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Optimizing Foamed Bitumen Bound Asphalt Mixture Design Using Neural Network

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Abstract
Effective design of bituminous mixes for road pavements requires a robust understanding of their mechanical properties to ensure durability and safety. Conventional experimental methods for assessing these properties are time-consuming and costly. To address this challenge, advanced machine learning techniques have gained prominence in predicting bituminous mix behaviour. In this study, we focus on predicting Marshall Stability (MS) and Flow (MF) of foamed bitumen bound asphalt pavements using essential input parameters: Temperature, Foam Content, Expansion Ratio, and Half-Life. Leveraging a neural network model, accurate prediction equations and surface analyses were developed for optimizing pavement design. Furthermore, integration equations are also introduced to enhance the accuracy of the methodology. Sensitivity and Parametric Analyses provide insights into parameter impacts, and R-squared measures model goodness of fit. The research work presented not only streamlines pavement design but also advances the understanding of intricate input-output relationships in bituminous mixtures.
Keywords
foamed bitumen, warm mix asphalt, asphalt pavements, Marshall-tests, asphalt parameter prediction model

1 Introduction

The quest for robust and efficient road pavements to withstand climate conditions and ever-increasing heavy traffic loads demands effective design of asphalt mixtures. Insufficient mechanical properties in pavement materials can give rise to an array of detrimental consequences, including the emergence of low-temperature or fatigue cracks, stripping of aggregate grains, and permanent pavement deformations. These issues pose significant threats to the service life of pavements and the safety of road users [1]. Hence, characterizing mixture performance based on composition is essential for optimizing the procedure of mix design [2, 3]. Conventional experimental methods assessing bituminous mix performance [4, 5] necessitate costly laboratory experiments and skilled labour, making any composition change in bitumen content, type, or aggregate gradation rather time-consuming and costly [2]. To expedite this process, researchers have focused on developing numerical or mathematical relationships for the mechanical behaviour of asphalt mixtures, enabling quick and accurate predictions. Advanced machine learning (ML) methods, such as artificial neural networks (ANN) [6, 7], have gained popularity for their reliability and prediction capabilities. ML techniques are increasingly used to model complex behaviours of pavement engineering materials [8, 9], and data mining in material, civil, and pavement engineering has been widely reported due to rapid ML advancements [10]. Soft computing methods (SCMs) and artificial intelligence techniques (AITs), like hybrid ANNs with support vector machines (SVM) and adaptive neuro-fuzzy inference systems (ANFIS), have facilitated various models alongside conventional statistical models [11–13].

Specifically, ANNs mimic biological neural networks [14–16], while ANFIS combines fuzzy algorithms and ANNs [17, 18]. The method of genetic programming, known as MEP (Multivariate Evolutionary Polynomial Regression), stands out as an efficient and powerful alternative for predicting complex and nonlinear problems [19].

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MEP has shown promise in material engineering for predicting properties, among others, tensile and compressive strength [20], Marshall parameters [19], soil classification [21], and deformation moduli [22].

Traditionally, fewer data points and limited correlations in governing parameters were limitations in prior statistical studies for predicting Marshall Stability (MS) and Marshall Flow (MF) of asphalt pavements [23]. Moreover, laboratory tests for MS and MF are time-consuming and costly [24, 25]. To address these challenges, researchers have employed ANN and ANFIS approaches using basic input parameters for predicting MS and MF [24, 26, 27].

In this research study, the primary objective is to develop a model that reliably predicts Marshall Stability (MS) and Flow (MF) of asphalt mixtures with foamed bitumen binder using key input parameters that are both straightforward and cost-effective. The following four essential properties were chosen as input parameters: Temperature (T), Percentage of Foamed Bitumen Content (FBC), Expansion Ratio (EX), and Half-Life (HL). These selected input parameters play a critical role in determining the performance of the asphalt mixtures and are readily obtainable in practical scenarios. The output parameters of the study are MS (corrected Stability in kg) and MF (flow in 0.25 mm), which are essential indicators of pavement durability and load-carrying capacity. By leveraging these input parameters and applying advanced modelling techniques, a robust and accurate prediction model was established. It can significantly contribute to optimizing pavement design and ensuring long-lasting and safe road infrastructure.

This research work strives to enhance the prediction process for asphalt pavement properties and create an equation that will be using and leading to more efficient and cost-effective road designs.

2 Data collection and pre-processing

A comprehensive and detailed dataset comprising numerous data points was meticulously examined to develop predicting models utilizing the advanced ANN approach. Bitumen of grade 50/70 was consistently used across all datasets under consideration. Additionally, exhaustive tests related to foamed bitumen, coarse, and fine aggregates were meticulously conducted. The distribution of these datasets plays a pivotal role in gauging the effectiveness of the models developed [14]. Factors such as data characteristics, input-output parameter relationships, and data size significantly influence the model's accuracy [28]. To achieve optimal predictions for MS and MF, four input parameters were carefully selected for the ANN approach, ensuring the model's efficiency and simplicity. In determining the correlation of the output parameters (MS and MF) based on the distribution of all input parameters, the Spearman rank coefficient was employed, as illustrated in Tables 1 and 2. Previous research highlights the importance of avoiding excessive inputs with low correlation to the desired output, as it can negatively impact the model's performance and lead to unnecessary complexity [29, 30].

In the pursuit of modelling excellence, we embarked on a transformative method, amalgamating all elements together, creating a unique and dynamic approach referred to as "complex".

3 Machine learning models

The parameter selection is the initial step in developing the appropriate models. In this case: MS, MF = f (T, EX, HL, FBC).

3.1 Neural Network Architecture

Fig. 1 presents the architectural design of the neural network specifically tailored for predicting Stability and Flow in foamed bitumen mixtures. This neural network is crafted as a Feedforward Neural Network (FFBP) with a single hidden layer containing 18 neurons. The network takes four inputs, namely Temperature, Foam Content, Expansion Ratio, and Half-life, and produces two outputs, Stability and Flow. Each neuron in the hidden layer employs the Rectified Linear Unit (ReLU) transfer function, while the output neurons use the Linear transfer function. The model's parameters (weights and biases) are skillfully optimized using the Levenberg-Marquardt algorithm, facilitating faster convergence during training.

