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*Original Article*

# Performance Prediction of Moroccan Pavements Using Artificial Neural Networks

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***Abstract -*** *Given its contribution to the country's economic, social and tourist development, road infrastructure is of paramount importance to the Kingdom of Morocco. Internationally, Morocco ranks 17th in a world ranking by the International Monetary Fund (IMF), which provides a new assessment of the quality of roads across the country, with an average speed of 95 km/h. Locally, the Ministry of Equipment and Water organizes surveys to measure the ISU surface index. This index is based on the following parameters: cracking, tearing and potholes. According to the survey conducted in 2020, the results show that 62.70% of the road network is in good to fair condition, an improvement of 9.2% compared to 2012. The Kingdom demonstrates this position by improving its road infrastructure and ensuring better accessibility between major cities. In this context, improving operating conditions through maintenance projects has always been a topic of discussion among decision-makers. This disorganized maintenance generates unplanned expenses and additional costs, which can increase the cost of annual action plans. Hence, a need to rely on Pavement Management Systems (PMS) to ensure a well-balanced maintenance strategy. The objective of the study presented in this article is to simulate the performance of Moroccan pavements using artificial neural networks. Due to their reliability and high accuracy, Artificial Neural Networks are chosen to model the problem of this study. This is based on visually inspecting a section of the Moroccan national road N1 using an automated car. Through this inspection, the pathologies affecting this section are observed and measured, from which the PCI pavement condition index is calculated. Then, a model is chosen and approved by cross-validation and sensitivity study. Simulation using neural networks proves to be a good sign for developing this application to build a Moroccan PMS.*

***Keywords -*** *Pavement Condition Index PCI, Performance, Distress, Artificial Neural Network, Pavement Management System (PMS).*

## 1. Introduction

Given the current challenges of road network maintenance, decision-makers have become concerned with managing rehabilitation and redevelopment projects. On this, pavement management systems are invented as a tool to make such decisions. The first step is to collect data either from databases or following visual inspections. The second step is to model the performance of the pavements to decide the maintenance actions according to the funds available at the final stage. Through this study, a modeling of the performance of the pavements is put into practice for a section of a national road in the Kingdom of Morocco. Following an inspection by the National Center of Studies of Rabat, a database is then composed to observe the degradations affecting the surface. To evaluate the performance of the section, the PCI pavement condition index is chosen following the subjective evaluation of the degradations of the pavement, and it is a numerical index widely used to evaluate the structuring and the operability of the pavements [1]. In order to calculate the pavement condition index included as output data, the severity of five different types of degradations observed in each section was included as input data. Among 25 trained models, a specific architecture is chosen due to its reliability and accuracy. To take advantage of it, a cross-validation is then implemented to validate the proposed architecture. Then, it is challenged by a sensitivity analysis in order to see and measure the impact of each input on the model output, clearly designating the degradation that largely influences the pavement performance. The established model has reached a good level of accuracy, so it can be an option for developing performance prediction models.

## 2. Methodology

Based on visual inspection data collected by the National Center for Road Studies using six cameras mounted on an automated car, this inspection compiles data from continuous road sections into images and videos to be used in the current study. These data, which concern a section of 5600 m$^2$, are provided in a file for analysis by sections of 7 m width and 8 m length. The analysis is aligned with the assessment of pathologies identified on the roadway. Through the analysis of the severity and types of deterioration, the roadway condition index and subtracted values are calculated. Due to their high accuracy, as proven by multiple studies, artificial neural networks are used in this study to develop the model using MATLAB. The PCI is the output value in the network construction process, and the weights of the deteriorations are used as input values.

In this study, in order to choose the appropriate architecture, 25 different topologies are tested, with 70% of the data for training, 15% for validation and 15% for testing. Then, the errors, such as root mean square error and multiple determination coefficient, are illustrated in order to measure the performance of the models. Subsequently, a cross-validation is performed to choose the best-performing model. Finally, a sensitivity analysis is performed on the input data to question the impact of each degradation individually on the pavement performance.

## 3. Results

### *3.1. State of the Art*

#### *3.1.1. Performance*

The word performance appeared for the first time in 1979 and is systematically used in an evaluation context, implicitly (performance management, performance steering) or explicitly (performance evaluation), so evaluating performance means giving it its value [2]. In civil engineering, specifically in the infrastructure sector, performance refers to the structural and functional responses of pavements to the actions of elements such as traffic, environmental conditions and the materials constituting the structure [3]. Performance is also defined as the way in which pavement conditions change or fulfil their intended function with accumulated use [4][5].

