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# ADVANCED PREDICTIVE MODELING OF PAVEMENT CONDITION INDEX USING ARTIFICIAL NEURAL NETWORKS: A COMPREHENSIVE CASE STUDY IN TEXAS

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**Abstract**

Roadways are pivotal to a nation's economic growth, making effective pavement management systems (PMS) essential for maintaining highway networks cost-efficiently. This research explores the potential of forecasting the Pavement Condition Index (PCI) for flexible pavements using Artificial Neural Networks (ANNs) alongside the Long-Term Pavement Performance (LTPP) database. The study considers various factors, including age, traffic volumes, temperature, humidity, precipitation, freezing, and layer thickness (A.C. Base-Subbase-Subgrade). Utilizing data from 60 sections in Texas, USA, without overlays (classified as SPS-1 by LTPP), the ANN model was developed in MATLAB to predict PCI. The findings reveal the model's exceptional accuracy in forecasting PCI, with correlation coefficients ($R^2$) exceeding 90% for all sections. This indicates the robust applicability of ANN models in predicting pavement conditions, facilitating effective road maintenance planning.

**Keywords**: ANNs; PCI; predict; forecast; flexible pavement; Pavements and roads; artificial intelligence.

## 1. Introduction

Building a reliable system for moving goods and people is essential and demands substantial investment. The quality of pavement is a cornerstone of a region's economic prosperity. With the rise in motorization, highways have become more significant, reflecting a nation's civilization level. Surface deterioration remains a prevalent issue, affecting sustainability, costs, and safety. Forecasting the condition of pavements is essential for proper management, yet poses significant challenges for transportation agencies due to financial constraints. Precise forecasting necessitates substantial investment and proper repair and rehabilitation to maintain safe and efficient operation. Over time, pavements deteriorate because of materials used, environmental conditions, and traffic loads, resulting in reduced road safety and higher costs. Researchers are investigating different forecasting methods to improve design, construction practices, and maintenance approaches. For newly constructed roadways, design approaches that minimize maintenance costs by considering local conditions are recommended. For existing highways, the fastest and most cost-effective maintenance plans are essential. Predicting pavement performance through both functional and structural evaluations helps

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engineers and administrators tackle challenges in rehabilitation, maintenance, and distress prediction, ensuring roads remain serviceable (Mills, 2010).

Over time, various parameters and factors have been identified to evaluate pavement conditions based on pavement type. This encompasses factors such as pavement roughness, materials used, climatic conditions, crack density, faulting, rutting, distresses, pavement surface characteristics, the Long Term Pavement Performance (LTPP) database, axle load spectra, and pavement structural capacity (Ali et al., 2024; Han et al., 2023; Hu et al., 2022). A case study on highway network-level pavement repairs employed a ranking system to prioritize five factors: structural strength, age, traffic loads, road gradient, and pavement performance (Li et al., 2018). Choosing factors relies on the assessment's specific objectives, the type of pavement in question, and the data at hand. Customized performance prediction models for each pavement management system (PMS) are crucial for directing maintenance and rehabilitation efforts, while also ensuring compliance with Quality Control Plans throughout the concession period (Jorge & Ferreira, 2012). Thus, it's essential to update PMS to reflect evolving pavement conditions. Road infrastructure agencies must address the significant challenge of optimizing pavement repair strategies while balancing a multitude of factors.