Table 1 Correlation for parameters of Stability

	T	FBC	EX	HL	S
T	1				
FBC	0.57142857	1			
EX	0.57142857	0.98976582	1		
HL	−0.19047619	0.47619048	0.47619048	1	
S	−0.21428571	−0.4047619	−0.4047619	−0.23809524	1

Table 2 Correlation for parameters of Flow

	T	FBC	EX	HL	F
T	1				
FBC	0.35714286	1			
EX	0.35714286	0.98976582	1		
HL	0.14285714	0.47619048	0.47619048	1	
F	−0.61904762	−0.4047619	−0.4047619	−0.23809524	1

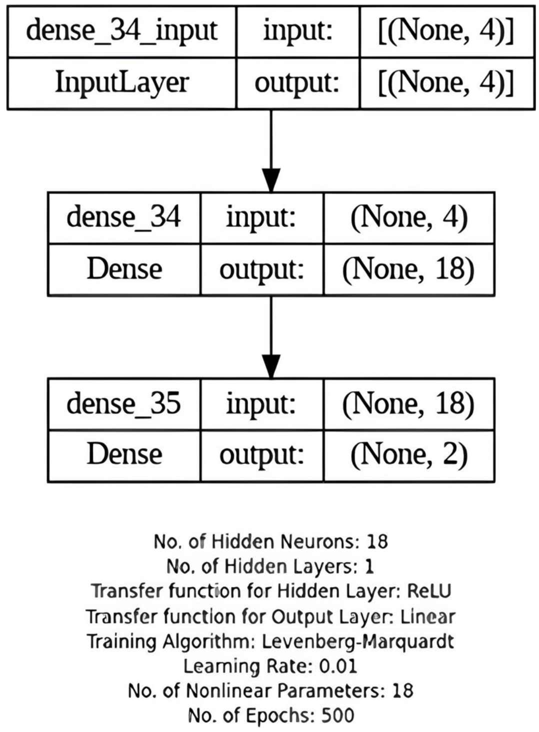

Fig. 1 Structure of neural network

To ensure efficient learning, the network employs a learning rate of 0.01. A total of 18 nonlinear parameters are involved in this intelligent architecture. The neural network undergoes rigorous training for 500 epochs, iteratively refining its performance and accuracy.

3.2 Training and validation loss

Fig. 2 showcases the dynamic behaviour of the neural network's training and validation loss over 500 epochs, using Mean Squared Error for the evaluation. The training loss represents the disparity between the predicted Stability and Flow values and the true values within the training dataset. Similarly, the validation loss measures the dissimilarity for a separate validation dataset. As the neural network undergoes training, the optimization process aims to minimize these losses, leading to increasingly accurate predictions. It is vital for both training and validation losses to converge, indicating that the model is adept at generalizing to new, unseen data.

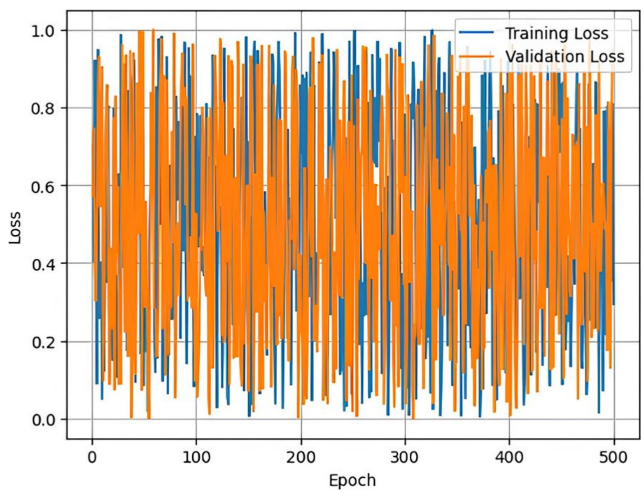

Fig. 2 Dynamic behavior of the neural network

Overall, the resulted charts help assess the performance and architecture of the neural network model, providing valuable insights into the prediction of Stability and Flow in foamed bitumen mixtures based on the specified inputs. To make accurate predictions for Stability and Flow, the model is trained on a dataset containing input features (Temperature, Foam Content, Expansion Ratio, and Half-life) and corresponding Stability and Flow values. The raining process aims to minimize the difference between the predicted values and the actual values, resulting in a reliable model for predicting Stability and Flow for different input combinations. (Loss function used is MSE).

4 Results and discussion

4.1 Equations involved

During the forward propagation phase, the output of each neuron based on the input values and the current weights of the network were calculated. The following equation [31] is used to compute the output of a neuron in the hidden layer (Fig. 3):

$$h_i = \sigma\left(\sum_{j=1}^{n} w_{ij}^{(1)} \times x_j + b_i^{(1)}\right), \quad (1)$$

where:

- h_i: is the output of the i^{th} neuron in the hidden layer,
- $w_{ij}^{(1)}$: is the weight connecting the ith neuron in the hidden layer to the jth input node,
- x_j: is the j^{th} input value,
- $b_i^{(1)}$: is the bias term associated with the i^{th} neuron in the hidden layer,
- σ: is the activation function (e.g., sigmoid, tanh, ReLU, etc.).

Similarly, the output of a neuron in the output layer is computed using the following equation:

$$O_k = \sigma\left(\sum_{i=1}^{m} w_{ki}^{(2)} \times h_i + b_k^{(2)}\right), \quad (2)$$

where:

- O_k: is the output of the k^{th} neuron in the output layer,
- $w_{ki}^{(2)}$: is the weight connecting the k^{th} neuron in the output layer to the i^{th} neuron in the hidden layer,

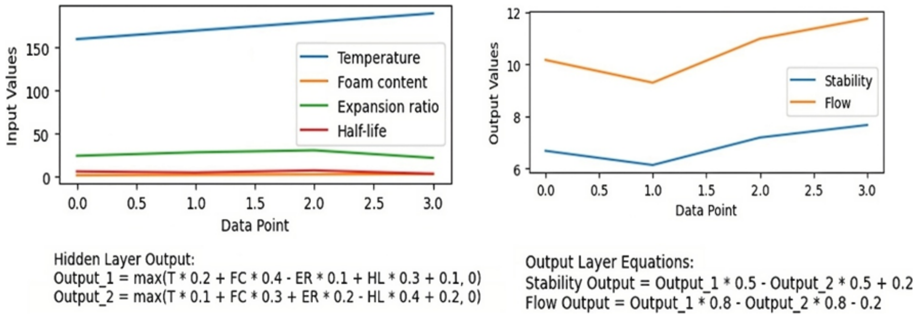

Fig. 3 Method of computation in hidden layer

- h_i: is the output of the i^{th} neuron in the hidden layer,
- $b_k^{(2)}$: is the bias term associated with the k^{th} neuron in the output layer.

In the pursuit of enhancing our predictive model's accuracy, we delve into determining the optimal values for the input parameters using a surface analysis. By visualizing the relationship between multiple input parameters and the corresponding output values, the combination of parameters can be pinpointed that yields the highest predicted outcomes.

