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MACHINE LEARNING MODELLING THE RUT DEPTH OF WMA MIXTURES WITH VARIABLE RECLAIMED ASPHALT PAVEMENT (RAP) AND FOAMED BITUMEN CONTENT

Abstract

Introduction. Rutting of flexible, super flexible and semi-rigid pavement structures is a typical and frequently decisive condition parameter, form of pavement deterioration. That is why, any research result in the field can have of high importance for the road engineers.

Problem Statement Rutting poses a significant challenge to asphalt pavements, causing permanent deformation under heavy loads, particularly in warm and wet conditions.

Purpose. This pavement distress type has — in addition to riding comfort challenges — important traffic safety consequences (e.g. aquaplaning), as well. The research work concentrates on the influence of the use of warm mix asphalt, reclaimed asphalt material and foamed bitumen binder on the rut depth of asphalt pavements.

Materials and Methods. In integration of machine learning techniques, a Feedforward Neural Network model was presented to analyse the relationship between pavement rut depth and Reclaimed Asphalt Pavement (RAP) content. The model, trained for RAP content ranging from 0 % to 100 %, showcased varying R-squared values, with the highest at 50 % RAP content. Additionally, a Gaussian Process Regression (GPR) model was employed, highlighting the significant effects of RAP content between 75 % and 100 %. Sensitivity analysis on the GPR model provided insights into parameter effects, while the significant influence of the number of wheel passes on pavement rut depth values emphasized the importance of optimal road maintenance timing.

Results The results of the machine learning model indicated a R-squared value of 0.476 for 0 % RAP content and higher values for mixtures containing RAP, with the highest value of 0.897 was found for 50 % RAP content in the asphalt mixture. A Gaussian Process Regression (GPR) model applied showed paradoxical effects between 75 % and 100 % RAP content. The derivative of the predicted mean rut depth as a function of RAP content revealed varying effects on Rut depth values in the case of different RAP content ranges. Sensitivity analysis on the GPR model was conducted by varying parameters such as Length Scale, Noise Level, and Amplitude. The results of this analysis provided insights into how changes in these parameters affected the mean squared error (MSE) for their various combinations. The influence of the number of wheel passes on rut depth values was examined, showing a significant increase in rut depth after 12,000 passes and reaching its maximum value after 20,000 passes.

Keywords**:** foamed bitumen; warm mix asphalt; reclaimed asphalt pavement; Neural Network; GPR; Machine learning.

Introduction

Rutting, a common distress in asphalt pavements, occurs when the pavement surface de-forms permanently due to repeated heavy loads, particularly in warm and wet conditions. This deformation can compromise the smoothness and safety of roads. It necessitates a thorough understanding of its underlying mechanisms and effective mitigation strategies [1]. Several experimental studies, such [2], [3] have played a crucial role in unravelling the complexities of pavement rutting. Among the various tests used to characterize rutting, the Hamburg wheel tracking test (HWTT) stands out as a widely recognized method for simulating the effects of heavy traffic loads on asphalt pavements [4].

Researchers have also investigated the potential of different additives, including SBS, rubber, and recycled materials, to reduce rut depth. Lv et al. [5] found that modifying asphalt mixes with SBS polymers led to decreased pavement rut depth, albeit with optimal additive dosages needing identification. Similarly, Ziari et al. [6] observed significant reductions in rut depth with increased rubber content in asphalt mixes.

Temperature variations during testing have also been investigated, researchers highlighting the importance of adjusting testing protocols to accurately reflect real-world climate conditions. This adaptation is crucial for ensuring that testing outcomes align with the actual performance of asphalt pavements [7].

Furthermore, the integration of advanced machine learning techniques, exemplified by the work of Majidifard et al. [8], offers a promising avenue for predicting rut depth based on asphalt properties. By leveraging convolutional neural networks (CNN), these models provide efficient and cost-effective means for pavement design and material screening, in line with the evolving methodologies advocated by Buss et al. [9]. In essence, these interdisciplinary efforts underscore the importance of comprehensive research and innovative methodologies in addressing rutting issues in asphalt pavements.

Experimental

Determination of aggregate gradation

Mixed operations involved the use of gradations containing 100% reclaimed asphalt pavement (RAP), 75 % RAP, 50 % RAP, 25 % RAP, and 0 % RAP (consisting entirely of virgin aggregate), all adhering to standard specifications [10], [11], [12] as shown in **Fig. 1**. The maximum specific gravities (Gmm) for these gradations were recorded as follows: 2.464, 2.471, 2.476, 2.468, and 2.474, respectively.

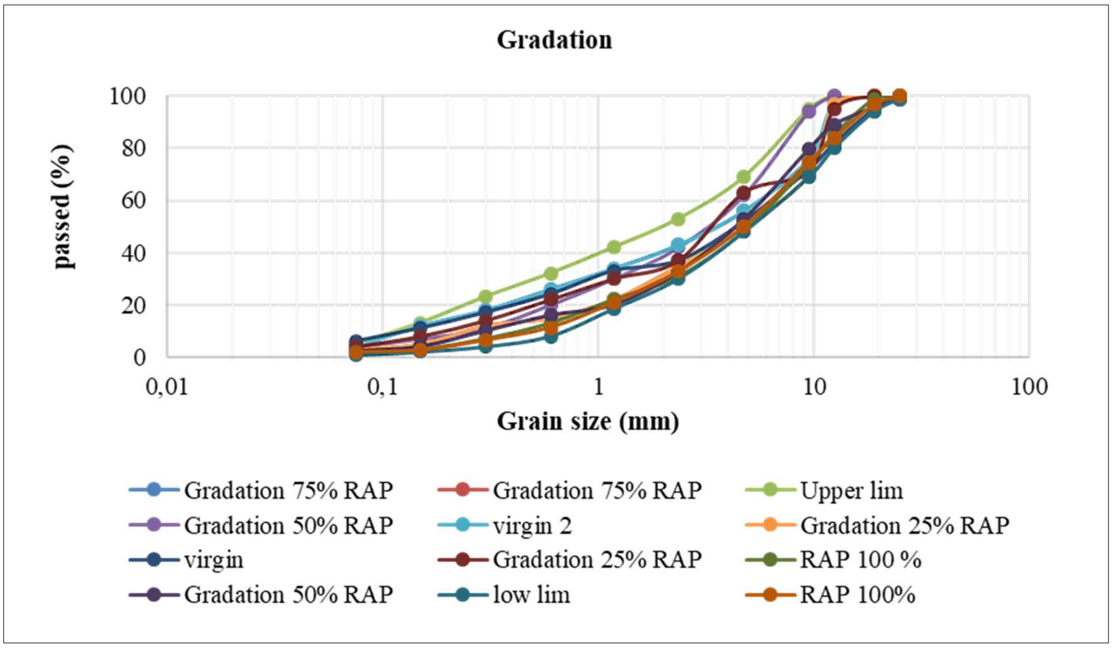

Figure 1 — Gradations selected

Bitumen type

The test series applied bitumen penetration grade 70/100 as binder. It met the prescribed standard criteria [13]. **Table 1** presents the characteristics of the bitumen applied.

In order to use this bitumen in foaming process, it achieved a half-life of 10.2 s and an expansion ratio of 12.6 times specifically with a 2 % water content at a bitumen temperature of 170 °C.

Table 1

Bitumen characteristics

Bitumen type	Penetration, 0,1 mm	Loss on heating, m %	Softening point, ºC	Flash point, ºC
70/100	82.6	– 0.4 %	46.6	238

Machine learning models

Feedforward Neural Network (FNN)

Mixed operations involved the use of two gradations containing 100 % reclaimed asphalt pavement (RAP), two with 75 % RAP, two with 50 % RAP, two with 25 % RAP, and two consisting entirely of virgin aggregate all adhering to standard specifications (**Fig. 1**). The maximum specific gravity (Gmm) for these gradations were recorded as follows: 2.464, 2,471, 2.476, 2.468 and 2.474, respectively.

The Feedforward Neural Network (FNN), also known as a Multi-layer Perceptron (MLP), consists of multiple layers of neurons, including input, hidden, and output layers. The activation function used in the hidden layers is Rectified Linear Unit (ReLU), and the output layer does not have an activation func- tion.

Mathematically, the output y_i (excitation) of a node [14] is computed as:

$$y_i = \varphi_i \left(\sum_{j=1}^{n^i} w_j^i \cdot z_j^i + b^i \right), \quad (1)$$

where n^i are the total incoming connections, z^i is the input, w^i is the weight, b^i is the bias, and φ_i is the activation function at the i^{th} node to limit the amplitude of the output the node.

The model is trained using mean squared error (MSE) loss and optimized using the Adam optimizer. The performance metrics used are mean absolute error (MAE) and R-squared [15].

Gaussian Process Regression (GPR)

Gaussian Process Regression (GPR) is a powerful machine learning technique used for regression analysis. It is particularly valuable when dealing with problems where the relationship between input variables and output variables is complex and uncertain. GPR belongs to the class of non-parametric methods, meaning it doesn't make assumptions about the underlying distribution of the data [16].