In the context of pavement performance modeling, the challenge is to find the best representation to relate construction material variables to performance as a function of traffic levels and roadway structure [6]. The derivation of such relationships is too resource-hog to be developed using traditional computational methods [7].

The concept of predicting pavement performance is based, with several citations, by Carey and Irick in the context of the AASHTO road test carried out in the years just before 1960 [8]. Over time, the use of computer technology has allowed the use of more sophisticated approaches. Researchers have developed several methods, including [9]:

- Regression models (AASHTO 1962, George et al. 1989, Madanat and Ibrahim 1995, Prozzi and Madanat 2000, Yu et al. 2007, Prozzi and Hong 2008, Pan et al. 2011),
- Probabilistic methods (El-Basyouny and Jeong 2010, Liu and Gharaibeh 2014),
- Markovien approaches (Butt et al. 1987, Jiang et al. 1988, Yang et al. 2005),
- Neural network methods (Fwa and Chen 1993, Alsugair and Al-Qudrah 1998, Terzi 2007),
- The fuzzy logic approach (Bianchini and Bandini 2010, Terzi 2013) and others.

In order to predict the performance of pavements, several indices can be used, such as:

- PCI: Pavement Condition Index,
- IRI: International Roughness Index,
- PDI: Pavement Degradation Index,
- PCR: Pavement Condition Rating,
- PSI: Pavement Service Index; and others.

In addition, the pavement condition index is the widely used numerical index for assessing pavement structure and operability [1]. This index is initially developed by the US Army Corps of Engineers for PAVER [10]. Its assessment is initiated by visual inspection identification of the pathology type, severity, and degree.

Through calculation, different types of pathologies with changeable severities are gathered into a single PCI value. The index ranges from 0 (worst possible condition) to 100 (newly constructed) [11].The method of calculating the performance index of asphalt concrete pavements can be summarized in the following steps [10]:

1. Determination of roadway damage and its severity;
2. Determination of deduction values from deduction value curves for each distress;
3. Reduction of the number of values deduced from the maximum number allowed using the equation:

$$m_i = 1 + \frac{9}{98} \times (100 - HDV) \tag{1}$$

Where mi = maximum allowed number of deduction values and HDV = largest individual deduction value.

4. Determination of q, the number of inferred values greater than 2.
5. Determination of the total deducted value (TDV), which is the sum of all deducted values.
6. Determination of the corrected deduced value (CDV) based on the correction curves using q and the TDV.
7. Reduction of the smallest deduction value greater than 2 to exactly 2.
8. Repeat steps 4 to 7 until q equals 1.
9. Determination of maximum CDV (CDVmax) and calculation of PCI using the equation:

$$PCI = 100 - CDV_{max} \tag{2}$$

*3.1.2. Artificial Neural Network*

*Presentation*

Artificial neural networks are defined as machine learning algorithms that mimic the human brain process to predict performance by modeling biological neurons consisting of nodes and links [1]. They are composed of several simple, interconnected processing elements to process information through a dynamic state response to an external input [12]. These elements are neurons connected by directed links, each of which has a weight associated with it and which is acquired at the time of learning. These weights are used by the network to solve a particular problem [9].

Some functions that neural networks are capable of performing include [9]:

- Classification;
- Model Matching;
- Model Completion;
- Optimization;
- Simulation.

In order to constitute a neural network, it is imperative to establish the following elements [13] :

- The architecture, which is a connection diagram between neurons,
- The activation function of neurons,
- The learning algorithm is a method of determining the weight of connections.

*ANN Architecture*

The neural network architecture is responsible for configuring nodes and their connections [8]. It defines essential configuration parameters such as the number of layers, the number of nodes in each layer, and the interconnection between nodes [1]. Generally, a neural network is unable to learn enough from the training dataset with too few hidden neurons, while with too many hidden neurons, the network tends to memorize the training dataset instead of generalizing the acquired knowledge [9].