A three-dimensional surface plot was constructed that maps the input parameters onto the horizontal axes and the predicted output (either Stability or Flow) onto the vertical axis. The surface plot offers a comprehensive view of how changes in input values interact to influence the output predictions. Peaks and valleys in the surface illustrate areas of higher or lower predicted values, allowing us to identify the optimal parameter combination that leads to the desired outcome.

Additionally, the concept of R-squared (coefficient of determination) is also utilized to quantify the goodness of fit of the model. R-squared measures the proportion of the variance in the dependent variable (output) that can be explained by the independent variables (inputs). A higher R-squared value indicates a better fit of the model to the data.

By combining the surface analysis and R-squared evaluation, the identification of the parameter configurations was strived that exhibit strong explanatory. This dual approach aids in refining the model, ensuring that it not only produces accurate predictions but also provides insights into the underlying relationships between the inputs and outputs (Fig. 4).

4.2 Verification of asphalt foaming model

The model was built using 420 laboratory results. 300 of them with 5 variable values of FBC (1.5–3.5 %), increased by 0.5%, and 60 variable values of both EX and HL. At the same time, the rest of data set (120) was obtained with

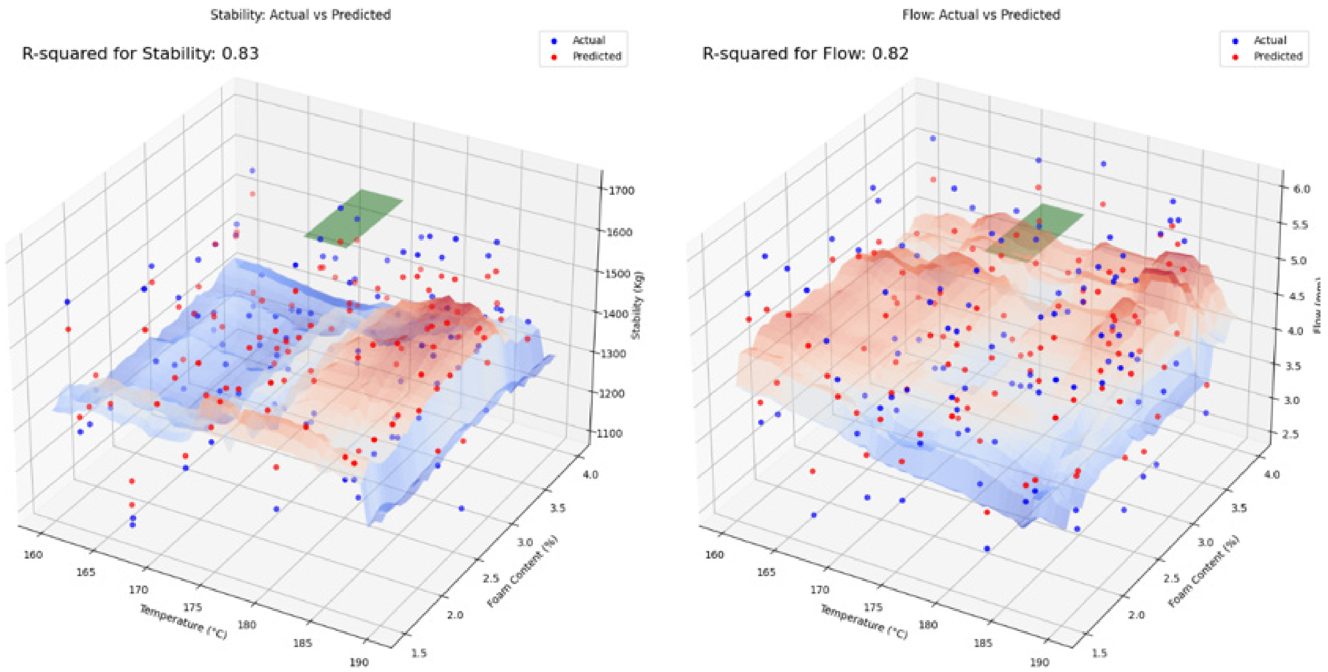

Fig. 4 R-squared and optimal values

4 variable values of Temperature (160–190 °C), increased by 10 °C, 80 % of these data was used to build the model and the remaining 20% served for the checking process.

Fig. 5 represents the resulting heatmap visually, which describes the strength and direction of the relationships between these variables. The heatmap uses a colour spectrum ranging from cool (blue) to warm (red) to indicate the strength of the correlation. Dark blue indicates a strong negative correlation (close to −1), meaning that as one variable increases, the other tends to decrease. Dark red indicates a strong positive correlation (close to 1), meaning that as one variable increases, the other also tends to increase. Lighter shades represent weaker correlations, closer to 0. The diagonal line of the heatmap represents the correlation of each variable with itself, which is always 1 since it is perfectly correlated with itself. The correlation does not imply causation; it merely indicates the statistical association between variables [31].

Overall, the heatmap results provide valuable insights into the relationships between the input and output variables, aiding in understanding the factors that influence Stability and Flow in asphalt pavements.

4.3 Scatter Plots

The Scatter Plots in the analysis play a pivotal role in visually encapsulating the intricate relationships between input variables and the corresponding output predictions of the neural network model. The resulted plots serve as a direct window into how changes in inputs reverberate through the model, resulting in varying predictions for Stability and Flow. By juxtaposing input values against output predictions, these Scatter Plots lay bare the patterns, trends, and potential outliers within the data. Each point on the plot represents an instance, where the model has made a prediction based on specific input parameters. The placement of these points along the plot's axes reveals the extent of influence each input wields over the outputs (Fig. 6).

The Scatter Plots bring to light the nuances within the Temperature, Foam Content, Expansion Ratio, and Half-Life inputs and their impact on Stability and Flow predictions. Clusters of points, their dispersion, and any discernible trends provide immediate visual insights into how the neural network's internal calculations translate into real-world predictions (Fig. 7).

This visual representation is instrumental in making informed decisions about model adjustments, identifying potential areas of improvement, and gaining a deeper understanding of the model's performance. The Scatter Plots are more than just visual aids; they are analytical tools that help us navigate the complex landscape of inputs and outputs in our neural network model, guiding us towards enhanced predictions and a refined model architecture.