Over the past decades, data analysis has been instrumental in the development of new materials, as well as in maintenance planning, repair, and pavement design (Khichad & Vishwakarma, 2024). Numerous research efforts have evaluated the effectiveness of concrete pavements susceptible to fatigue-related damage (Khichad et al., 2022; Khichad et al., 2023; Vishwakarma & Ingle, 2020). Recognizing the critical flexural stress is essential in pavement design; however, current guidelines vary due to differing underlying assumptions (Vishwakarma & Ingle, 2019; Vishwakarma & Ingle, 2017, 2018). These results provide crucial insights into critical stress distribution, facilitating comparisons between various guidelines and supporting the design of pavements. Whether it's machine learning, regression analysis, artificial neural networks (ANNs), or PMS, each algorithm follows distinct steps according to identified variables. These methods explore the use of cutting-edge materials, construction techniques, and design methodologies to improve structural durability, integrity, and long-term performance. For example, Soltani et al. (2023) employed response surface methodology to assess the effects of aggregate size, water-cement ratio, and cement content on compressive strength, porosity, and permeability in pervious concrete pavement (Soltani et al., 2023). Fawaz Alharbi and Omar Smadi (2019) used ANNs to predict pavement performance in Iowa, utilizing data from the Iowa Department of Transportation (DOT) which included pavement condition data and traffic loading. An ANN model was employed to forecast ride quality, cracking, rutting, and faulting indices for various pavement types. Database sets were randomly divided using JMP software, with 70% of the data allocated for training and 30% for testing and validation of the ANN model. In addition, traditional multiple linear regression models were created and evaluated against the ANN models. The results indicated that the ANN models provided more accurate predictions than the MLR models (Alharbi, 2018). Sanja Dimter et al. (2018) employed ANNs to determine a global performance indicator and select appropriate pavement management services (PMS). The selection of a suitable maintenance strategy is complex, involving parameters such as road classification, traffic volume, and current pavement condition. The study examined the potential of using ANNs to evaluate


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existing pavement conditions. The findings demonstrated that ANNs could be effectively used to enhance rehabilitation and maintenance strategies (Josipa DOMITROVIĆ, 2018). Mehran Mazari and Daniel D. Rodriguez (2016) examined two sets of pavement roughness data from the LTPP database. They utilized the first dataset to refine and develop a roughness prediction model employing a gene expression programming technique. Using this hybrid approach, they predicted the International Roughness Index, achieving interactive and satisfactory results that matched existing prediction models in the literature. To enhance the generalization of the proposed models, future research could benefit from including a wider array of pavement structural properties, roughness data, and traffic indices (Mazari & Rodriguez, 2016).

The primary objective of this research is to develop predictive models for the Pavement Condition Index of flexible pavements, allowing for accurate future forecasting. By employing advanced artificial neural network (ANN) methodologies, this study leverages the extensive LTPP database. Through this approach, we aim to identify key variables and patterns that influence pavement deterioration and performance over time. The findings will provide valuable insights for transportation agencies, enabling them to plan more effective maintenance and rehabilitation strategies, optimize resource allocation, and ultimately enhance the longevity and safety of pavement infrastructure. This research not only contributes to the existing body of knowledge but also offers practical solutions for managing and preserving critical road networks efficiently.

## 2. ANNs Principles:

ANNS is a machine-learning technique that mimics the structure of the human brain by utilizing many artificial neurons. The activation level of each neuron in an artificial neural network (ANN) is determined by applying an activation function to the many inputs that each neuron receives(Hammerstrom, 1993). Because of their adaptability, neural networks are able to deduce answers from the data that is given to them, frequently identifying very subtle associations. Data that just slightly differs from the data that they were trained on initially are processed appropriately by ANNs with generalization capabilities. They also offer some fault tolerance because they can manage missing or erroneous data. Sundry is advantageous for pavement prediction modeling among the useful characteristics of ANNs as illustrated by Hewitson and Crane. Its capacity to depict any random nonlinear function is its main characteristic. ANNs come in various forms and architectures, making them highly versatile with numerous applications in road and traffic engineering (Bianchini & Bandini, 2010). Neural networks have generally been applied to solve a number of challenging pavement engineering challenges that have been documented. Nowadays, many of the issues in pavement performance modeling can be resolved with the application of neural networks (Hammerstrom, 1993).

## 3. Methodology:

Pavement data from Texas, in the United States, are utilized to determine the key zones covered by this research technique. after the necessary data collection from LTPP. ANNs were employed in this study to predict pavement performance. The following figure shows the flow chart of the methodology used in the research in Figure 1.

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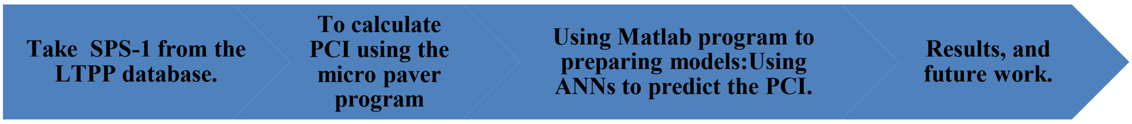


Figure 1 Flowchart of the methodology used in the research

## 4. Gathering of data:

This study focuses on segments from the Specific Pavement Studies (SPS) within the LTPP database. The SPS sections track newly built or existing pavement sections undergoing maintenance or rehabilitation (Elkins et al., 2003). Specifically, the chosen sections are identified by the SPS-1 symbol. Table 1 samples a detailed breakdown of the number of sections and their locations in Texas as recorded in the LTPP database for this study.

