AKADÉMIAI KIADÓ

# Optimizing asphalt foaming using neural network

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### ABSTRACT

This study uses a three-layer backpropagation neural network combined with particle swarm optimization to control the foamed bitumen in cold recycling technology. The foaming process of bitumen is non-linear and depends on dynamic temperature. By developing a neural network model, this study effectively captures the complex relationships between temperature, water content, air pressure, and the expansion ratio and half-life of foamed bitumen. The integration of particle swarm optimization enhances the accuracy and convergence of the neural network model by optimizing the initial weights. This optimization process improves the model's ability to predict and control the quality of foamed bitumen accurately. It serves as a valuable tool for the rapid development of high-quality cold asphalt design.

### KEYWORDS

foamed bitumen, warm mix asphalt, particle swarm optimization, machine learning

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## 1. INTRODUCTION

Cold recycling technology is considered one of the most important renewable construction methods, which is used for saving energy in addition that its environmentally and economic advantages [1]. Foamed bitumen, a unique material produced through a specialized process, involves the injection of water and air into hot bitumen at temperatures ranging from 150 to 180 °C [2]. This distinctive technique induces a reaction between the water and hot bitumen, resulting in a heat exchange phenomenon. Therefore, the water transforms into steam and is forcefully introduced into the bitumen structure under pressure. This interaction gives rise to numerous bitumen bubbles that encapsulate vapor within their composition [3]. The resulting product, characterized by its foamed texture and enhanced properties, offers a range of unique applications and advantages in various fields.

The difficulty in studying the foamed asphalt changes is that the bitumen foam formation process is a non-linear process, as it depends on the dynamic temperature [4, 5]. The foaming quality measurement parameters are ER, which is defined as the ratio of the maximum volume to the original volume before the foaming process, HL, which is the time when the maximum volume needs half of the expansion volume [6, 7]. As many factors affect the performance of asphalt foam, the three most influential factors are temperature (T), water content (WC) and air pressure (AP). In engineering applications, the optimal amount of water needed to foam asphalt is between 2% and 4% of the asphalt mass [8], the minimum value of ER is 8 times and HL is 6 s [9]. Due to the importance of foamed asphalt in these applications, it is necessary to create a foamed asphalt control model with its parameters to determine the best value for each variable and to improve the foam quality. All of them are mean to achieve the rapid development of high-quality cold asphalt design [10].

The neural network model stands out as a distinctive approach in the realm of data-driven modeling, as it effectively establishes connections between input and output data, without necessitating an in-depth understanding of the underlying internal processes [11, 12]. This unique characteristic has rendered neural network models highly sought-after and widely employed in addressing complex modeling challenges across diverse fields. By leveraging the power of neural networks, researchers and practitioners have been able to tackle intricate problems that would otherwise prove arduous or impractical using traditional methodologies. The versatility and efficacy of neural network models have solidified their position as a go-to solution in numerous domains, revolutionizing the way complex modeling problems are approached and solved. There is a parametric model, which is created by Wang [5], its function is control the foamed bitumen quality based on the experimental results, but it turned outfaced at difficult to be applied in the engineering because of the large and complicated calculation [7].

This incorporation of Particle Swarm Optimization (PSO) not only improved the prediction accuracy of the neural network model but also contributed to a more robust and precise characterization of the asphalt foaming behavior. The combined utilization of neural networks and PSO showcases a novel methodology that can be applied to similar modeling problems, providing valuable insights, and paving the way for improved understanding and control of asphalt foaming processes.

## 2. MACHINE LEARNING MODELS

Machine learning is a branch of Artificial Intelligence (AI) [13], encompasses three primary approaches for solving problems.

*Supervised learning:* In this approach, a computer is trained using a dataset that consists of input data along with corresponding output datum. All that, to learn a general rule or function that can map given inputs to their respective outputs. This sort is commonly used for tasks as classification and regression [14].

*Unsupervised learning:* Unsupervised learning algorithms operate without specific guidance. They aim to discover patterns or structures within input data without the presence of labeled outputs. Unsupervised learning techniques include methods for data visualization, dimensionality reduction, and clustering, enabling the identification of inherent patterns within the data [15].