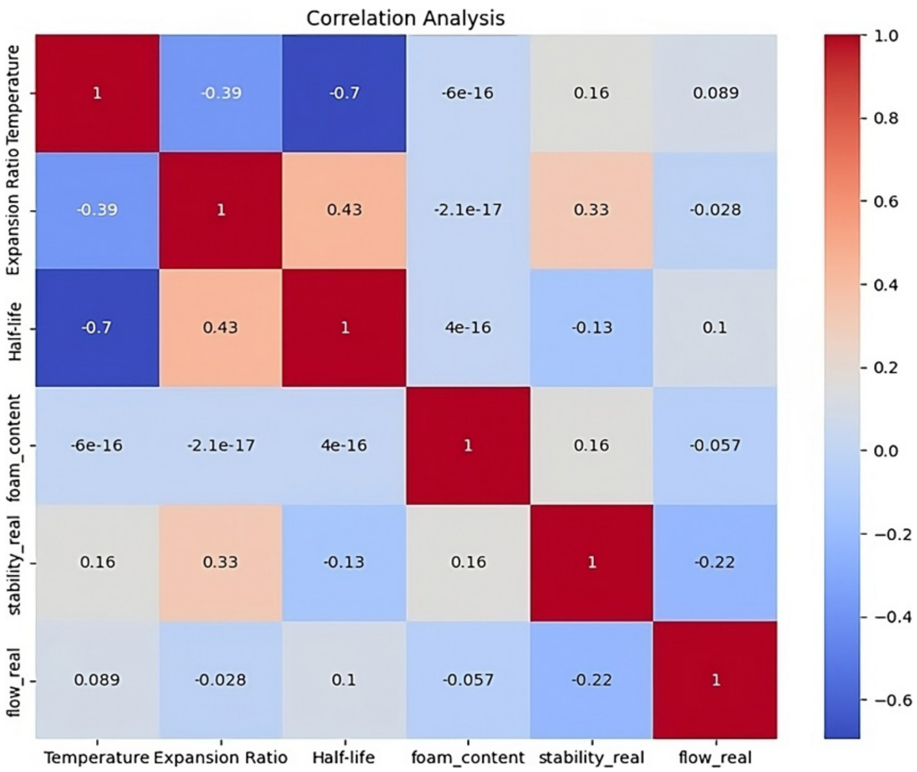

Fig. 5 Correlation analysis

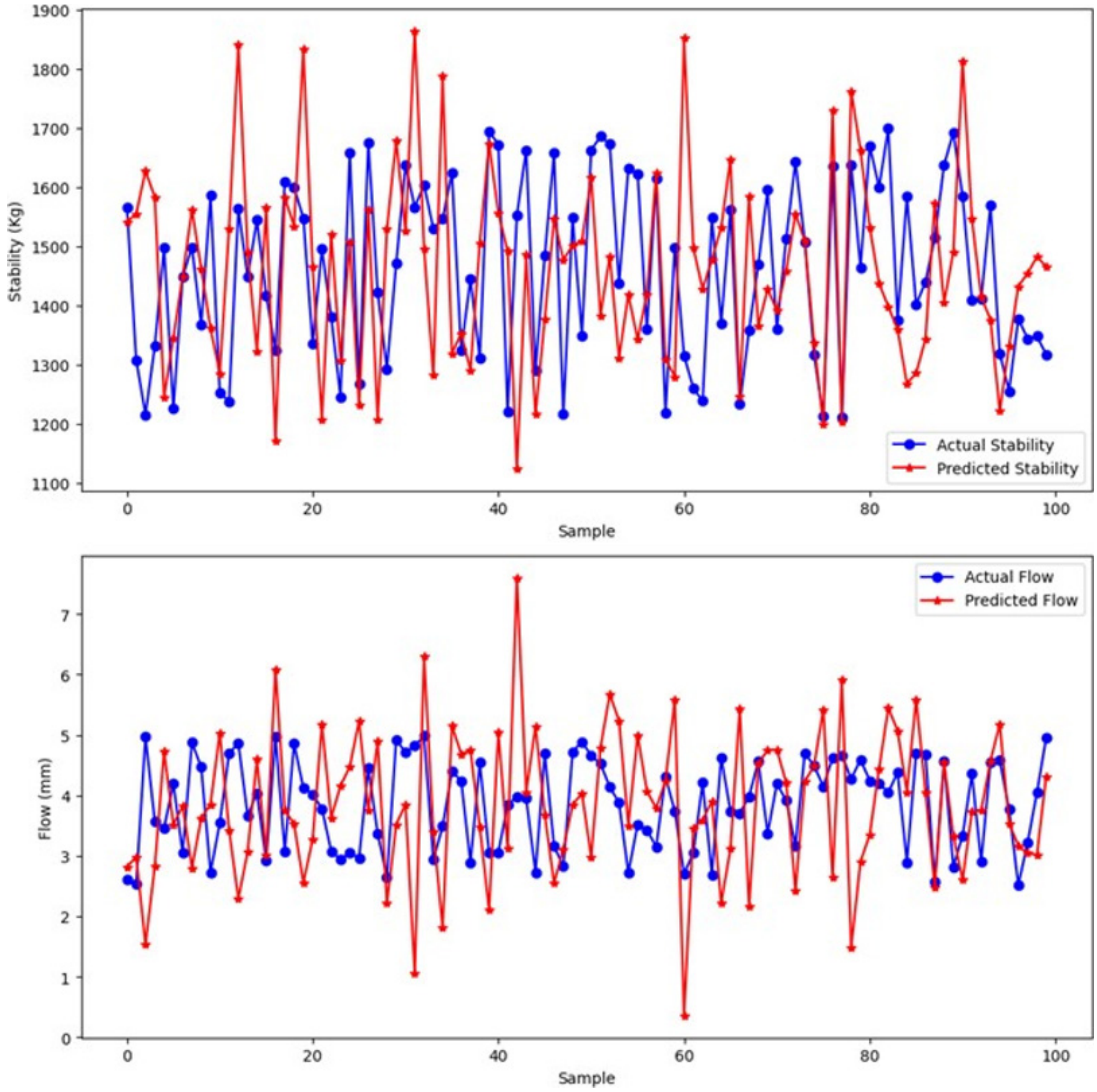

Fig. 6 Effects of changed inputs for Stability and Flow

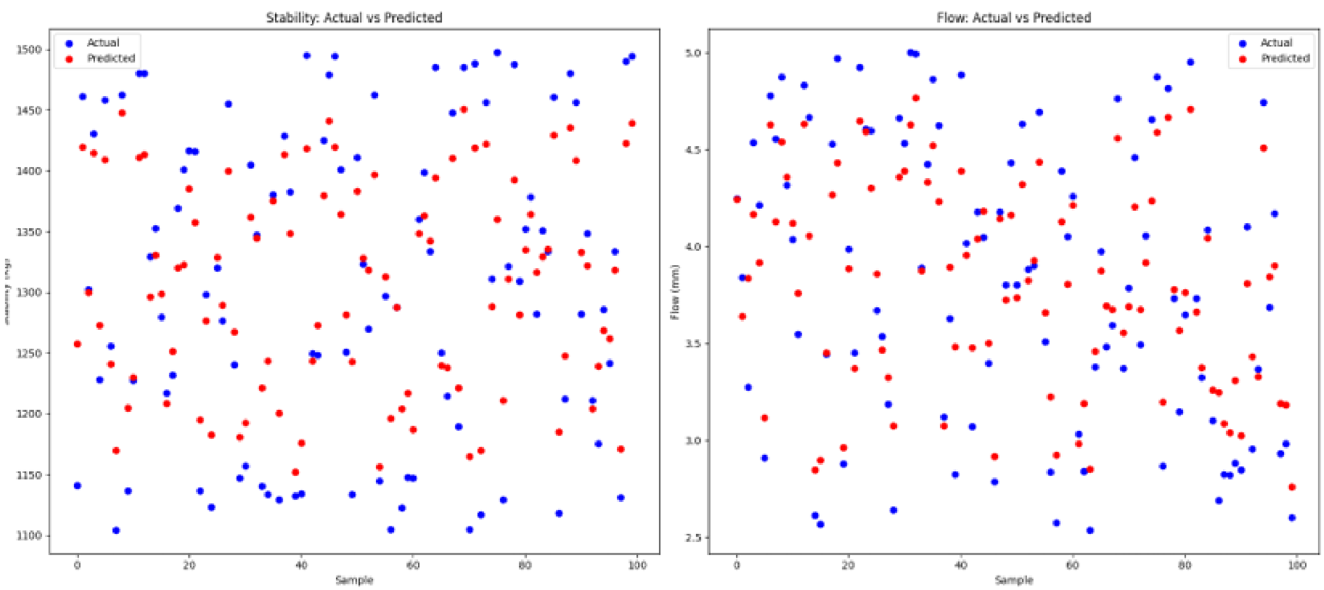

Fig. 7 Scatter plots

4.4 Sensitivity and Parametric Analysis

Sensitivity and Parametric Analyses stand as critical pillars in comprehending the intricate dynamics of complex systems, such as the neural network model we employed. These analyses allow us to unravel the intricate relationships between inputs and outputs, offering invaluable insights into the model's behaviour and its responsiveness to various factors [32]. Sensitivity Analysis strives to decipher the influence of individual input variables on the model's outputs, uncovering which inputs wield the most profound impact. In parallel, Parametric Analysis dives into the consequences of altering specific parameters while keeping other variables constant, fostering a deeper understanding of the system's intricacies [33].

In our scenario, both Sensitivity and Parametric Analyses were undertaken on a neural network model crafted for predicting two key outputs: Stability and Flow, with four input parameters in play – Temperature, Foam Content, Expansion Ratio, and Half-Life. Sensitivity Analysis made it possible to quantify the sensitivity of each output to these inputs, unraveling the core drivers behind the model's predictions. The impact of each parameter was quantified using following equations [31]:

Equation (3) for the calculation of the sensitivity of each input parameter on the neural network model's outputs:

$$K_i = N_{\max}\left(x_i\right) - N_{\min}\left(x_i\right), \tag{3}$$

where:

- K_i: is the sensitivity of the output to the i^{th} input parameter,
- $N_{\max}(x_i)$: is the maximum predicted value of the output when the i^{th} input parameter (x_i) is at its maximum value,
- $N_{\min}(x_i)$: is the minimum predicted value of the output when the i^{th} input parameter (x_i) is at its minimum value.

Equation (4) calculates the range of predicted values of the output (N) due to variations in i^{th} input parameter (x_i).