Table 1. thickness layers, Climate data, traffic data, age and PCI data for SPS-1 in LTPP sections.

| State Code | SHRP-ID | Age | Asphalt Concrete | | | Base | | Engineering Fabric (in) | subbase | | Engineering Fabric (Woven Geotextile) (in) | Subgrade (untreated) (in) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | A.C layer 3 (in) | A.C layer 2 (in) | A.C layer 1 (in) | Bound (treated) (in) | Unbound (granular) (in) | | Bound (treated) subbase (in) | Unbound (granular) (in) | | | Annual Average Precipitation (mm) | Annual Average Temperature (deg C) | Annual Average Freeze Index (deg C deg da | Annual Average Humidity Min-Max (%) | 18-Kip ESAL (KESAL) |

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| | | | | | | | | | | | | | | | ys) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 48 | 116 | 0.71 | 0 | 2.2 | 2.6 | 10.9 | 0 | 0 | 12 | 0 | 0 | 0 | 626.7 | 24.3 | 0 | 66.5 | 427 |
| 48 | 117 | 0.15 | 0 | 0 | 4.7 | 4 | 3.5 | 0 | 12 | 0 | 0 | 0 | 678 | 22.8 | 1 | 66.5 | 415 |
| 48 | 117 | 0.71 | 0 | 0 | 4.7 | 4 | 3.5 | 0 | 12 | 0 | 0 | 0 | 626.7 | 24.3 | 0 | 66.5 | 427 |
| 48 | 117 | 2.13 | 0 | 0 | 4.7 | 4 | 3.5 | 0 | 12 | 0 | 0 | 0 | 613.6 | 24.1 | 0 | 66.5 | 440 |
| 48 | 117 | 2.86 | 0 | 0 | 4.7 | 4 | 3.5 | 0 | 12 | 0 | 0 | 0 | 436.6 | 24 | 0 | 69 | 453 |
| 48 | 117 | 3.58 | 0 | 0 | 4.7 | 4 | 3.5 | 0 | 12 | 0 | 0 | 0 | 545.9 | 23.7 | 0 | 69.5 | 321 |
| 48 | 118 | 0.15 | 0 | 0 | 3.1 | 7.5 | 1.7 | 0 | 24 | 0 | 0 | 0 | 678 | 22.8 | 1 | 66.5 | 415 |
| 48 | 118 | 0.71 | 0 | 0 | 3.1 | 7.5 | 1.7 | 0 | 24 | 0 | 0 | 0 | 626.7 | 24.3 | 0 | 66.5 | 427 |
| 48 | 118 | 2.13 | 0 | 0 | 3.1 | 7.5 | 1.7 | 0 | 24 | 0 | 0 | 0 | 613.6 | 24.1 | 0 | 66.5 | 440 |
| 48 | 118 | 2.86 | 0 | 0 | 3.1 | 7.5 | 1.7 | 0 | 24 | 0 | 0 | 0 | 436.6 | 24 | 0 | 69 | 453 |

| | | Age | Alligator | Block cra | Long. and Trans. | Patching | Pothole | shoving | bleeding | raveling | pumping | PCI |
|---|---|---|---|---|---|---|---|---|---|---|---|---|

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| State Code | SHRP-ID | | crack | | | cking | | | cracking | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | L | M | H | L | M | H | L | M | H | L | M | H | L | M | H | A | M | H | L | actual |
| 48 | 116 | 0.71 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 100 |
| 48 | 117 | 0.15 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 100 |
| 48 | 117 | 0.71 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 100 |
| 48 | 117 | 2.13 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 100 |
| 48 | 117 | 2.86 | 0 | 0 | 0 | 0 | 0 | 0 | 7.7 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 100 |
| 48 | 117 | 3.58 | 0 | 0 | 0 | 0 | 0 | 0 | 36.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 93 |
| 48 | 118 | 0.15 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 100 |
| 48 | 118 | 0.71 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 100 |
| 48 | 118 | 2.13 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 100 |
| 48 | 118 | 2.86 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 100 |