In GPR, the fundamental idea is to model the relationship between input variables x and output variables y as a joint Gaussian distribution. This distribution represents a prior belief about how the data might be related before observing any actual data points. As new data points are observed, the distribution is updated, allowing for more accurate predictions [17].

The basic equation of GPR can be represented as follows:

$$f(x) \sim GP\left(m(x), k\left(x, x'\right)\right), \quad (2)$$

where — $f(x)$ is the function to be modeled;
— x and x' are input variables;
— $m(x)$ is the mean function, representing the expected value of $f(x)$;
— $k\left(x, x'\right)$ is the covariance function, also known as the kernel function, which captures the relationship between (x) and (x') [18].

The kernel function plays a crucial role in GPR. It determines the smoothness and the shape of the predicted function. Commonly used kernel functions include the Gaussian kernel, linear kernel, polynomial kernel, and RBF kernel [16].

To make predictions using GPR, given a set of observed data points X_{obs} and their corresponding output values Y_{obs}, the posterior distribution of f(x) conditioned on the observed data is computed. This is given by:

$$p((f(x) | X_{obs}\,,\ Y_{obs}\,,\ x) = N\ (\mu(x), \sigma\ (x)), \quad (3)$$

where — $\mu(x)$ is the mean of the posterior distribution, representing the predicted value of $f(x)$;
— $\sigma\ (x)$ is the covariance matrix of the posterior distribution, capturing uncertainty in the prediction [19].

Evaluation of GPR typically involves assessing the predictive performance of the model on unseen data. Common evaluation metrics include mean squared error (MSE), mean absolute error (MAE), and R-squared [18]. Real-world applications of GPR span various domains, including finance, environmental science, engineering, and healthcare. It has been used for tasks such as time series forecasting, anomaly detection, and modelling complex physical processes [16]. This regression was used for predicting rut depth based on the number of passes and different contents of Reclaimed asphalt materials (RAP) and it was defined using a RBF kernel. The model was trained for each RAP percentage, then predictions were made for all RAP percentages using the trained model.

Results

A Feedforward Neural Network model was defined using TensorFlow's Keras API. The model was trained for each RAP content in a range of 0-100. Training histories were plotted to visualize training and validation loss (MSE) and mean absolute error (MAE) over 1 000 epochs for each RAP content (**Figs 2 – 6**). In addition to that, the model was trained separately for each RAP content, and R-squared was less than 0.5 (0.476) with mixture contain 0 % RAP and achieved high values (0.897) with mixture containing 50 % RAP, and for other mixtures were (0.461, 0.869 and 0.874 with mixtures containing 25 %, 75 % and 100 % RAP, respectively.