*Reinforcement learning:* Reinforcement learning involves a computer or agent operating within a dynamic environment [16]. The algorithm learns to perform a specific goal-oriented task and receives feedback, typically in the form of rewards or penalties, to reinforce its learning process. By optimizing its actions based on received feedback, the algorithm aims to maximize its cumulative reward.

Furthermore, hybrid approaches as semi-supervised learning, offer a combination of supervised and unsupervised techniques, and can be tailored to specific problem domains [17–22]. In the context of predicting foamed bitumen content by analyzing aggregate gradation, bitumen type, and mixture properties, the problem can be considered a regression task. As the study falls within the realm of supervised learning, which involves predicting continuous values, various supervised machine learning techniques are available for regression problems, including Random Forest, Support Vector Regression, Artificial Neural Networks, and others. These algorithms can be employed to develop accurate models for predicting foamed bitumen content, enhancing our understanding and control of the foaming process.

## 3. BITUMEN FOAMING MODEL

### 3.1. BP neural network model

To address the task of bitumen foaming control, a three-layer BackPropagation (BP) neural network model was employed, recognized as one of the most widely used Artificial Neural Network (ANN) architectures [18, 19]. The BP neural network exhibits favorable properties that make it suitable for various applications, including its ability to comprehend nonlinear mappings. In this research, a three-layer configuration was adopted, consisting of an input layer, a hidden layer, and an output layer [20].

The model was designed to focus on three key factors: temperature, water content, and air pressure, which served as the input parameters for the neural network. The experimental results provided the target values, namely the Expansion Ratio and Half-life, which were the outputs of the network [21].

The neural network architecture consisted of three input neurons and two output neurons, reflecting the number of input and output factors being considered. This configuration necessitated the inclusion of a single hidden layer to facilitate the complex mapping process [22–25]. The overall structure and connectivity of the neural network model are illustrated in Fig. 1.

By leveraging this unique three-layer BP neural network, the study aimed to construct an asphalt foaming control model, allowing for effective regulation and monitoring of the foaming process. The model's capability to capture

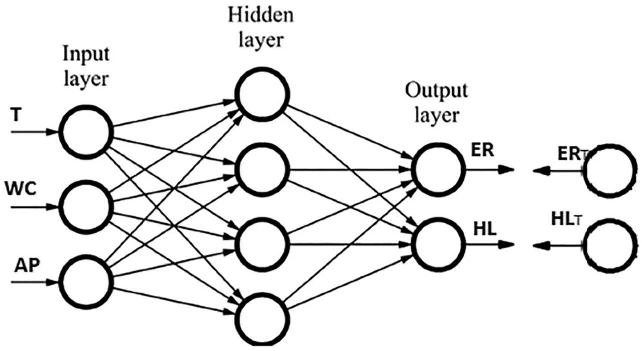



*Fig. 1.* Architecture of the neural network model

nonlinear relationships and its incorporation of the specific input factors and target outputs make it a valuable tool for achieving accurate predictions and optimizing bitumen foaming outcomes.

In the context of optimizing the initial weights of a BP neural network, the hidden layer plays a crucial role in influencing the prediction accuracy. The number of neurons within this layer significantly impacts the network's performance. Based on experimental findings, a formula is commonly used to determine the appropriate number of hidden neurons, which is equal to the square root of the product of the input layer nodes and the output layer nodes. In the case of our network configuration, with 3 input nodes and 2 output nodes, the optimal number of neurons in the hidden layer is determined to be 16.

To further enhance the performance of the BP neural network, PSO can be employed. PSO aims to find the optimal set of initial weights for the network by mimicking the behavior of a swarm of particles moving through a search space. By iteratively adjusting the weights, the PSO algorithm seeks to improve the network's convergence and prediction accuracy.

To implement PSO for weight optimization in the presented neural network model it is needed to define the specific problem, including the desired network architecture and the relevant equations. In this case, the network consists of 3 input nodes, 2 output nodes, and a hidden layer with 16 neurons. The PSO algorithm will work to optimize the initial weights, thereby enhancing the network's performance and its ability to accurately predict the desired outputs. This combination of BP neural network and PSO optimization provides a unique and effective approach to improve the accuracy and effectiveness of the bitumen foaming prediction model.

***3.1.1. Problem definition.*** The problem is to find optimal initial weights for the neural network model. These weights will affect the performance of the network during the training phase, and by optimizing them, it is aimed to improve the network's overall accuracy and convergence speed.