*Activation Function*

The processing of each neuron simply involves a weighted summation plus a transfer function [9]. Transfer functions are generally used as neuron activation functions depending on the characteristics of the problem studied, which are:

- Sigmoid function: $\frac{1}{1+e^{-x}}$
- The Gaussian function: $e^{x^x x}$
- The hyperbolic tangent: tanh(x)
- The hyperbolic secant: sech(x)

*Learning Algorithms*

A learning algorithm defines the method by which weight values will be assigned to connections [8]. According to the learning rules, the learning ability is obtained by adjusting the signs and magnitudes of their weights [9].

Learning algorithms are classified into three categories [8]:

- Supervised learning;
- Self-organized learning;
- Reinforcement learning.

*Applications*

Many applications can be cited for applications of artificial neural networks. For example, Owusu-Ababio [13] applied them in order to model the performance of a thick asphalt pavement using the PDI degradation index. It was concluded that the ANN model outperforms the MLR model regarding standard error and R-squared value [9]. Another example is Jalal [14], who worked on predicting the condition of the pavement in service by working on the optimization of the model condition and using qualitative variables as inputs. The study showed the effectiveness of this optimization in improving the accuracy of the model and decreasing the calculated error. A last example is Jyh-Dong [15], who analyzed the relationship between IRI and pavement degradations using a backpropagation neural network methodology. This modeling consists of evaluating the applicability of IRI to be treated as a critical representation index of pavement degradation. They concluded that the neural network has a strong prediction and analysis capability. We present in the following table some advantages and disadvantages of artificial neural networks based on applications.

**Table 1. Advantages and disadvantages of some examples of ANN models**

| Researchers | Advantages | Disadvantages |
|---|---|---|
| Abdellah Alsugair et Ali A. AlQudrah [1] | Artificial neural networks have shown a high-reliability rate, making them suitable for implementation in a road management system. | A single network of neural networks is not enough to cover the entire margin of PCI values; hence, three models were created for each group. |
| YANGCAI HUANG AND RAYMOND K. MOORE [16] | Artificial neural networks have a higher capacity to predict the probability of the level of distress linked to roughness compared to multiple regression methods. | The network of neurons that predicts two binary outing methods does not reach the same success rate compared to the network of neurons with a single mode, which predicts a single exit. |

| | | |
|---|---|---|
| Jidong Yang [9] | The neural networks have been shown to be sophisticated models and intensive calculation methods; hence, calculation speed is no longer a major concern. | Recurrent Markov's chain exceeds artificial neural networks in terms of forecast over one year. |
| Habib Shahnazari; Mohammad A. Tutunchian; Mehdi Mashayekhi; and Amir A. Amini [11] | The basic model on artificial neural networks presents inferential calculation errors compared to the model based on genetic programming, hence more reliable details of the value of the PCI. | The model requires training with new cases when more data are available. |
| M. Jalal, I. Floris et L. Quadrifoglio [14] | The optimal model of artificial neural networks considerably improves the performance and precision of the model. | The normal model based on artificial neural networks requires optimization to increase the precision of the prediction. |
| Jyh-Dong Lin et al [15] | The network of neurons with retro-propagation offers a strong capacity for prediction and analysis. | The need for equipment of automatic inspection devices to produce information on the roughness of the road in the form of IRI. |
| Hasan Ziari, Jafar Sobhani, Jalal Ayoubinejada et Timo Hartmann [17] | Based models on artificial neural networks predict the future of the condition of the road with satisfactory and long-term satisfactory precision. | The model needs to be involved with all the variables that act on the shoe's performance. |

### *3.2. Case Study*

#### *3.2.1. Presentation*

This research is established with the aim of modeling the performance of roadways of the Moroccan road network. It is based on the road database information collected from the RN1 national road of the Kingdom of Morocco. The database information was collected using an automated car by the National Highway Studies Center. For a surface of 5 600,00 $m^2$ divided into 100 sections of 8m length and 7m width, the main types of distress observed are:

- Alligator cracking (m2);
- Bleeding (m2);
- Block cracking (m2);
- Long/Trans cracking (m2);
- Rutting (m2).

The distresses studied in this case are the most common distresses observed in this roadway. However, other types were not considered in this study. According to the Mechanistic-Empirical Pavement Design Guide, alligator cracking and long/trans cracking are load-related cracking [18]. Alligator cracking most often begins at the bottom of the wearing course and continues progressing towards the pavement surface, whereas long/trans cracking initially appears at the pavement surface [19].