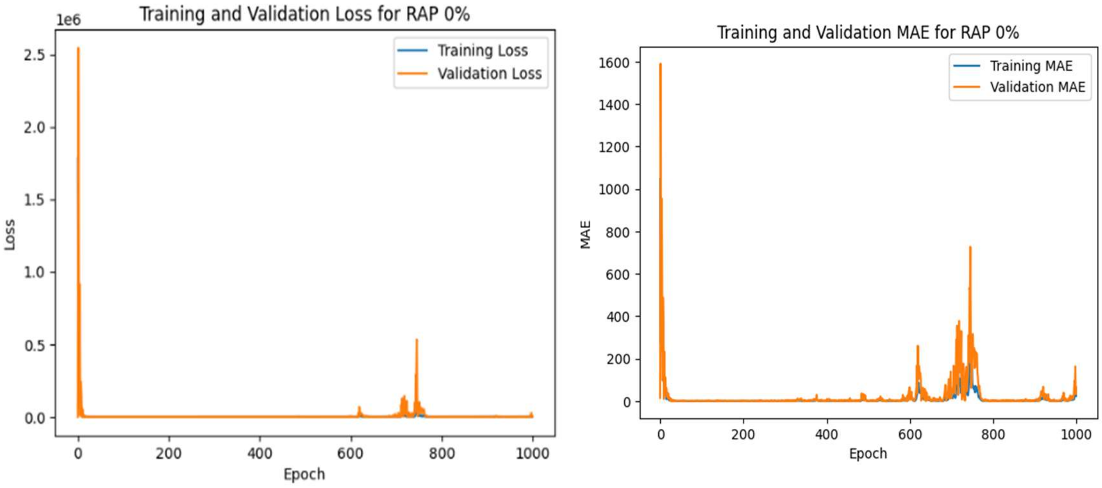

Figure 2 — Training history for mixtures containing 0 % RAP

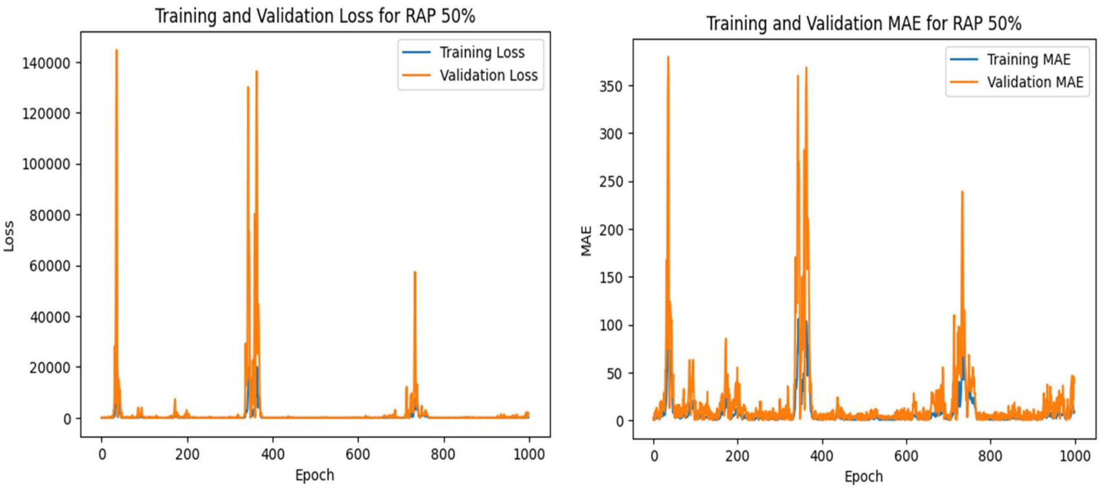

Figure 3 — Training history for mixtures containing 25 % RAP

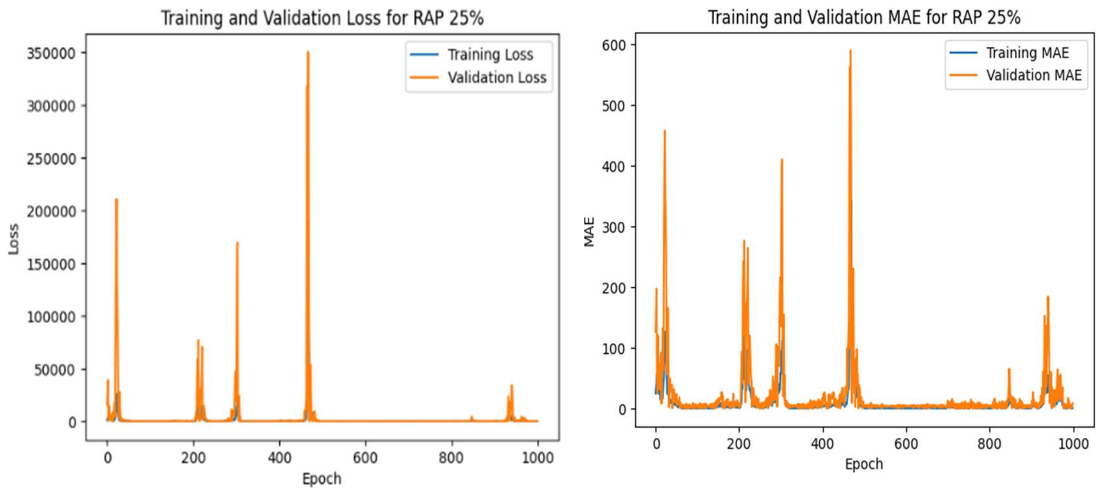

Figure 4 — Training history for mixtures containing 50 % RAP

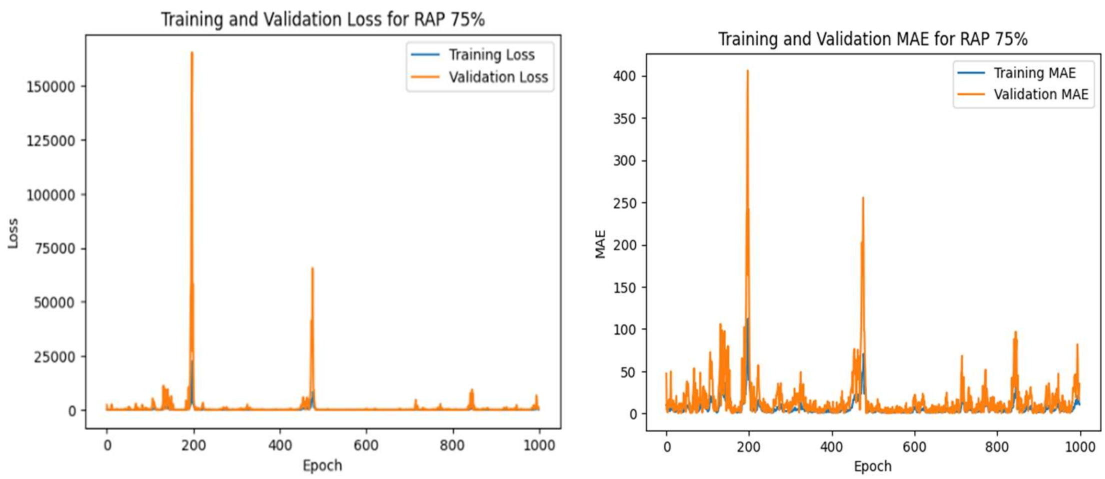

Figure 5 — Training history for mixtures containing 75 % RAP

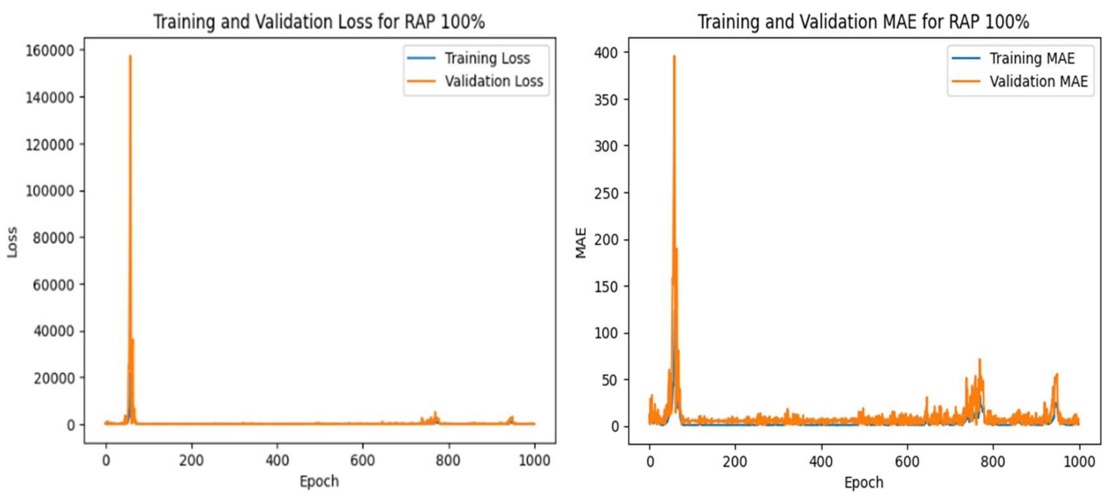

Figure 6 — Training history for mixtures containing 100 % RAP

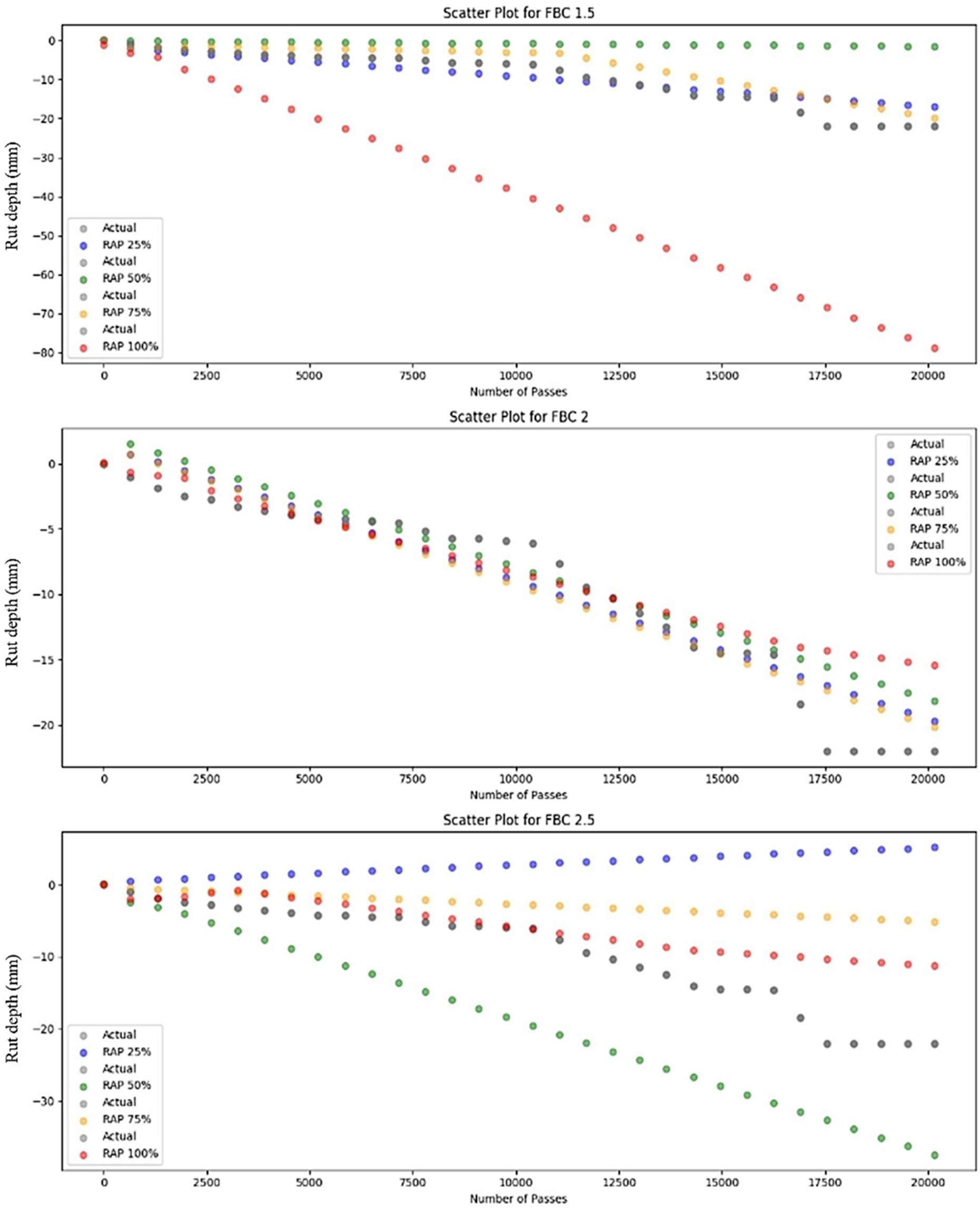

Figure 7 — Scatter plot for asphalt mixtures with 1.5 %, 2.0 % and 2.5 % of FBC

Correlation analysis for different RAP and FBC combinations were created. For each FBC value, scatter plots were created to compare actual and predicted rut depths for different RAP contents, and to observe the relationship between the number of wheel passes and rut depth in case of different RAP contents (**Fig. 7 and Fig. 8**).

The predicted values of rut depth with 25 % RAP content went out of the ordinary with 2.5 % of FBC and achieved failure with 3.5 % of FBC when number of wheel passes amounted to 7,500.

The predicted values of rut depth with 50 % RAP content went out of the ordinary with 1.5 % and 3.5 % of FBC and still equal to 0.

The predicted values of rut depth with 75 % RAP content achieved the most relatable values but with one super values with 2.5 % of FBC equal to — 10 mm when number of wheel passes surpassed 20,000.

The predicted values of rut depth with 100 % RAP content went out of the ordinary with 1.5 % and 3.5 % of FBC, and achieved super rut depth with 2.0 %, 2.5 % and 3.0 % of FBC with maximal rut depth equal to —14 mm when number of wheel passes were above 20,000.