***3.1.2. Neural network architecture.*** The neural network architecture consists of an input layer, a hidden layer, and an output layer. The input layer has 3 nodes; the hidden layer has 16 nodes, and the output layer has 2 nodes.

***3.1.3. Equations involved.*** a) Forward propagation

During the forward propagation phase, the output of each neuron based on the input values and the current weights of the network are calculated. The following equation is used to compute the output of a neuron in the hidden layer:

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

where $h_i$ is the output of the $i$th neuron in the hidden layer; $w_{ij}^{(1)}$ is the weight connecting the $i$th neuron in the hidden layer to the $j$th 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; $\sigma$ 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:

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

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

b) Error calculation

During the training phase, the error between the predicted outputs and the desired outputs is also calculated. The error can be computed using various metrics, as Mean Squared Error (MSE) or cross-entropy loss. Let's consider the MSE for simplicity:

$$E = \frac{1}{2n}\sum\nolimits_{k=1}^{n} (d_k - O_k)^2, \tag{3}$$

where $E$ is the mean squared error; $n$ is the number of training samples; $d_k$ is the desired output for the $k$th training sample; $O_k$ is the predicted output for the $k$th training sample.

## 3.2. Particle swarm optimization

PSO is a population-based optimization algorithm inspired by the collective behavior of birds and fish, proves useful in optimizing the initial weights of BP neural networks. In a BP neural network, multiple layers of interconnected nodes represent neurons, and the network adjusts the weights associated with neuron connections to minimize output error. Conventionally, initial weights in BP networks are randomly set or determined using heuristics, but finding optimal weights is crucial for enhancing network performance and convergence speed. PSO can address this challenge by treating the initial weights as particles in a search space. The algorithm initializes a population of particles, with each particle representing a potential solution (a set of initial weights). These particles are then iteratively updated based on personal best solutions and the best solution discovered by any particle in the population. During each iteration particles adjust their positions (weights) by considering their velocity, influenced by personal and global best solutions. PSO leverages social interactions and information sharing among particles to guide the search towards promising weight regions that yield improved performance. The fitness function evaluates the neural network's performance with the current set of initial weights, and the process continues until a stopping criterion is met, as reaching a maximum number of iterations or achieving satisfactory performance. By integrating PSO into the optimization of initial weights, BP neural networks benefit from a more efficient and effective search process. PSO intelligently explores the weight space, promoting convergence and potentially enhancing overall network performance.

By applying the PSO algorithm to optimize the initial weights of the BP neural network, the weights that minimize the error function can be found, thus improving the network's performance. The PSO algorithm iteratively updates the positions and velocities of particles, allowing them to explore the weight space and converge towards an optimal solution.

## 4. VERIFICATION OF ASPHALT FOAMING CONTROL MODEL

After verifying the linear regression model on foamed bitumen data, the following results and summary were obtained (Fig. 2).

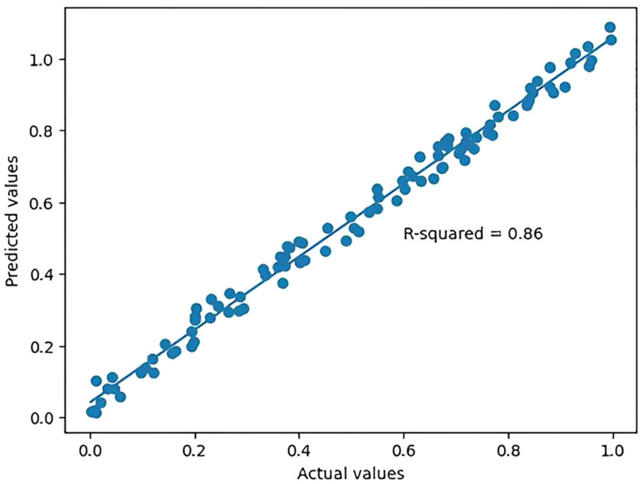



*Fig. 2.* R-squared for designed model

### 4.1. Model performance

The R-squared value indicates that approximately 86.3% of the variation in the target variables (Expansion Ratio and Half-life) can be explained by the input variables (Temperature, Water content, and Air pressure). Additionally, the mean squared error provides an estimate of the average squared difference between the actual and predicted values, which in this case the amount is 0.032.