This type of cracking is load-related and results from asphalt fatigue under traffic loads in combination with environmental effects [20]. However, block cracking is a very widespread form of degradation in the case of flexible pavements. Among the catalyst factors of this pathology is the volume of traffic [21]. Furthermore, bleed is defined as a shiny surface created by a film of bituminous binder on the pavement surface and becomes sticky [22]. It happens when the asphalt binder fills the aggregate voids in hot weather and then expands onto the pavement surface [23]. Similarly, rutting develops from the increase of repeated load until the final failure of the pavement structure, and it is one of the most widespread pathologies on roads [24].

Two photos taken from the RN1 national road are illustrated in the figure 1.

**Fig. 1 Two photos taken from the national road N1**

In those figures, the five distresses can be observed. The PCI values of the 100 sections, which vary from 0 to 100 (failed to excellent rating), are used to develop the ANN model.The range of the values of the PCI was determined by Shahin and Kohn [10] in order to interpret the results found.

**Table 2. Interpretation of the rating scale of the PCI [Shahin and Kohn, 1981]**

| Rating scale | Interpretation |
|---|---|
| 0-10 | Failed |
| 10-25 | Very Poor |
| 25-40 | Poor |
| 40-55 | Fair |
| 55-70 | Good |
| 70-85 | Very Good |
| 85-100 | Excellent |

After calculating the PCI value for all cases, 26% of them were in the range of 25 to 39, which means a poor condition rating of the roadway, while 12% of the cases were in the range of 85 to 100, which means an excellent condition rating.

*3.2.2. Application of the Neural Networks in the Case Study*
*Training Sets Preprocessing*

Preprocessing input data involves presenting training sets that are acceptable to the network. Preprocessing represents normalizing the feature values. The normalization process can be accomplished through dividing features values by a constant, dividing by the maximum value that a feature could have within the scope of the network, or using any function that satisfies the transfer function range.

The functions of the normalization process are [25] to:

- Reduce the variability of the ranges of feature values;
- Group training sets that pertain to each class close to each other;
- Disperse the training sets that pertain to other classes;
- And reduce the possibility of early network saturation.

Normalization process may be necessary if there is a wide difference between the ranges of feature values [1]. The normalizing approach used in this study is to divide each distress type's weighting by 120% of the maximum weighting available in all training sets. The purposes of this normalization process are to maintain all distress weightings between 0.0 and 1.0 and to ensure that the neural network prototype is used up to 20% more than the worst pavement condition appearing in the observations while adapting new observations.

Training the neural network consists of initializing the correlation coefficients of the three phases (learning, testing and validation), then initializing the number of neurons per hidden layer, knowing that we tested one hidden layer, then two hidden layers up to five hidden layers and going from 1 to 5 neurons for the first hidden layer.

The creation of a new neural network (net) that contains standardized inputs and outputs, a certain number of hidden layers and neurons per layer, involves the use of a transfer function corresponding to each layer (Tansig for the hidden layer and Purelin for the output layer), a Trainlm learning algorithm which uses Levenberg-Marquardt backpropagation techniques.

Here is a recap of the properties used to train the network:

**Table 3. Training properties**

| | | | | | |
|---|---|---|---|---|---|
| Training function | trainlm | | | | |
| Adaptation learning function | learngdm | | | | |
| Network type | feed-forward pack prop | | | | |
| transfer function | purelin | | | | |
| | Number of neurons | | | | |
| Number of layers | 1 | 2 | 3 | 4 | 5 |
| 1 | Network 111 | Network 112 | Network 113 | Network 114 | Network 115 |
| 2 | Network 121 | Network 122 | Network 123 | Network 124 | Network 125 |
| 3 | Network 131 | Network 132 | Network 133 | Network 134 | Network 135 |
| 4 | Network 141 | Network 142 | Network 143 | Network 144 | Network 145 |
| 5 | Network 151 | Network 152 | Network 153 | Network 154 | Network 155 |

*3.2.2. Results*

The twenty-five networks were studied, and network 115 demonstrated the lowest RMSE; it is selected for simulation, and its structure is presented in the figure below.