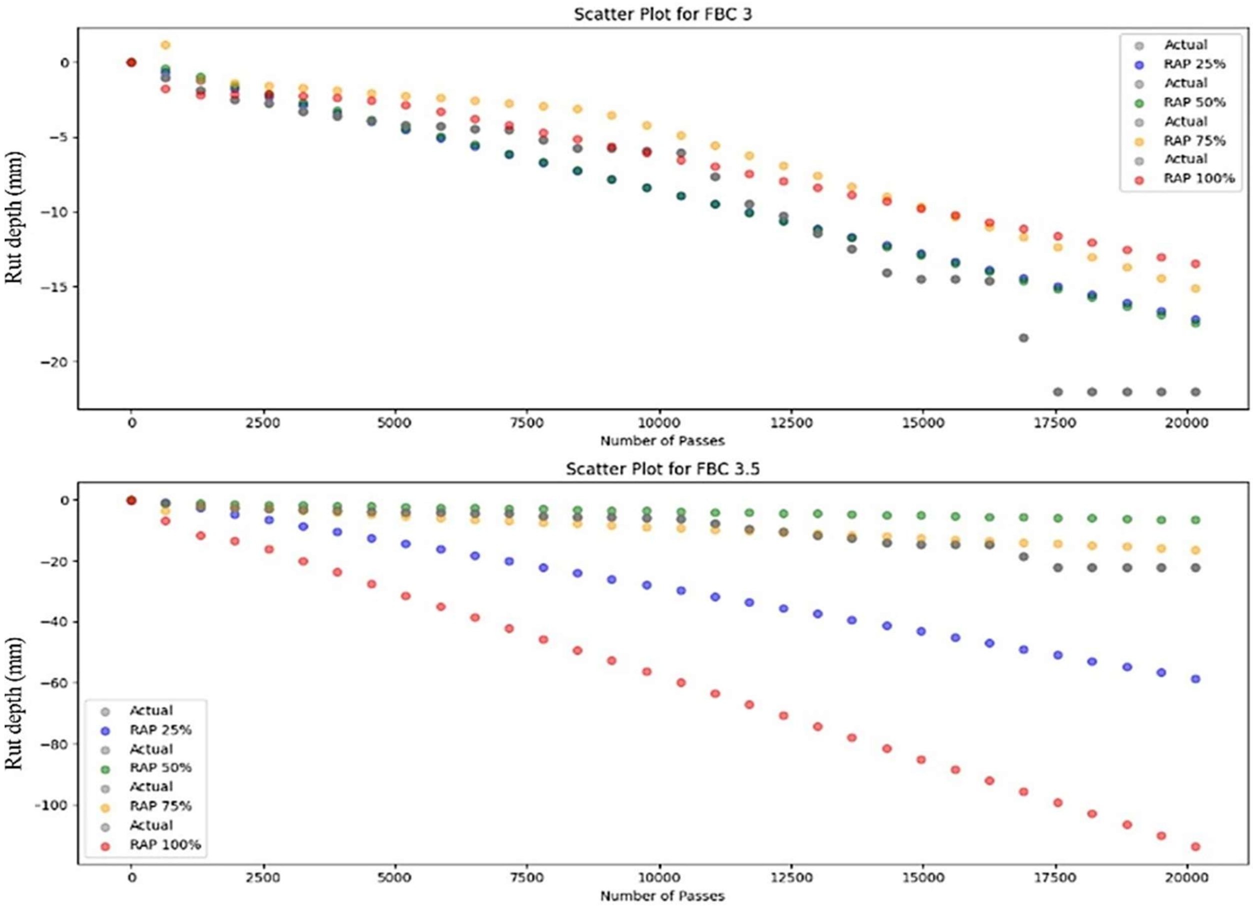

Figure 8 — Scatter plot for asphalt mixtures with 3.0 % and 3.5 % of FBC

A new model was built using Gaussian process regression to model the relationship between rut depth and RAP content.

Figure 9 shows the mean predicted rut depth as a function of RAP content. Each point represents the mean Rut depth for a specific RAP content, along with error bars representing the standard deviation of Rut depth at each RAP content. The solid line shows the mean predicted Rut depth, while the shaded area around it shows the uncertainty (standard deviation) in the prediction. As it can be seen, the most negative effective of RAP content is in a range of 80 – 85 %. **Figure 10** presents the derivative of the predicted mean Rut depth with respect to RAP content. It indicates how much the Rut depth is affected by changes in RAP content with the following results. The RAP content between 25 % and 50 % decreases the cracking resistance; in the range of 55 – 70 %, an increase can be detected in the cracking resistance; between 80 % and 90 %, this parameter decreases sharply; in the last phase up to 100 %, the cracking resistance improves again.

Figure 9 — GPR for rut depth as a function of RAP content

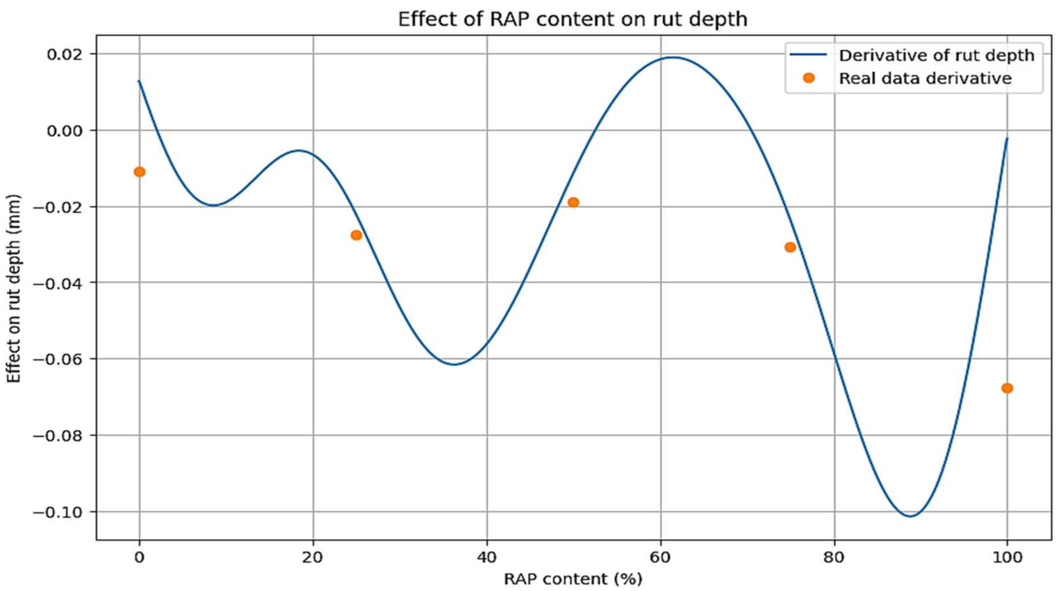

Figure 10 — The influence of RAP content on rut depth

In **Figure 11**, in addition to the investigation of the impact of RAP content on rut depth, the influence of the number of wheel passes on the anticipated rut depth values is identified. This analysis was performed cumulatively for each set of 750 passes, starting from the initial 750 passes and continuing in increments (e.g., effects of 750 passes, followed by 1,500 passes, then 2,250 passes etc.). The rut depth reaches its maximum value after 20,000 wheel passes and experiences a significant increase after 12,000 passes. The results of this analysis can contribute to the determination of the optimum time for road maintenance.

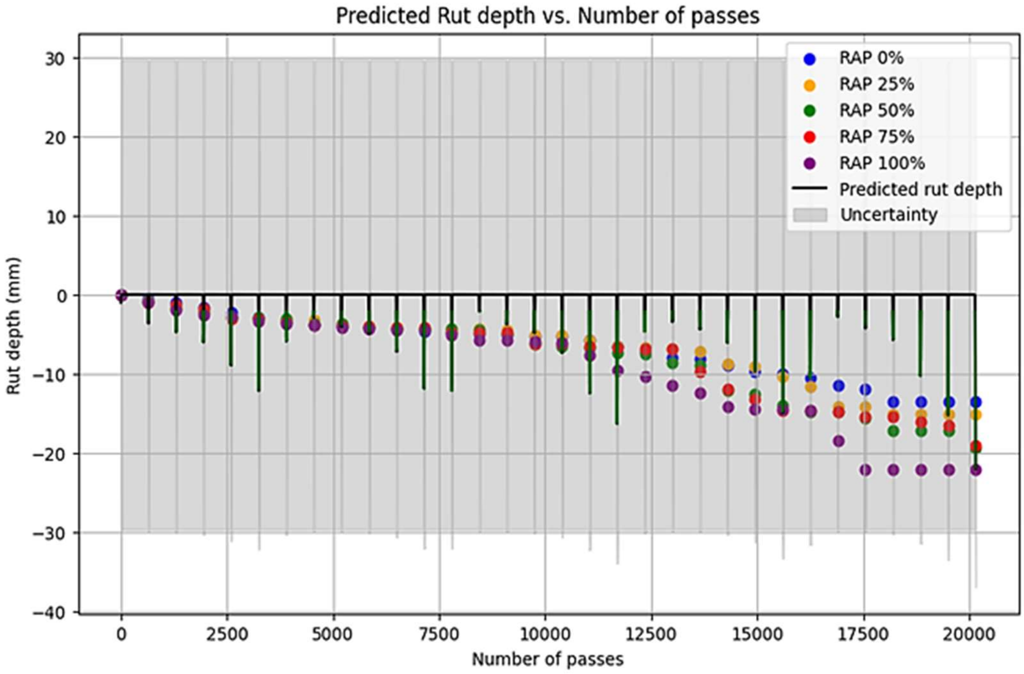

Figure 11 — The influence of the number of passes on rut depth values

Figure 12 illustrates that the GPR model used 80 % of the data for training and the remaining 20 % for testing the model resulting *R*-squared equal to 0.52 as it can be seen in **Figure 13**.