$$S_a = \frac{K_i}{\sum_n^{j=1} K_i} \times 100, \tag{4}$$

where:

- S_a: is the sensitivity analysis value or the sensitivity of the output to the i^{th} input parameter as a percentage,
- K_i: is the sensitivity of the output to the i^{th} input parameter, as calculated in Eq. (3),
- $\sum_n^{j=1} K_i$: is the sum of sensitivities across all input parameters.

Equation (4) compared how each input parameter can affect the model's output. It is performed by dividing the sensitivity of each input parameter (K_i) by the total sensitivity of all input parameters added together. It is expressed in percentage. So, the input parameters could be identified, which have the biggest impact on the model's predictions.

It was found that, for Stability, the Expansion Ratio carries a monumental influence, while for Flow, it is the Foam Content that exerts the most substantial sway. The Parametric Analysis allowed us to delve deeper into these relationships. Through a meticulous exploration of each parameter's effects on the outputs, a comprehensive understanding of their contributions was formulated. Notably, the Expansion Ratio displayed a steep decline in Stability as it escalated Fig. 8, while Foam Content exhibited a proportional rise in flow with its ascent as shown in Fig. 9. By blending the insights of Sensitivity and Parametric Analyses, a panoramic comprehension of our model's inner workings was gained. Armed with equations and a granular understanding, we stand poised to make targeted refinements to the model, optimizing its architecture, and zeroing in on pivotal parameters. Ultimately, this synergy of analyses allows not only to enhance the model's predictive process but also to gain a deeper understanding of the intricate interplay between inputs and outputs, all within the realm of Stability and Flow prediction.

4.5 Empirical equations

The next step in the analysis is the formulation of the empirical equations that have crystallized from former comprehensive exploration. The resulted equations constitute a concise representation of the intricate relationships revealed between the input parameters and the predictions