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## 5. Creation of Training Sets:

This research utilized the LTPP database and focused on flexible pavement sections, employing a standardized approach to extract the required data from LTPP. To start, a single database was created to gather data on distresses for the areas of the site that were being watched. The standard table includes every component used in the research, as indicated in Table 1. These components include the section code, age, traffic volumes, temperature, humidity, precipitation, freezing, and the thickness of each pavement layer. Along with the three severity levels (low, medium, and high) for each distress in the segment, the age of the section was also recorded. The micro-paver program computed the PCI value. The present study involved the collection of 60 sections from the LTPP, as indicated in Table 1. A pavement condition index model was developed by utilizing many inputs for each section, including the thickness of each pavement layer and variables related to temperature, humidity, freezing, and precipitation according to location in Taxes. As **Figure 2**. Data sets according to SHRP-ID in Taxes from the flexible pavement database.

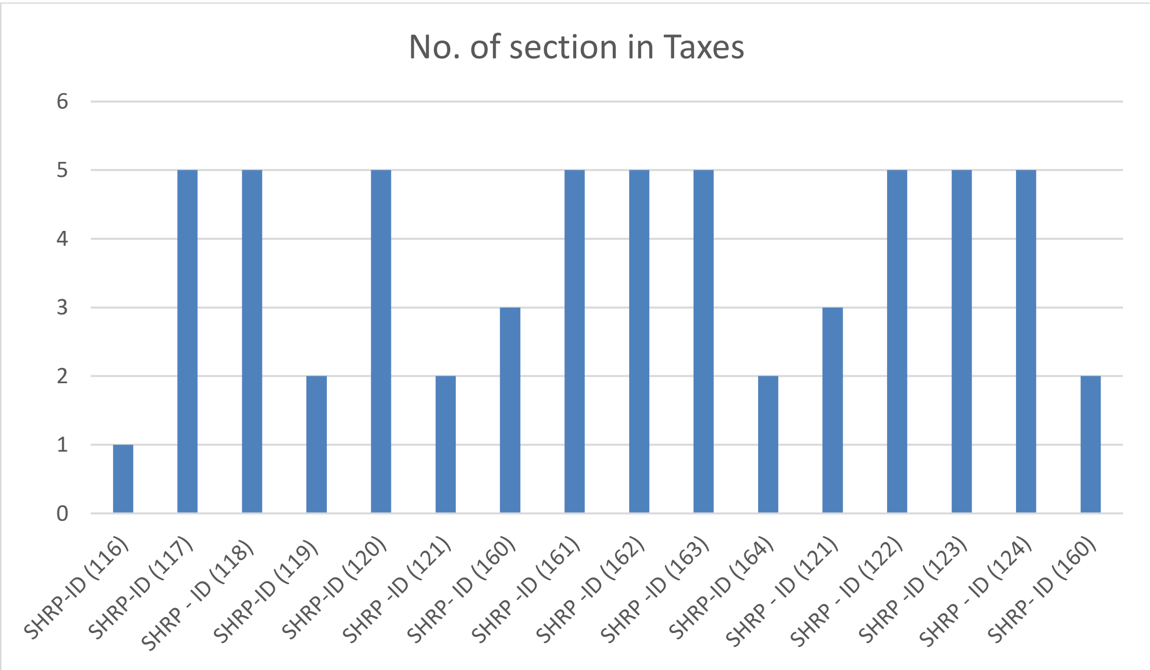


**Figure 2.** Data sets according to SHRP-ID in Taxes from the flexible pavement database.

## 6. Evaluation of ANN Models for Flexible Pavement:

In constructing the models, we concentrated on variables influencing pavement performance, such as service life, traffic, pavement layer thickness, environmental factors, climate data, and distresses. These elements contribute to a comprehensive database detailing the construction, traffic, materials, performance, and environment of the test sections. Key inputs for developing the ANNs model included road code, layer thicknesses, climate data (temperature, humidity, precipitation, freezing), age, traffic volumes, and all distress levels classified into three severity degrees (H-M-L), as illustrated in Figure 3.

The ANNs models were created using these input data. The sections of a MATLAB model building for ANNs must be split into two halves: 70% for the training phase and 30% for the

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testing phase [4]. The No. of layers in the model employed in that investigation is displayed in **Figure 4**. Data sets for testing and training were chosen at random from the flexible pavement database.