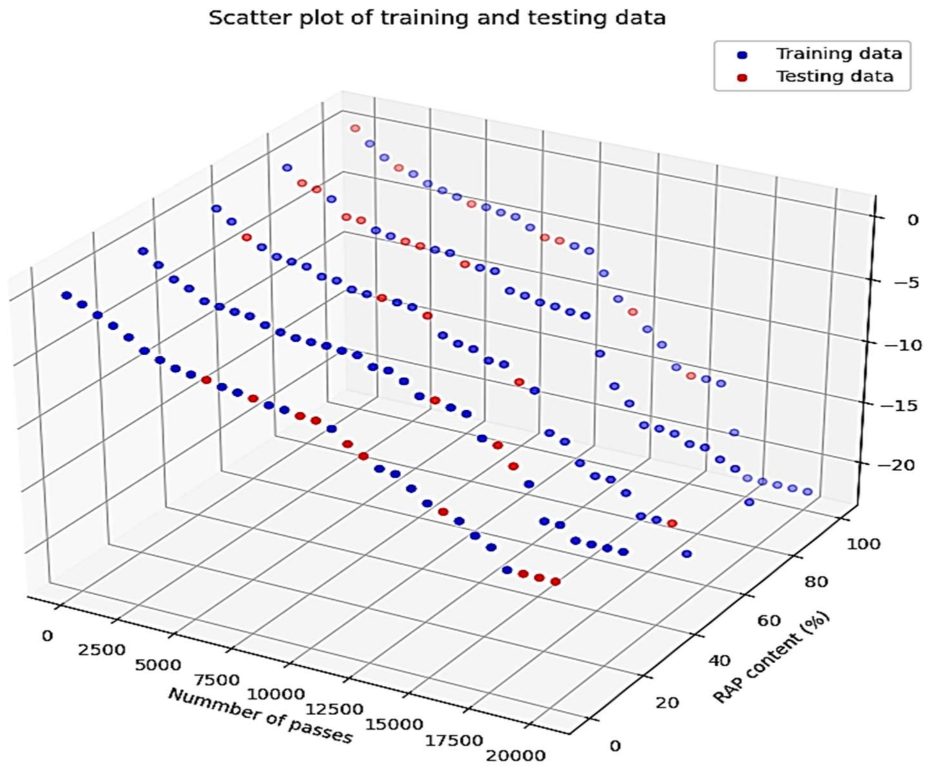

Figure 12 — Scatter plot using GPR model

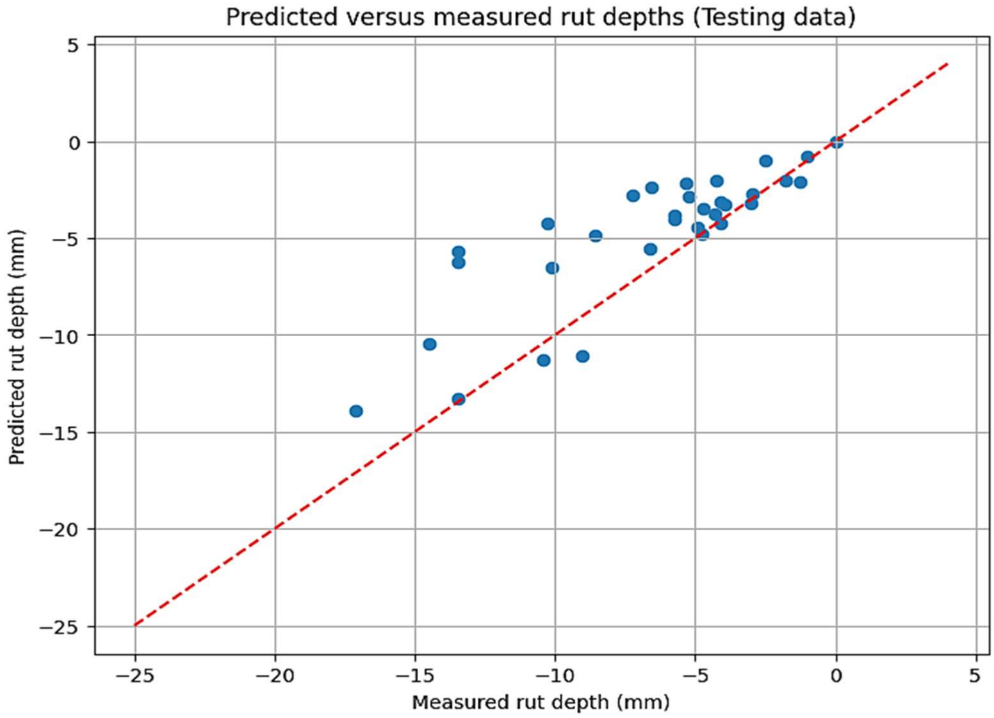

Figure 13 — Predicted rut depth as a function of measured testing data

Performance of ML models

Sensitivity analysis on a Gaussian Process Regression (GPR) model was conducted with varying parameters: length scale, noise level, and amplitude. For each combination of parameters, a GPR model is initialized and trained on the given dataset. Predictions were made using the trained model, and the mean squared error (MSE) between predicted and actual rut depths is calculated.

Figure 14 summarizes the results of MSE values against amplitudes and the x-axis was scaled logarithmically to accommodate the wide range of amplitude values. **Figs. 15 – 20** present each combination of length scale and noise level according to the group of data. It provides insights into how changes in amplitude affect the MSE for different combinations of length scale and noise level.

Length scale of 35.2 with noise level of 0.02 suggests that the GPR model is relatively smooth, with a length scale indicating that it considers points within a radius of approximately 35.2 units to be correlated. The noise level of 0.02 indicates the expected level of noise in the data. The length scale of 0.6 with noise level of 0.01 indicates a moderately smooth model with a slightly larger length scale compared to the previous one. The noise level of 0.01 suggests a low level of noise in the data. But length scale of 0.22 with noise level of 0 indicates that the model captures fine-grained variations in the data. The absence of noise (0 noise level) implies that the model assumes the data is without randomness. Length scale of 0.01 with noise level of 10 suggests that the model may be overfitting to noise in the data. Length scale of 100 with noise level of 1.28 considers points within a large radius to be correlated, potentially capturing broad trends in the data. The noise level of 1.28 indicates a moderate level of variability in the data. Length scale of 100 with noise level of 3.59 suggests that the model accounts for broader trends but may struggle to filter out randomness.

In summary, the length scale determines the smoothness of the model, with smaller length scales capturing fine-grained variations and larger length scales capturing broader trends. The noise level indicates the expected level of variability or randomness in the data.