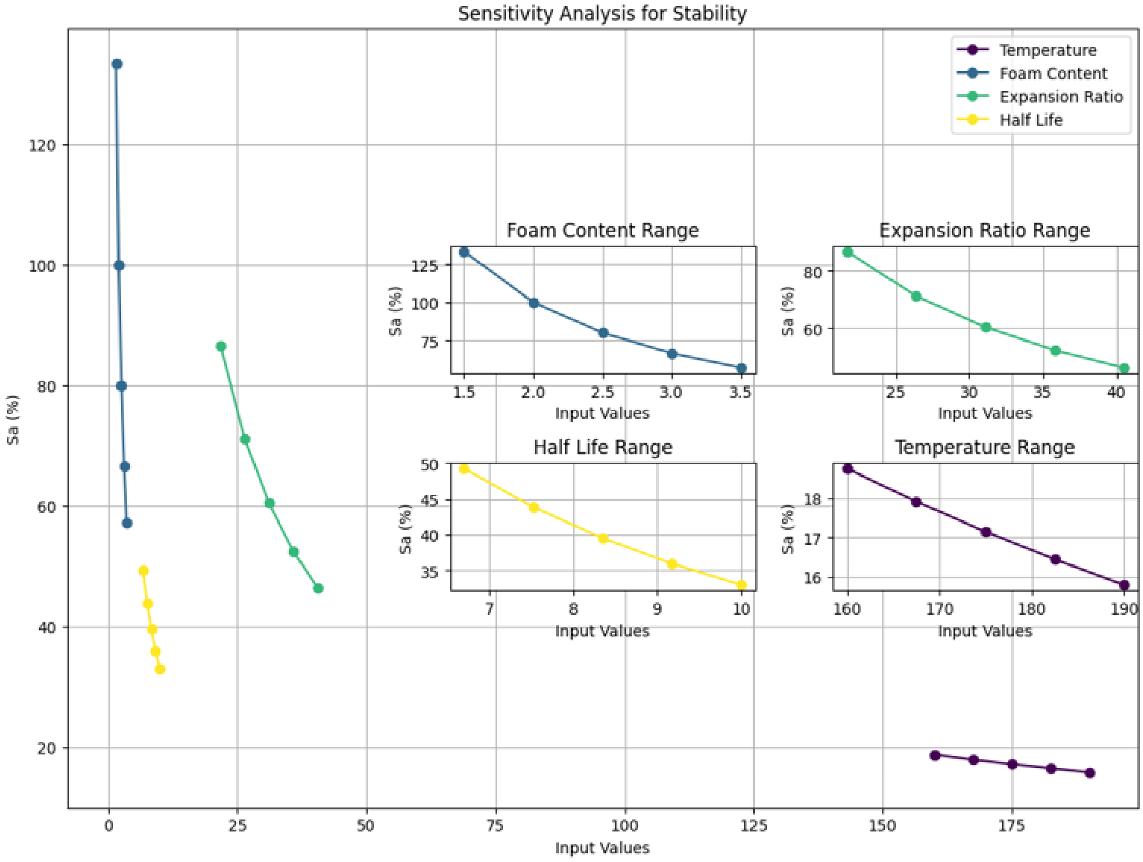

Fig. 8 Sensitivity and Parametric Analyses for Stability

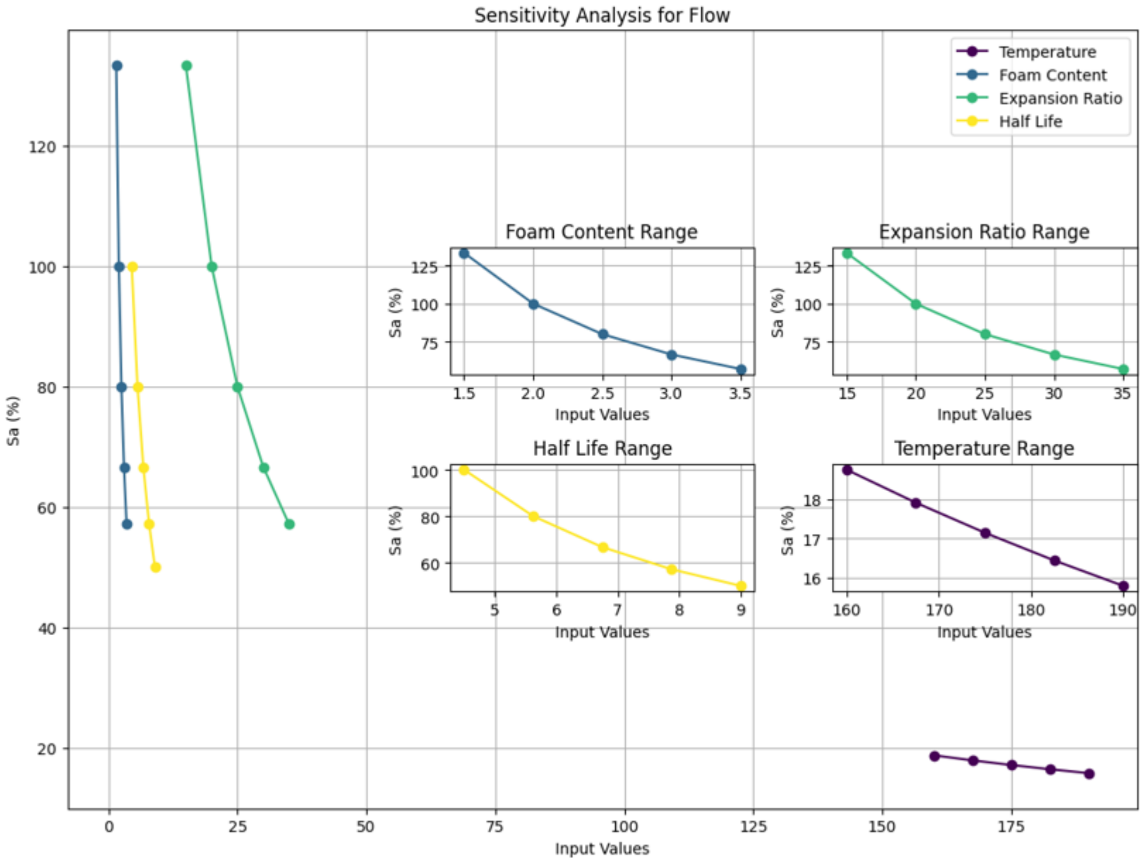

Fig. 9 Sensitivity and Parametric Analyses for Flow

for both Stability and Flow produced by our neural network model. The resulted equations encapsulate the underlying patterns and interactions governing the predictive behaviour of the model:

1. Equation for Stability:

$$
\begin{aligned}
\text{Stability} = {} & 0.0711 \times (\text{Temperature})^2 \\
& +0.4020 \times (\text{Expansion Ratio})^2 \\
& -0.2587 \times (\text{Half Life})^2 \\
& -6.5714 \times (\text{Foam Content})^2 \\
& -23.8693 \times (\text{Temperature}) \\
& -11.3102 \times (\text{Expansion Ratio}) \\
& -8.2693 \times (\text{Half Life}) \\
& +45.7905 \times (\text{Foam Content}) + 3271.1353.
\end{aligned}
\tag{5}
$$

2. Equation for Flow:

$$
\begin{aligned}
\text{Flow} = {} & -0.0005 \times (\text{Temperature})^2 \\
& -0.0068 \times (\text{Expansion Ratio})^2 \\
& +0.0099 \times (\text{Half Life})^2 \\
& +0.3048 \times (\text{Foam Content})^2 \\
& +0.1949 \times (\text{Temperature}) \\
& +0.3355 \times (\text{Expansion Ratio}) \\
& +0.1417 \times (\text{Half Life}) \\
& -1.5871 \times (\text{Foam Content}) - 18.2518.
\end{aligned}
\tag{6}
$$

Equations (5) and (6) embody the culmination of former meticulous analysis and allow us to predict the model's output values with consideration of the input parameters. To provide an intuitive understanding of the equations, charts were generated that visually depict the relationships they encode. The resulted charts illustrate the interplay between individual input parameters and the resultant outputs of Stability and Flow (Figs. 10 to 13). By merging the power of mathematical modelling with tangible visualizations, a comprehensive tool of comprehending was provided utilizing the insights gained from the analysis.