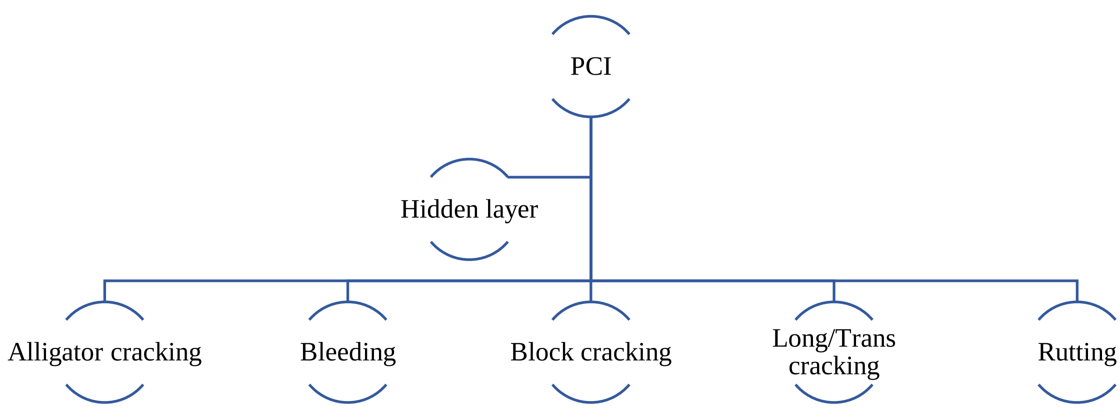


**Fig. 2 The ANN network**

The root-mean-square error of network 115 is illustrated in Figure 3. Its value is up to $4x10^{-3,}$ which is a low error. Then, the values of the coefficient of multiple determination for training, validation, test and all are illustrated in Figure 4.