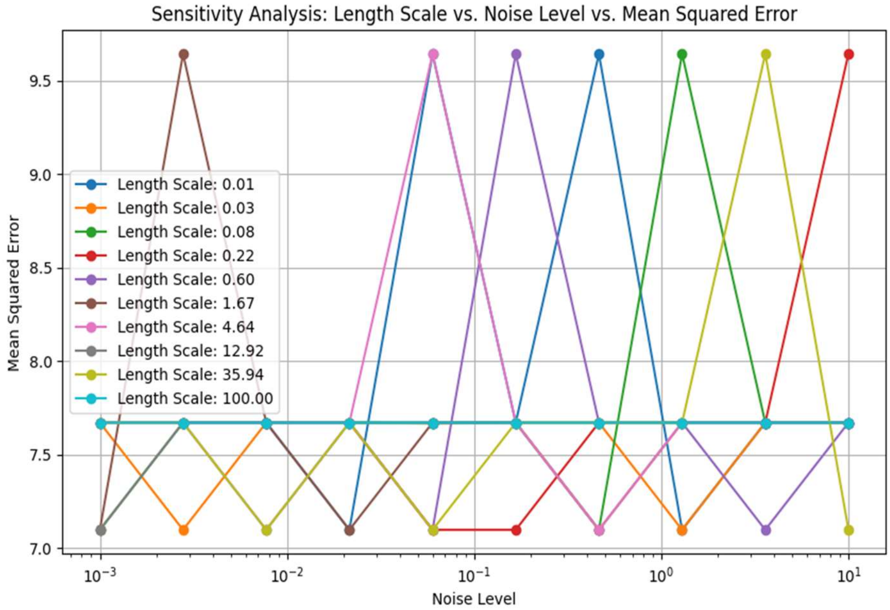

Figure 14 — Sensitivity analysis of GPR model

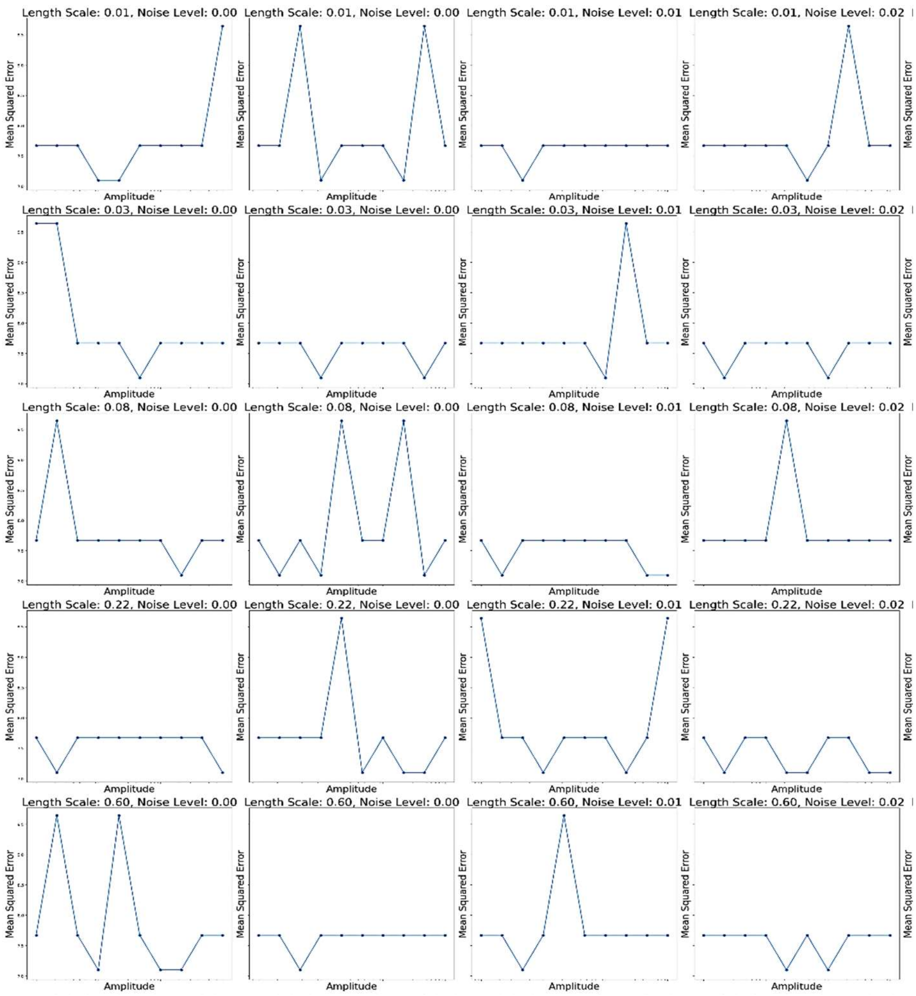

Figure 15 — Deep sensitivity analysis of GPR model, part 1

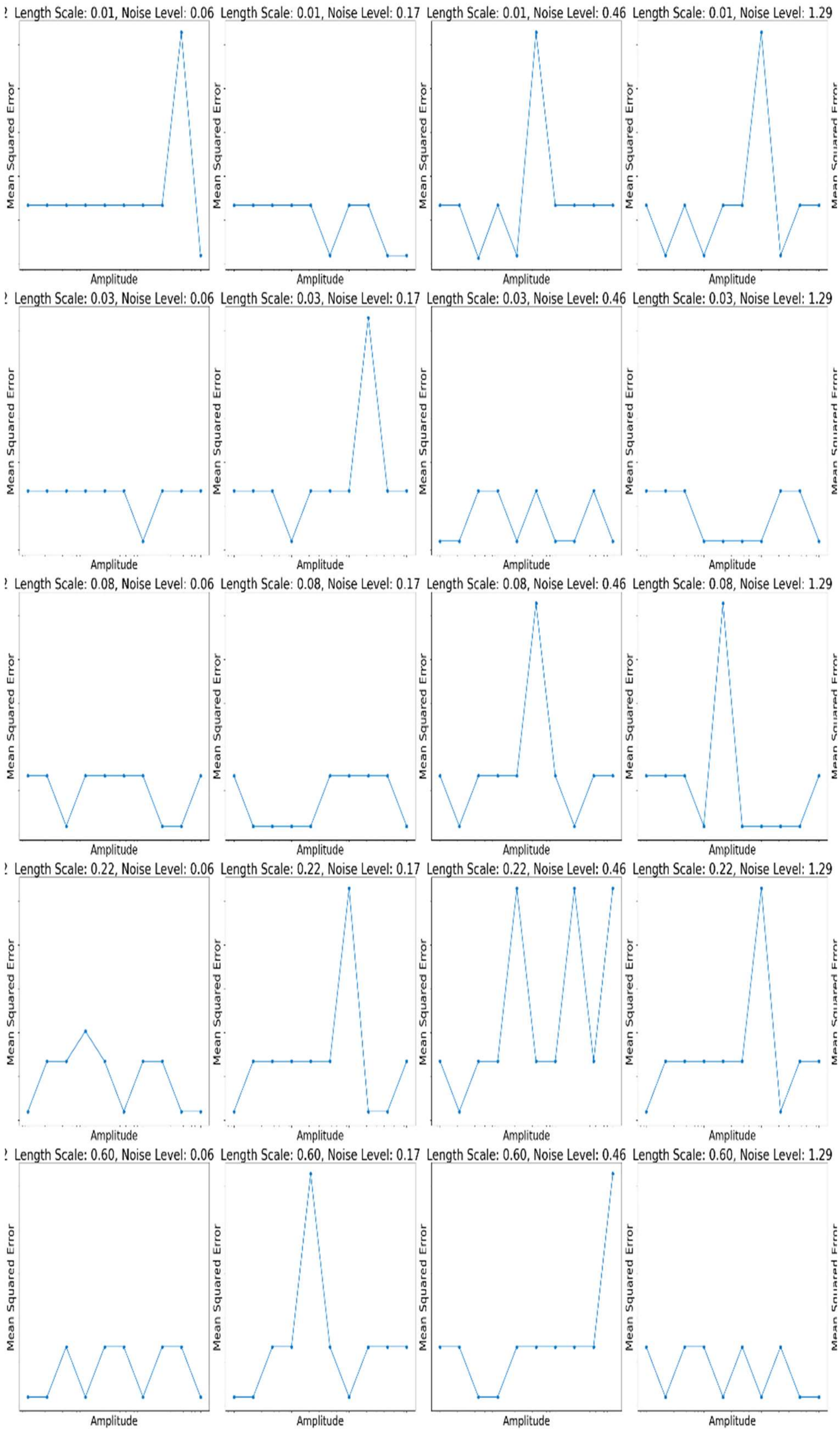

Figure 16 — Deep sensitivity analysis of GPR model, part 2

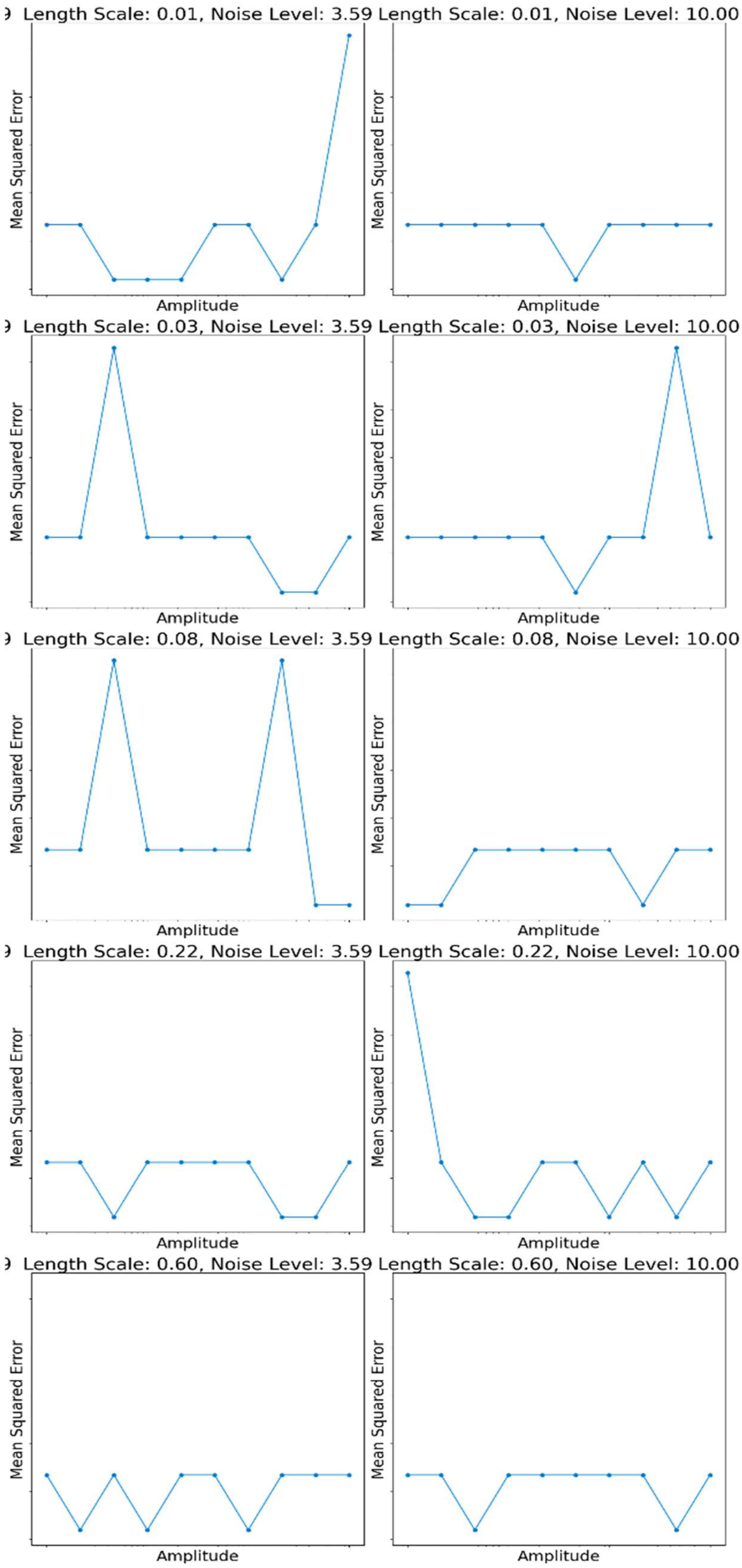

Figure 17 — Deep sensitivity analysis of GPR model, part 3

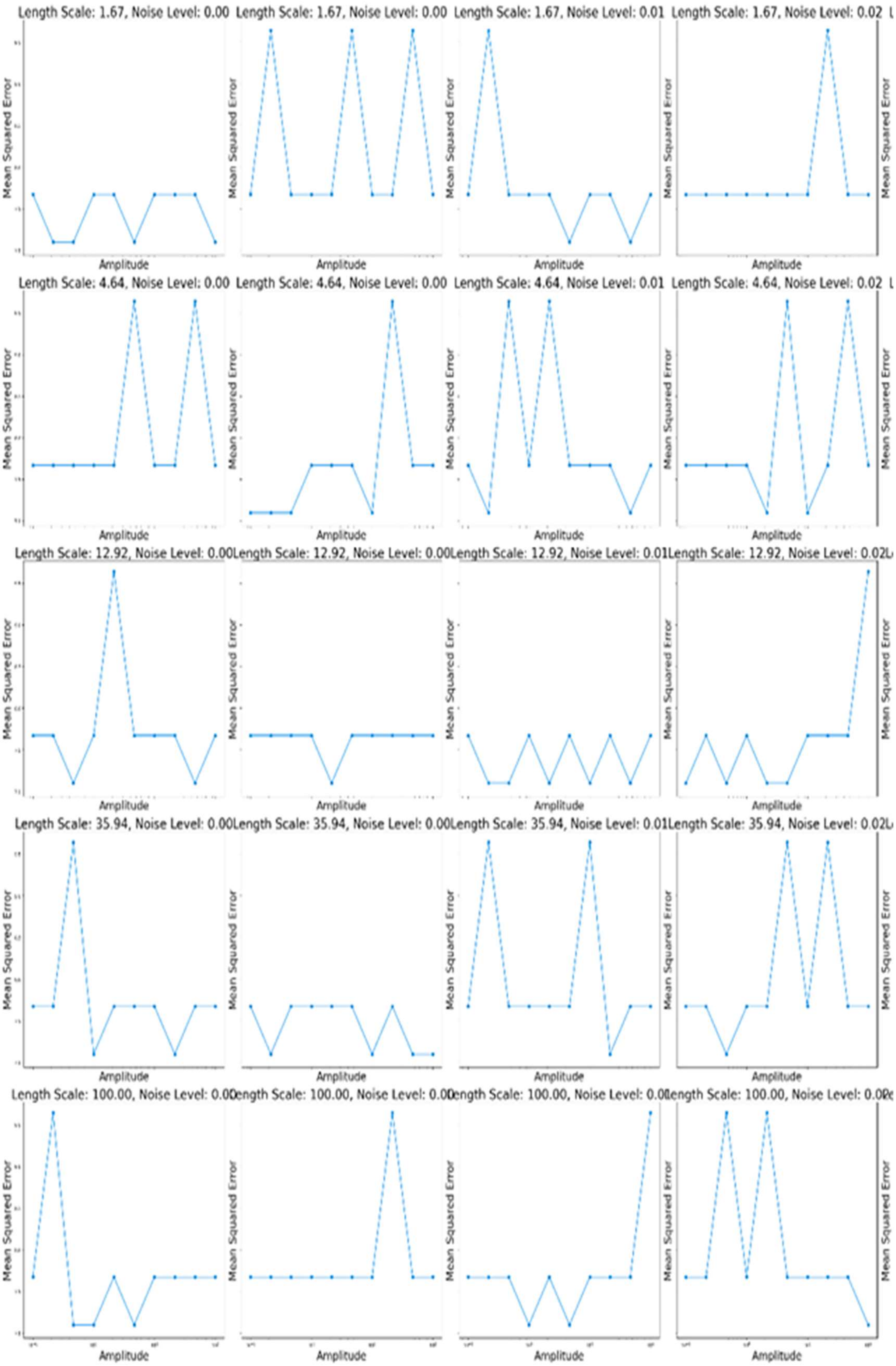

Figure 18 — Deep sensitivity analysis of GPR model, part 4

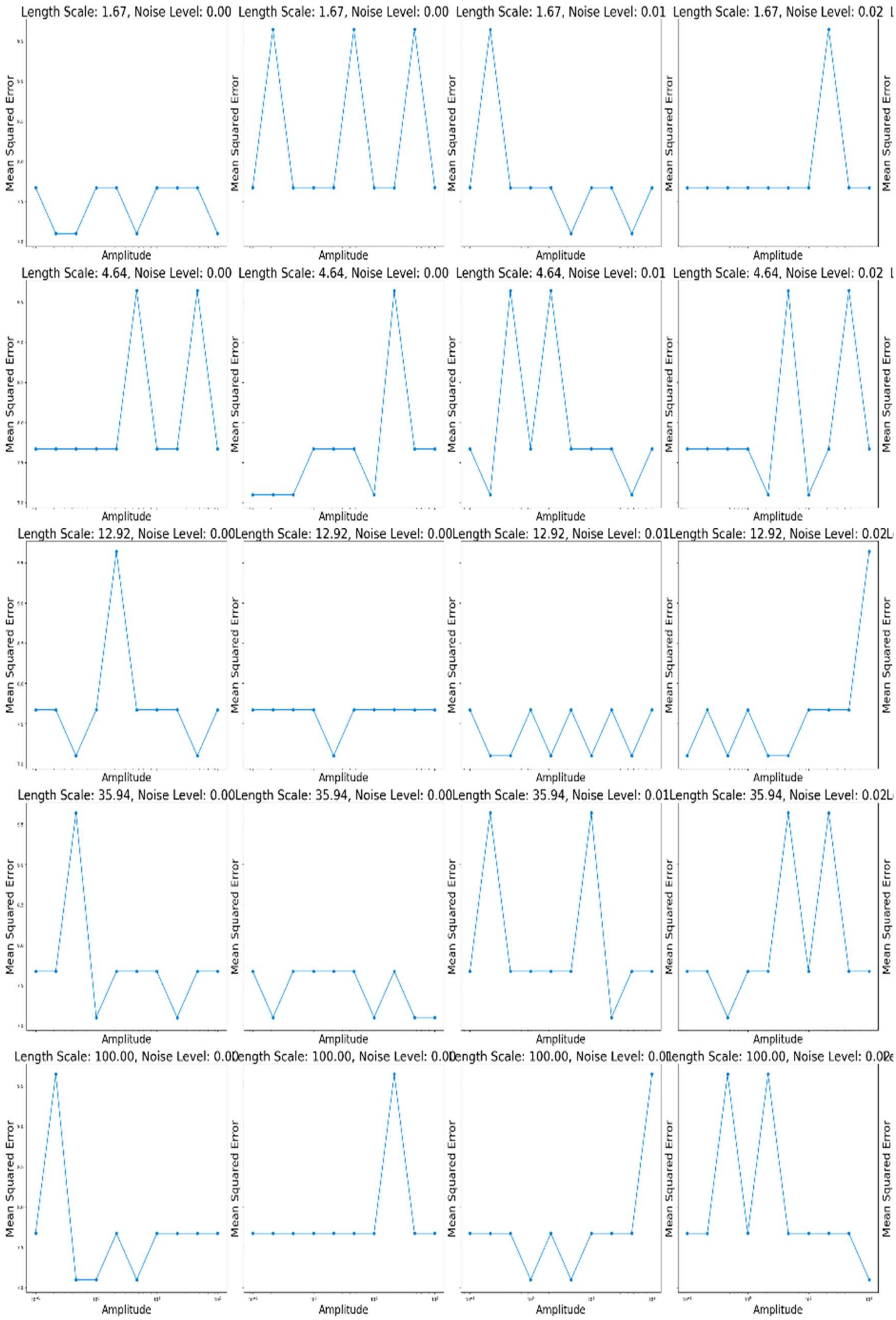

Figure 19 — Deep sensitivity analysis of GPR model, part 5

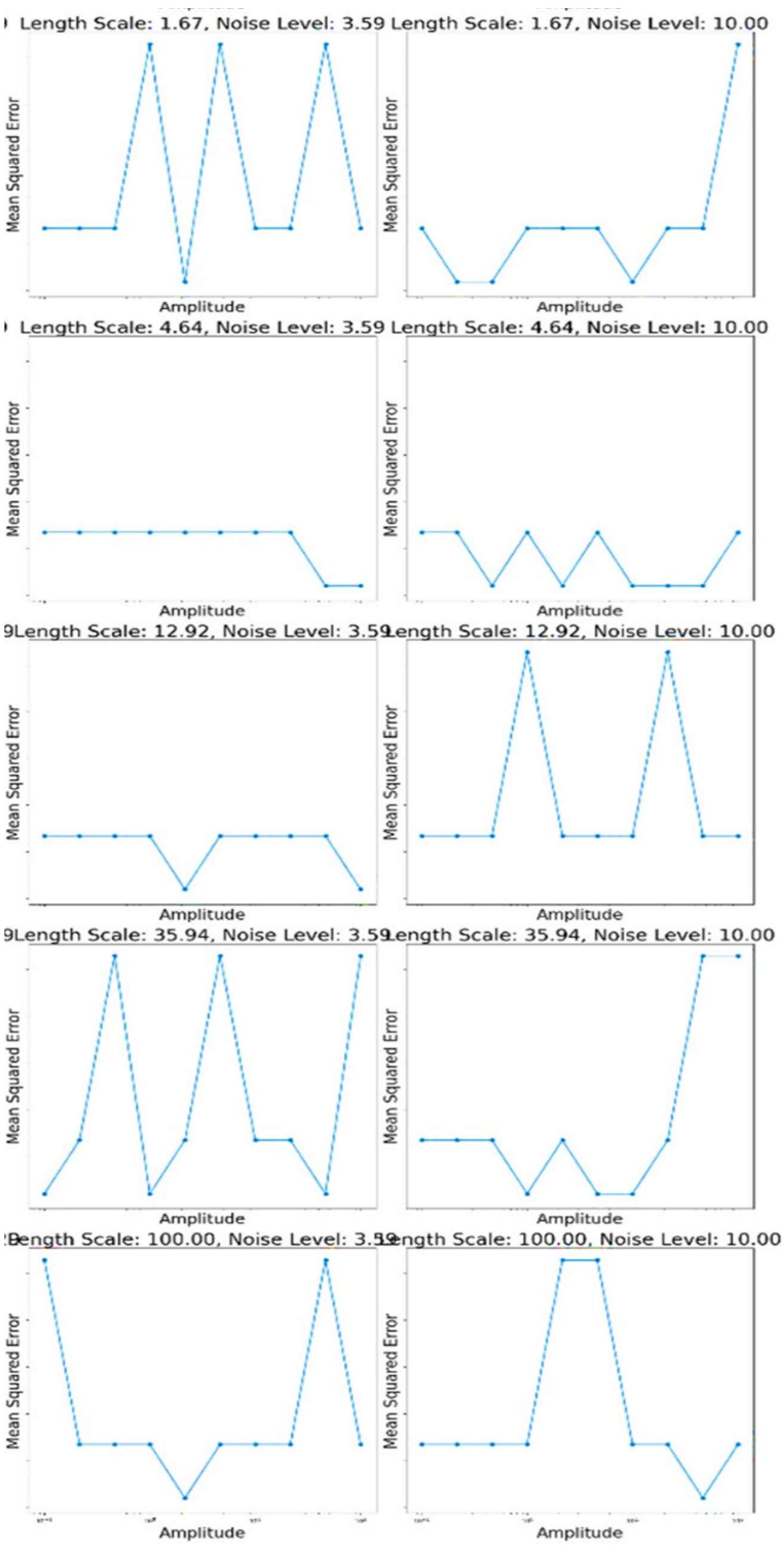

Figure 20 — Deep sensitivity analysis of GPR model, part 6

Conclusions

The main aim of the study was to develop a Feedforward Neural Network model for the analysis of the relationship between Rut depth values and Reclaimed Asphalt Pavement (RAP) content of asphalt mixtures.

The model was trained individually for different RAP content ranging from 0 % to 100 %. An optimizer ('adam') and a loss function ('mse') were used for the regression analysis. Training histories were visualized through plots showcasing training and validation loss (MSE), as well as mean absolute error (MAE) over 1 000 epochs for each RAP content selected. *R*-squared values were also calculated. Results indicated a *R*-squared value of 0.476 for 0 % RAP content and higher values for mixtures containing RAP, with the highest value of 0.897 was found for 50 % RAP content in the asphalt mixture.

Additionally, a Gaussian Process Regression (GPR) model was constructed in order to model the relationship between Rut depth and RAP content of asphalt mixture. The RAP content between 75 % and 100 % had most paradoxical effects. The derivative of the predict-ed mean rut depth as a function of RAP content revealed varying effects on rut depth values in the case of different RAP content ranges.