In our endeavor of achieving enhanced accuracy and deeper insights, a novel approach was introduced that involves integration equations. The resulted equations are designed to utilize the power of integration to capture even more nuanced relationships between the input parameters and the predictions for both Stability and Flow, as derived from the neural network model presented before.

For the Stability equation (Eq. (7)), the integration of the input parameters leads to the following refined form:

$$
\begin{aligned}
\text{Stability} = {} & -0.0873 \times \int \llbracket (\text{Temperature} \rrbracket) \\
& +0.6331 \times \int \llbracket (\text{Expansion Ratio} \rrbracket) \\
& -2.4588 \times \int \llbracket (\text{Half Life} \rrbracket) \\
& +3.3092 \times \int \llbracket (\text{Foam Content} \rrbracket) \\
& +3.3522 \times (\text{Temperature}) \\
& +10.6814 \times (\text{Expansion Ratio}) \\
& -7.7589 \times (\text{Half Life}) \\
& +14.0873 \times (\text{Foam Content}) + 482.8456.
\end{aligned}
\tag{7}
$$

Similarly for flow:

$$
\begin{aligned}
\text{Flow} = {} & -0.0009 \times \int \llbracket (\text{Temperature} \rrbracket) \\
& -0.0160 \times \int \llbracket (\text{Expansion Ratio} \rrbracket) \\
& +0.0094 \times \int \llbracket (\text{Half Life} \rrbracket) \\
& +0.2355 \times \int \llbracket (\text{Foam Content} \rrbracket) \\
& -0.0771 \times (\text{Temperature}) \\
& -0.0907[2] \times (\text{Expansion Ratio}) \\
& +0.2131 \times (\text{Half Life}) \\
& -0.3013 \times (\text{Foam Content}) + 17.4574.
\end{aligned}
\tag{8}
$$

These integration equations hold the potential to uncover subtler patterns and dependencies within the data. By considering the cumulative effect of the input parameters through integration, to provide an even more accurate representation of the complex relationships underlying the neural network's predictions was aimed at. The idea was incorporating this advanced methodology into the analysis in order to underscore our commitment to unraveling the intricate dynamics of the system and refining our predictive capabilities.

5 Conclusions

In the pursuit of efficient and cost-effective roadway pavements, the research work presented leverages advanced machine learning techniques to predict the critical properties of asphalt mixtures. By utilizing a neural network model, we have successfully established accurate prediction equations for Marshall Stability (MS) and Flow (MF), integrating essential input parameters. Through surface analyses and integration equations, we have unveiled intricate relationships between inputs and outputs, providing a more comprehensive understanding of the system's dynamics. Sensitivity and Parametric Analyses have illuminated the pivotal parameters and their impacts on

