and rutting prediction models. Moreover, a comparison between the two approaches was conducted. Based on the comparison and evidences of mean square error (MSE), the coefficient of determination (R^2), and %error values, results showed that the develoepd prediction models using ANN approach can be utilized in forecasting both fatigue and rutting distresses with high accuracy as compared to developed statistical models due to its brilliant mechanism in testing and evaluating a lot of data.

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