Sensitivity analysis on the GPR model was conducted by varying parameters such as length scale, noise level, and amplitude. The results of this analysis provided insights into how changes in these parameters affected the mean squared error (MSE) for their various combinations.

In addition, the influence of the number of wheel passes on rut depth values was examined, showing a significant increase in rut depth after 12,000 passes and reaching its maximum value after 20,000 passes. The outcome of this analysis can significantly contribute to the identification of the optimal timing for road maintenance interventions.

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МОДЕЛЮВАННЯ ГЛИБИНИ КОЛІЙНОСТІ ТЕПЛИХ АСФАЛЬТОБЕТОННИХ СУМІШЕЙ (WMA) З ВИКОРИСТАННЯМ ЗМІННОГО ВМІСТУ РЕЦИКЛЬОВАНОГО АСФАЛЬТОБЕТОННОГО ПОКРИТТЯ (RAP) І СПІНЕННОГО БІТУМУ

Анотація

Вступ. Утворення колій на покриттях гнучкої, супер-гнучкої та напівжорсткої конструкції є типовим і часто визначальним показником стану, а також формою руйнування дорожнього покриття. Тому будь-який результат досліджень у цій галузі може мати важливе значення для дорожніх інженерів.

Постановка проблеми. Колійність є серйозною проблемою для асфальтобетонних покриттів, викликаючи постійні деформації під дією важких навантажень, особливо у теплих та вологих умовах.

Мета. Цей тип руйнування покриття, крім впливу на комфорт під час їзди, має важливі наслідки для безпеки дорожнього руху (наприклад, аквапланування). Дослідження зосереджено на впливі використання теплих асфальтобетонних сумішей, рециклованого асфальтобетонного матеріалу та в’яжучого зі спіненим бітумом на глибину колій на асфальтобетонних покриттях.