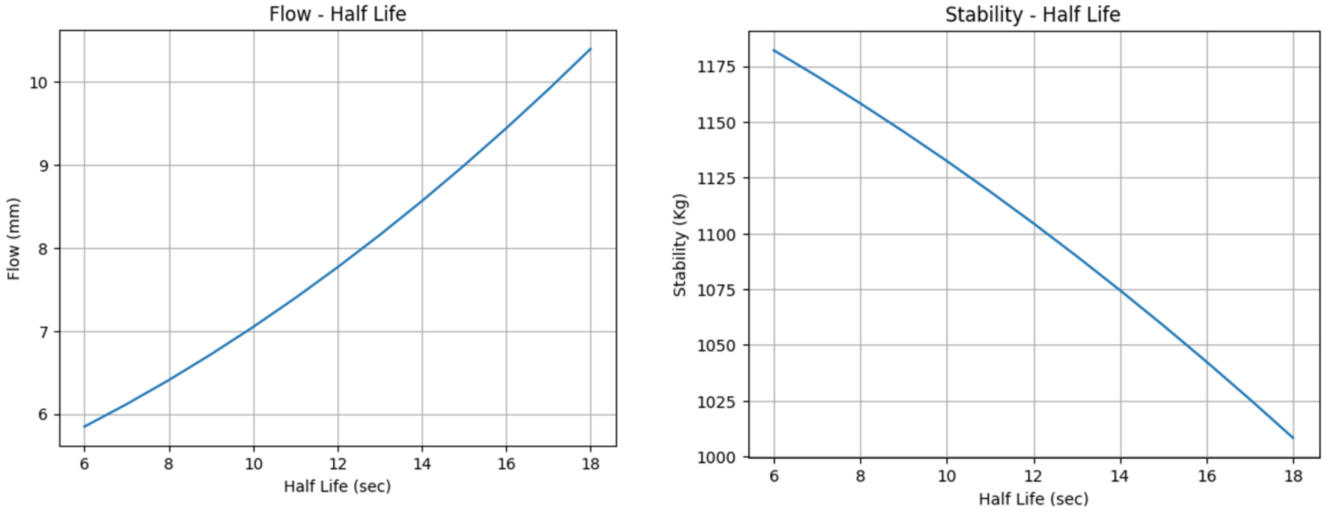

Fig. 10 Stability and Flow vs. Half Life

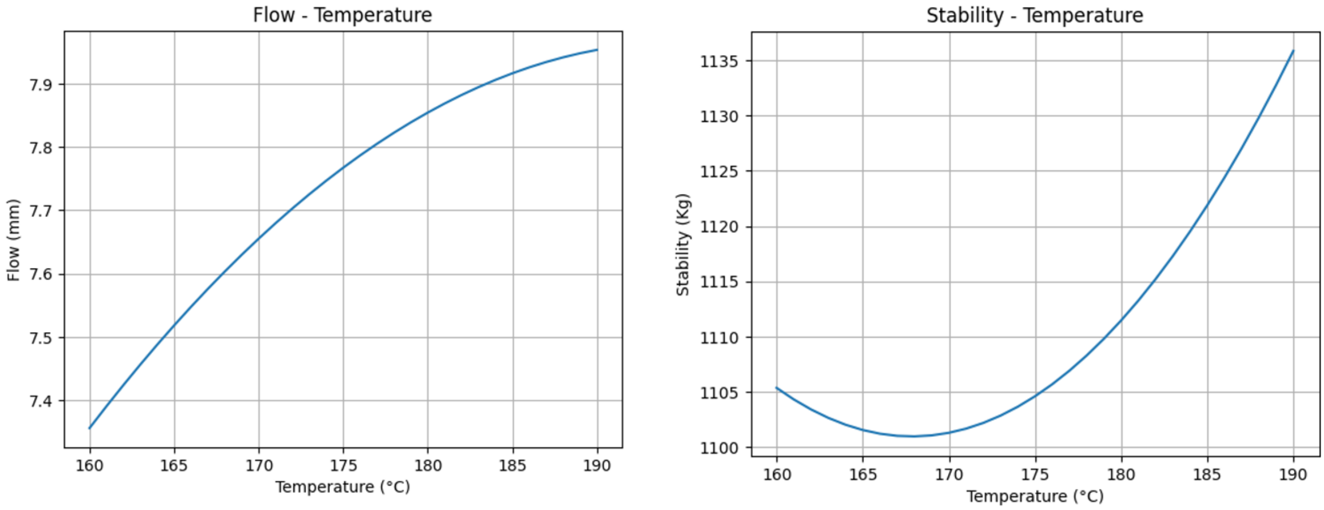

Fig. 11 Stability and Flow vs. Temperature

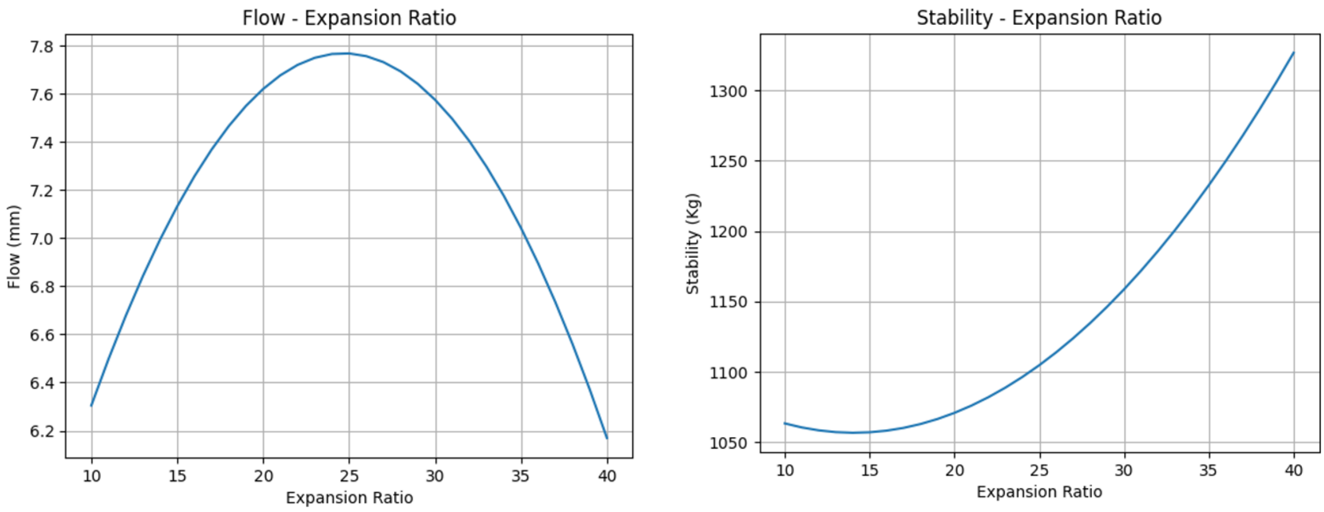

Fig. 12 Stability and Flow vs. Expansion Ratio

predictions, enhancing our ability to optimize pavement design. Additionally, R-squared measures have quantified the model's goodness of fit, ensuring the reliability of our predictions. This study not only contributes to efficient road infrastructure but also advances the domain's knowledge in material engineering and predictive modeling.

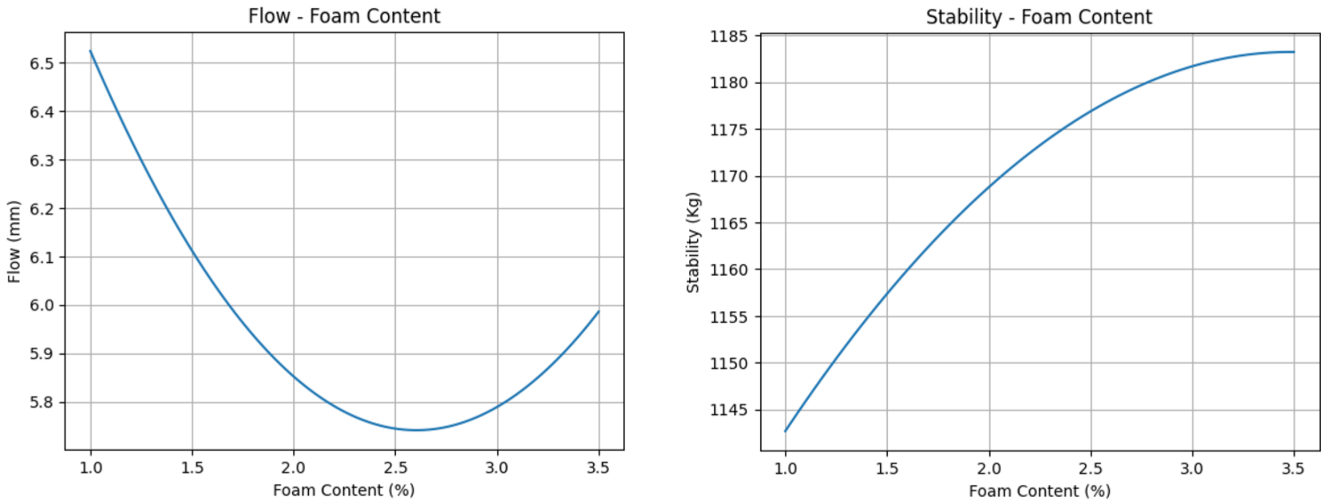

Fig. 13 Stability and Flow vs. Foam Content

In conclusion, this study stands as a testament to the power of modern computational techniques in revolutionizing pavement engineering. By embracing advanced machine learning, we've shifted the paradigm from resource-intensive experiments to swift, accurate predictions. The model's equations and insights into sensitivity, combined with the innovative integration equations, offer a holistic approach to understanding bituminous mix behaviour. This research not only advances the realm of pavement engineering but also paves the way for cost-effective, durable road infrastructure that can withstand the test of time and changing conditions. As we drive forward on the path of progress, this study serves as a beacon of innovation and knowledge in the field of material engineering and predictive modelling.

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