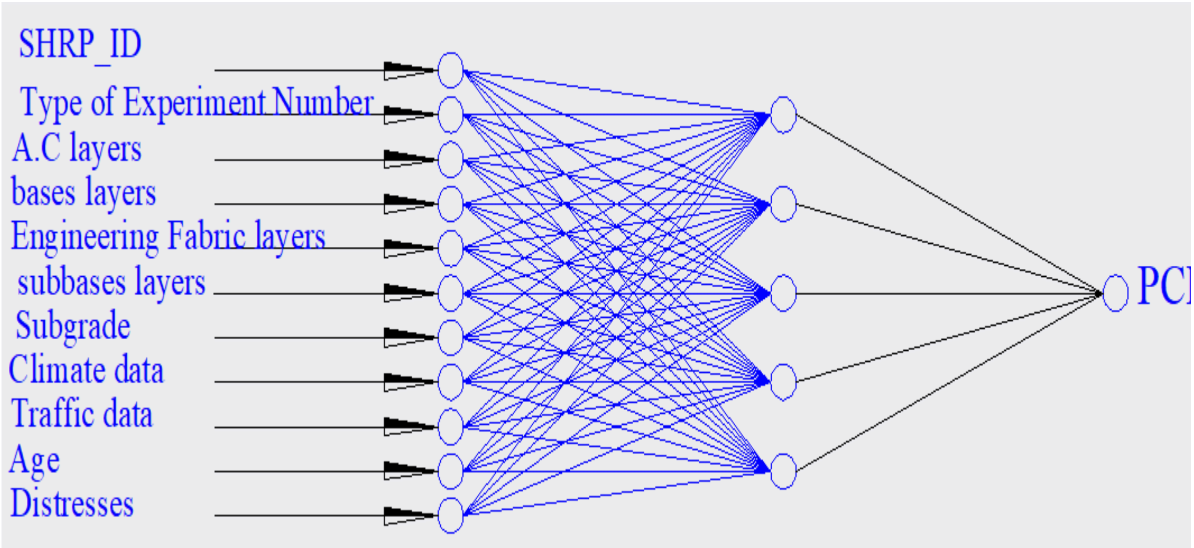


**Figure 3:** shows the PCI in ANN prediction model.

This study used a single model for a single subject; overlay was not utilized for handling the distress; the subject was SPS-1.As Figure 5 illustrates, the studies demonstrated great accuracy in PCI prediction. The model's correlation coefficient ($R^2$) was 98.5%, and the outcomes were outstanding.

The complex link between the number of big pavement factors and the PCI has been shown to be amenable to modeling by ANNs. The relationship between tested and actual PCI as well as the relationship between trained and actual PCI are demonstrated in the following. There is a clear linear connection between the values. As a result, demonstrate that the $R^2$ of the association between the actual PCI and the expected PCI is greater than 90%. The model is applied to the category based on various criteria, including actual PCI, temperature, humidity, precipitation, freezing, age, traffic volumes, and pavement layer thickness. The anticipated PCI value was the only output parameter.

Training and testing data sets were chosen at random from the flexible pavement database. The ANN models generated a higher coefficient of multiple values when compared to the testing data set and the actual PCI selected for the tested process. With a coefficient of multiple determination of 0.95442 for the testing data set, 0.97836 for the training data set, and 0.93355 for the validation data set, the created ANN models predicted the computed PCI values, as illustrated in Figure (4). As seen in Figure (5), the predicted data's coefficient of multiple, calculated using MATLAB software, was 0.9853. Hence, the analysis of variance for PCI is shown in Table 2, in detail.