### 4.2. Scatter plots

*Expansion Ratio*: The scatter plot comparing the actual and predicted values of the Expansion Ratio shows a reasonably positive linear relationship, indicating that the model can effectively predict this variable (Fig. 3).

*Half-life:* The scatter plot for the Half-life variable demonstrates a good agreement between the actual and predicted values, suggesting that the model captures the underlying patterns in the data (Fig. 3).

### 4.3. Correlation analysis

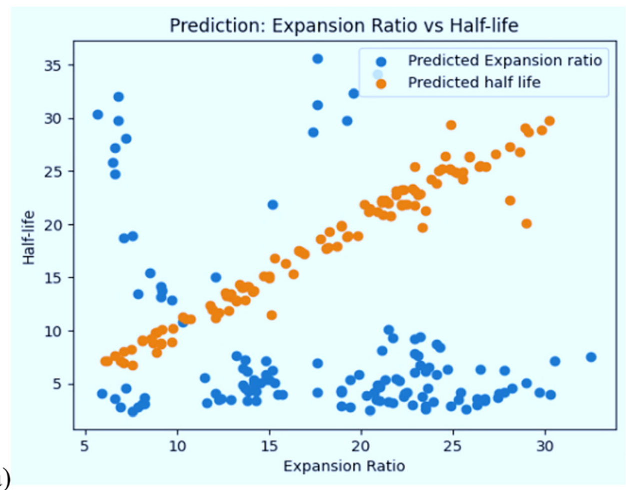
The correlation heatmap reveals the relationship between the input variables (Temperature, Water content, and Air pressure) and the output variables (Expansion Ratio and Half-life). It helps in identifying the variables that have a strong impact on the target variables and their interrelationships as it is shown in Fig. 4.

### 4.4. Model equation

The linear regression model equations can be expressed as follows:

$$\begin{aligned} \textit{Expansion Ratio} = {} & 0.213 \cdot \textit{Temperature} \\ & + 0.056 \cdot \textit{Water content} \\ & + 0.017 \cdot \textit{Air pressure} - 0.003, \end{aligned} \tag{4}$$

$$\begin{aligned} \textit{Half life} = {} & 0.038 \cdot \textit{Temperature} + 0.045 \cdot \textit{Woter content} \\ & + 0.014 \cdot \textit{Air pressure} + 0.002. \end{aligned} \tag{5}$$

a) 

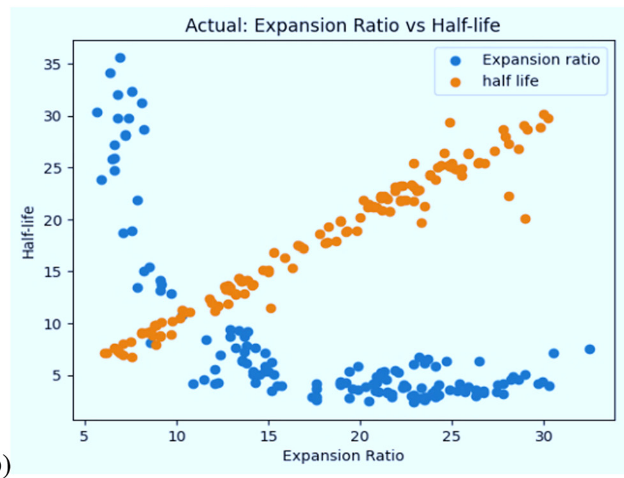

b) 


*Fig. 3.* a) Prediction values of ER and HL, b) Experimental results of ER and HL