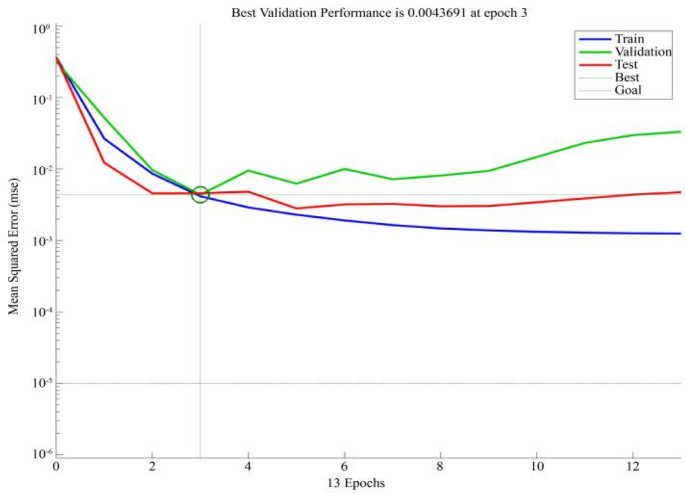


**Fig. 3 The shape of the 115's network RMSE error**

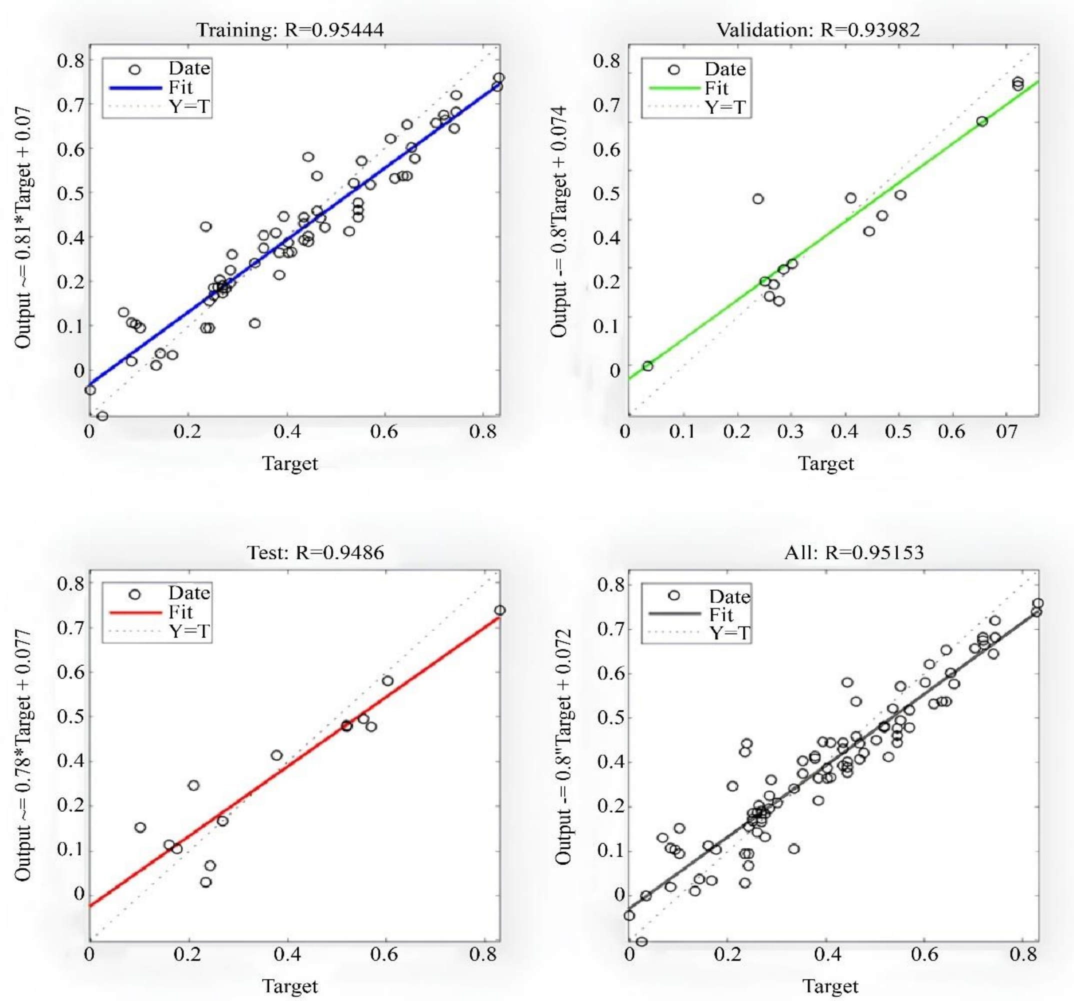


**Fig. 4 The 115's network $R^2$ errors**

The $R^2$ values are close to 1, hence better convergence between the real and prediction values.

Then, a sample of 10% of our data is simulated using network 115, and we obtain the predicted values of the sample as represented in Table 4.

**Table 4. Predicted values of the simulation**

| Predicted values |
|---|
| 0,28685 |
| 0,35886 |
| 0,26958 |
| 0,52436 |
| 0,024527 |
| 0,19262 |
| 0,53239 |
| 0,35886 |
| 0,5302 |
| 0,71691 |

## 4. Discussion

### *4.1. Analysis of Results*

The purpose of this research is to develop a main model that will be used to predict Moroccan road performance using artificial neural networks. The PCI is then calculated once the road section has been visually inspected and the pathologies influencing it have been determined. During the training of the 25 neural networks tested and following the calculation of the errors which gives very optimal values, minimum root-mean-square error values (RMSE= $4{,}3691 \times 10^{-3}$) and quadratic error values close to 1 ($R^2 = 0{,}954444$ for the training, $R^2 = 0{,}93982$ for the validation, $R^2 = 0{,}9486$ for the test and $R^2 = 0{,}95153$ for all) so that means a successful test. This initial result highlights the applicability of neural networks to local cases, hence the possibility of broadening our field of study to study a higher value margin.As a second step to obtain the most optimal model, an automatic verification generated by script on MATLAB to provide the best possible architecture, we obtain the same architecture initially proposed 1 hidden layer with 5 neurons. In order to confirm this architecture, cross-validation is proposed to evaluate the performance of the models precisely and maximize the use of the available data.

**Table 5. Results of cross-validation**

| Topology | Number of Layers | Neurons per Layer | Activation Function | MSE | $R^2$ |
|---|---|---|---|---|---|
| Topology 1 | 1 | 5 | purelin | 0.0037 | 0.8156 |
| Topology 2 | 1 | 10 | purelin | 0.0043 | 0.7874 |
| Topology 3 | 1 | 15 | purelin | 0.0065 | 0.7294 |
| Topology 4 | 2 | 5 | purelin | 0.0055 | 0.6976 |
| Topology 5 | 2 | 10 | purelin | 0.0121 | 0.6446 |
| Topology 6 | 2 | 15 | purelin | 0.0100 | 0.4934 |
| Topology 7 | 3 | 5 | purelin | 0.0037 | 0.7163 |
| Topology 8 | 3 | 10 | purelin | 0.0045 | 0.7302 |
| Topology 9 | 3 | 15 | purelin | 0.0102 | 0.5426 |