Матеріали та методи. З використанням технік машинного дослідження було представлено модель Нейронної Мережі Зворотного Зв’язку для аналізу залежності між глибиною колій і вмістом рециклькованого асфальтобетонного покриття (RAP). Модель, яку було протестовано на вміст РАР в діапазоні від 0 % до 100 %, показала різні значення коефіцієнта детермінації R^2, з найвищим показником при 50 % вмісту RAP. Крім того, була застосована модель Регресії на основі Гаусівських процесів (GPR), яка підкреслила значний вплив вмісту RAP в межах від 75 % до 100 %. Аналіз чутливості моделі GPR надав уявлення про вплив параметрів, а значний вплив кількості проходів коліс на значення глибини колій підкреслив важливість оптимального часу для обслуговування доріг.

Результати. Результати моделі машинного дослідження вказали на значення коефіцієнта детермінації R^2 рівне 0.476 для 0 % вмісту RAP та вищі значення для сумішей з RAP, причому найвищий показник 0.897 був виявлений для 50 % вмісту RAP в асфальтобетонній суміші. Модель Регресії на основі Гаусівських процесів (GPR) показала парадоксальні ефекти при вмісті RAP від 75 % до 100 %. Похідна від прогнозованої середньої глибини колій як функції вмісту RAP показала різний вплив на значення глибини колій у випадку різних діапазонів вмісту RAP. Аналіз чутливості з використанням моделі GPR був проведений шляхом зміни таких параметрів, як масштаб довжини, рівень шуму та амплітуда. Результати цього аналізу надали уявлення про те, як зміни в цих параметрах впливали на середньоквадратичну похибку (MSE) для їхніх різних комбінацій. Було досліджено вплив кількості проходів коліс на значення глибини колій, що показало значне збільшення глибини колій після 12 000 проходів та досягнення максимального значення після 20 000 проходів.

Ключові слова: спінений бітум, тепла асфальтобетонна суміш, рецикльковане асфальтобетонне покриття, Нейронна Мережа, Регресія на основі Гаусівських процесів (GPR), машинне дослідження.