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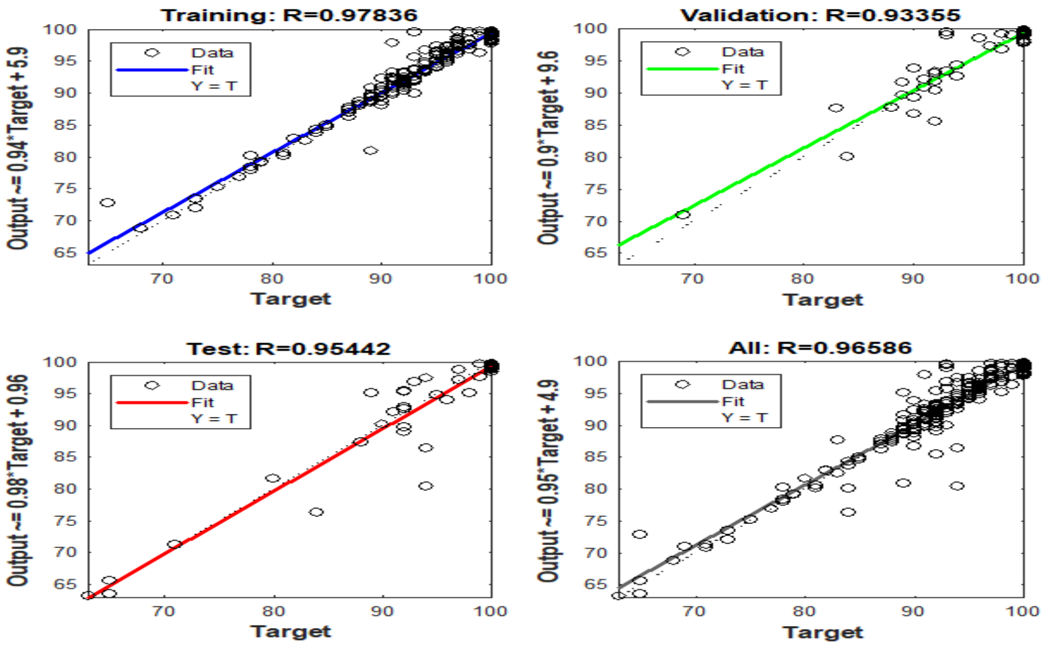


Figure 4: The relationship between the MATLAB program's expected and actual PCI.