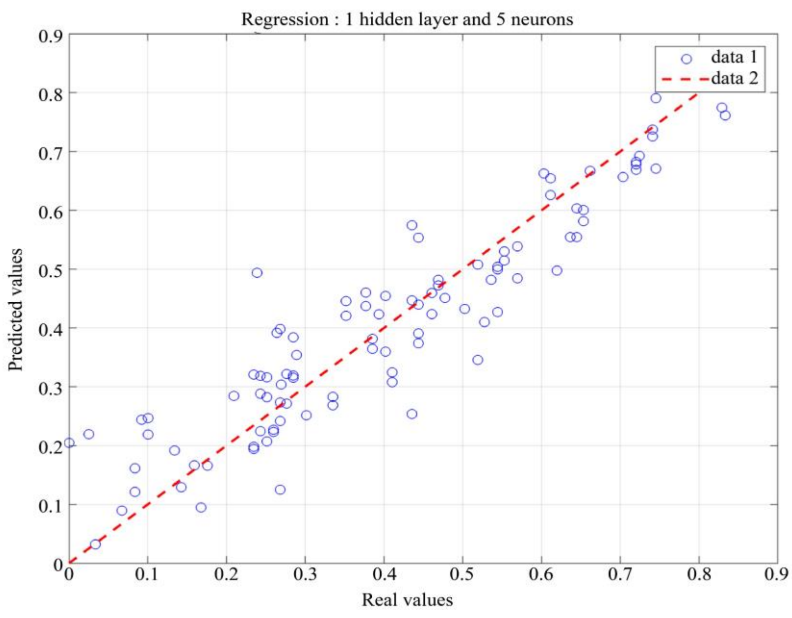


**Fig. 5 Regression of the chosen topology**

The difference in results found for the RMSE error and the $R^2$ coefficient is justified by:

- The first training is done using the graphical interface on MATLAB by changing the topology of the networks, while the second training is generated by script on MATLAB automatically.
- In the cross-validation part, the model is not trained on all the data simultaneously as in the graphical interface training.

Using both methods, the 1 hidden layer architecture with 5 neurons proves its performance in this case. As the architecture of a hidden layer with 5 neurons has been validated, a final study of data sensitivity is necessary in order to visualize the impact of each parameter on the PCI index. By varying the data by 3%, 5%, and 7%, as shown in the following table, the rutting pathology seems to be the variable that most impacts road conditions. Alligator cracking and block cracking, in addition to their similar nature and causes, come second among the factors impacting the PCI index.

**Table 6 . Output variation for different inputs under parameter changes**

| Variation of Parameters | Inputs | Variation of Output |
|---|---|---|
| 3% | Alligator cracking | [0.266 ; 0.271] |
| | Bleeding | [0.265 ; 0.270] |
| | Block cracking | [0.267 ; 0.272] |
| | Long/Trans cracking | [0.265 ; 0.270] |
| | Rutting | [0.264 ; 0.274] |
| 5% | Alligator cracking | [0.264 ; 0.272] |
| | Bleeding | [0.262 ; 0.274] |
| | Block cracking | [0.266 ; 0.271] |
| | Long/Trans cracking | [0.262 ; 0.274] |
| | Rutting | [0.260 ; 0.28] |
| 7% | Alligator cracking | [0.264 ; 0.274] |
| | Bleeding | [0.260 ; 0.275] |
| | Block cracking | [0.266 ; 0.272] |
| | Long/Trans cracking | [0.260 ; 0.275] |
| | Rutting | [0.245 ; 0.228] |

In order to give a clearer comparison with the existing literature, a comparative table below is presented on two artificial intelligence approaches used in the prediction of pavement performance.