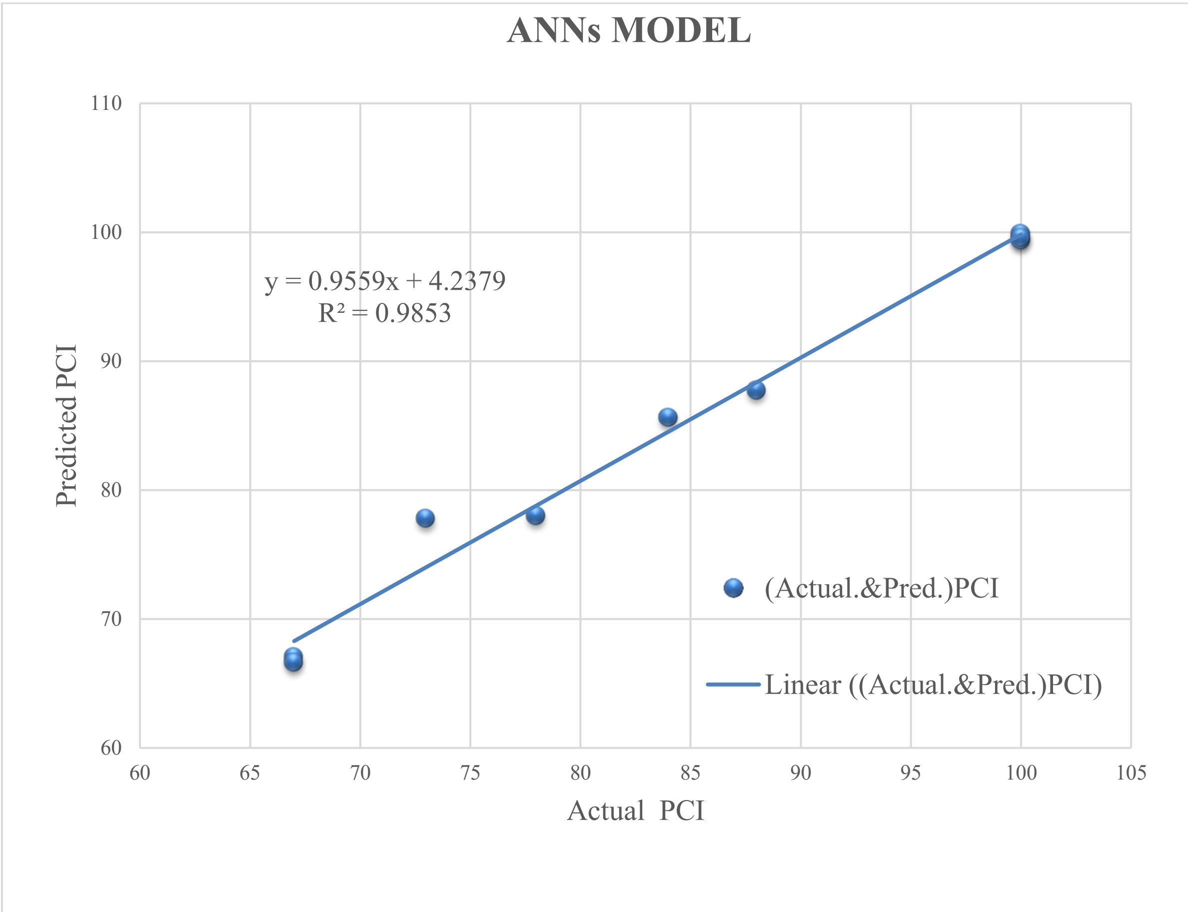


Figure 5: ANNS Model utilizing MATLAB program between Actual PCI and Expected PCI.

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Table 2. Summary Output of ANOVA for PCI

| *Regression Statistics* | |
|---|---|
| Multiple R | 0.992608679 |
| R Square | 0.985271989 |
| Adjusted R Square | 0.983167987 |
| Standard Error | 1.787664576 |
| Observations | 9 |

ANOVA

| | *df* | *SS* | *MS* | *F* | *Significance F* |
|---|---|---|---|---|---|
| Regression | 1 | 1496.519 | 1496.519 | 468.2848 | 1.13E-07 |
| Residual | 7 | 22.37021 | 3.195745 | | |
| Total | 8 | 1518.889 | | | |

| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* | *Upper 95%* | *Lower 95.0%* | *Upper 95.0%* |
|---|---|---|---|---|---|---|---|---|
| Intercept | -3.129192336 | 4.075259 | -0.76785 | 0.467682 | -12.7656 | 6.507264 | -12.7656 | 6.507264 |
| pred | 1.030692304 | 0.047629 | 21.63989 | 1.13E-07 | 0.918067 | 1.143318 | 0.918067 | 1.143318 |

RESIDUAL OUTPUT

| *Observation* | *Predicted actual* | *Residuals* | *Standard Residuals* |
|---|---|---|---|
| 1 | 77.27408357 | 0.725916 | 0.434107 |
| 2 | 99.32162264 | 0.678377 | 0.405678 |
| 3 | 87.3073578 | 0.692642 | 0.414208 |
| 4 | 65.98428205 | 1.015718 | 0.607412 |
| 5 | 65.57469524 | 1.425305 | 0.852349 |
| 6 | 99.83202147 | 0.167979 | 0.100453 |
| 7 | 99.53095625 | 0.469044 | 0.280494 |
| 8 | 85.13805971 | -1.13806 | -0.68057 |
| 9 | 77.03692127 | -4.03692 | -2.41413 |

PROBABILITY OUTPUT

| *Percentile* | *actual* |
|---|---|
| 5.555556 | 67 |
| 16.66667 | 67 |
| 27.77778 | 73 |
| 38.88889 | 78 |
| 50 | 84 |
| 61.11111 | 88 |
| 72.22222 | 100 |
| 83.33333 | 100 |
| 94.44444 | 100 |

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## 7. Conclusions

This study illustrates the development of an Artificial Intelligence(AI) approach to predict the PCI and could be successfully applied. The purpose of this research is to demonstrate that ANNs can accurately forecast the PCI. For huge pavement networks, ANNs can handle huge amounts of data. It was shown that ANNs are better and fitted for mapping the complex, nonlinear relationship between a huge number of pavement input parameters and the PCI values. The outcomes showed that using the MATLAB application, ANN models were able to forecast the PCI values accurately. According to the results, the correlation coefficient ($R^2$) for the data expected in the flexible pavement model is 98.5% for the category of sections. On the other hand, the outcomes show that the suggested approach has strong prospects for maintenance scheduling. It was deduced in this study that the suggested ANNS model was a useful tool for pavement maintenance and rehabilitation program planning and budget allocation in the PMS. We also suggest improvement of the model by changing the network type or training function or using another enough data of the pavement sections.

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