**Table 7. Existing literature**

| Researchers | Abdualmtalab Abdualaziz et al. [26] | Owor et al. [27] | Mohamed S. Yamany et al. [28] |
|---|---|---|---|
| Problematic | This study aimed to evaluate the performance of conventional and machine learning techniques used to predict (PCI) from (IRI). | The aim of the study is to develop a model capable of predicting PCI directly from an image. | This study aims to build individual pavement performance models for each state in the United States, using data from its own road network for use in its pavement management system. |
| Methodology | In this study, Random Forest and Support Vector Machine and ML techniques were used to develop a reliable and accurate PCI value based on IRI. | In this study, deep MTL is developed to implicitly learn features to simultaneously predict the type, extent, and severity and estimate the PCI of a pavement image. | In this study, using data on the condition of flexible interstate pavements from eight Midwestern states, three models were estimated: fixed parameter regression, random parameter regression, and artificial neural networks (ANN). |
| Errors | RF: $R^2$=0,997 and RMSE=1,095%, SVM: $R^2$=0,968 et SVM=3,569% | R2=0,75 and MAPE=10,5% | RP: $R^2$= 0,48 and MSE=0,0894, ANN: $R^2$=0,71 and MSE=0,0707 |
| Merits | This study will reduce the time required to process distress images for PCI determination and objectivize human opinion in evaluating roadway performance. | This study will greatly contribute to achieving comprehensive and automated PCI surveys at the network level. | This study validates the fact that ANNs are more accurate for modeling road surface roughness, given their ability to capture complex nonlinear relationships. |

| | | | |
|---|---|---|---|
| Perspectives | It is recommended that the accuracy of the models be improved and the databases used be expanded. | Further studies could be addressed by improving the model architectures and increasing the number of images. | This problem can be re-examined with a larger dataset containing information on pavement surface material, layer thickness, type of base course material, topography, construction quality, drainage, and the type and effectiveness of maintenance and rehabilitation interventions. |

### *4.2. Merits and Demerits of the Study*

The first of its kind at the national level, this study examined the applicability of neural networks through identifying pathologies affecting roads, particularly alligator cracking, bleeding, block cracking, long/trans cracking and rutting, subsequently facilitating their examination and evaluation. As a result of the sensitivity study, bleeding and long/trans cracking pathologies have not been shown to have a large impact on the pavement condition index. Given the limited number of samples taken into account, this study is only a basic founding step for a broad wave of research in this field of predicting the performance of road pavements in Morocco.

A future study will consider the major pathologies (Rutting, alligator cracking and block cracking) and other parameters in other models to evaluate pavement performance, such as the convolutional neural network. A subsequent comparative study will be necessary to demonstrate the results obtained in the present study with those of a convolutional neural network with the above-mentioned parameters.

### *4.3. Contribution*

By studying five different pathologies affecting the roads and modeling them by neural networks, an artificial intelligence method that has proven its performance, this study will contribute greatly to clarifying a study path to develop a personalized pavement management system for Moroccan roads, given their diversity. Also, this type of study will help decision-makers evaluate, plan, and carry out road network maintenance programs.

## 5. Conclusion

This study is established with the objective of studying models based on neural networks to determine the pavement condition index. According to the study, the use of neural networks has a number of important advantages over other assessment models, not only due to the ease of assessment provided but also the accuracy and objectivity of the calculations. Based on a large database collected by the national center for road studies in Rabat, an analysis of a road section is made in order to extract pathologies such as rutting, block cracking, long/trans cracking, bleeding and alligator cracking that this road network undergoes. A high-precision model based on artificial neural networks was subsequently studied, and the results made it possible to predict the PCI index. The PCI value was the model's output, while the input variables were the above-mentioned impairments. The main findings of the study are:

- Low error levels and errors that were within a tolerable range were displayed by the ANN model;
- The suggested model may be applied in the PMS and offer a trustworthy PCI prediction;
- The viability of the ANN approach in solving nonlinear issues was demonstrated.

In order to validate the studied model, cross-validation of several architectures was carried out to approve the chosen one. Also, the data have undergone sensitivity analysis to verify the credibility of their impact on pavement performance. Rutting, alligator cracking and block cracking seem to be the most critical parameters for pavement condition. Furthermore, as more data becomes available, the model used in this work may be retrained using fresh examples, increasing its accuracy even further.

## Authors' Information and Contributions

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- Experimental measurement and simulation of railway track Irregularities.
- Dynamic Behavior of a Railway Track Under a moving Wheel Load Modelled as a Sinusoidal Pulse.
- Periodic Structures as a Countermeasure of Traffic Vibration and Earthquake: A Review.

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