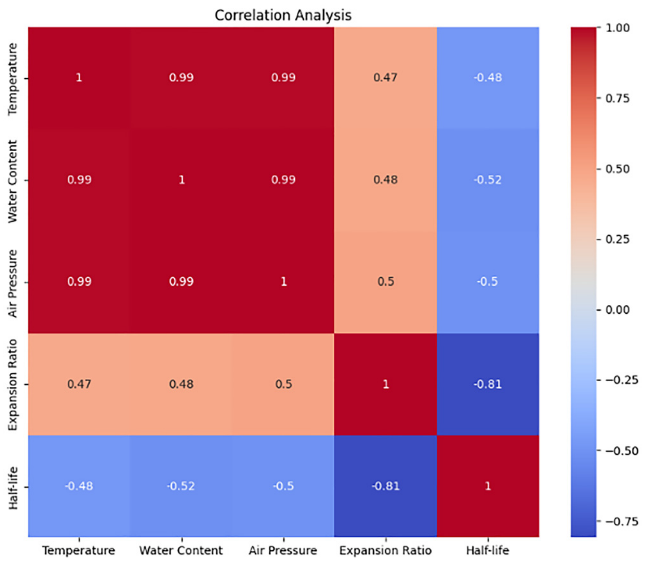



*Fig. 4.* Correlation values

These equations represent the relationship between the input variables (*Temperature*, *Water content*, and *Air pressure*) and the corresponding output variables (*Expansion Ratio* and *Half-life*) are based on the linear regression model. The coefficients in the equations indicate the impact of each input variable on the respective output variable. The intercept terms −0.003 and 0.002 represent the base value of the output variables when all input variables are zero.

In addition to that, by plugging in specific values for the input variables, the predicted values for the Expansion Ratio and Half-life can be calculated using these equations (Fig. 5).

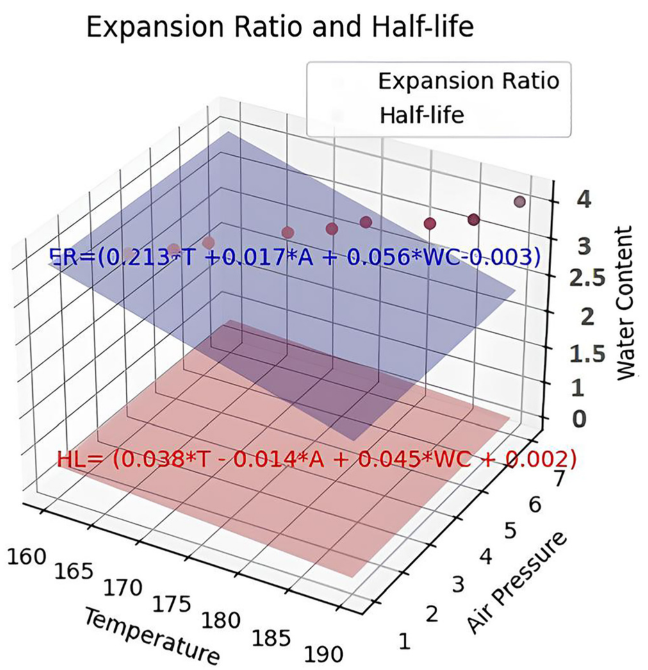



*Fig. 5.* Demonstration of Eqs (4) and (5) using the designed model

### 4.5. Optimal values

This model can predicate the optimal values after training the network; the results are shown in Fig. 6:

- The optimal water content that maximizes the Expansion Ratio is found to be 2.65%;
- The optimal temperature that maximizes the Expansion Ratio amounts to 178 °C;
- The optimal air pressure that maximizes the Half-life is 2.5 bar.

These results provide valuable insights into the relationship between the input variables and the target variables in the foamed bitumen application. The linear regression model demonstrates a good fit to the data, allowing for accurate predictions, and understanding of the influential factors.

## 5. CONCLUSIONS

Using the linear regression model on foamed bitumen data, valuable insights were gained and promising results achieved. The model demonstrated good performance with a high R-squared value of 0.863, indicating that approximately 86.3% of the variation in the target variables (Expansion Ratio and Half-life) can be explained by the input variables (Temperature, Water content, and Air pressure). Additionally, the MSE of 0.032 suggests that the model's predictions are, on average, quite close to the actual values. The scatter plots comparing the actual and predicted values for both the Expansion Ratio and Half-life show a reasonably positive linear relationship, indicating that the model effectively captures the underlying patterns in the data. This suggests that the model can be utilized to make accurate predictions for these variables.

Furthermore, the correlation analysis using a heatmap has provided insights into the relationships between the input variables (Temperature, Water content, and Air pressure) and the output variables (Expansion Ratio and Half-life). This analysis helps identify the variables that have a strong impact on the target variables and reveals their interrelationships.

The equations derived from the linear regression model allow us to quantify the relationships between the input and output variables. The coefficients in the equations represent the impact of each input variable on the corresponding output variable, while the intercept terms provide the base values of the output variables when all input variables are zero. These equations can be used to make predictions and understand the influential factors in the foamed bitumen application.

Overall, the results from this operation highlight the effectiveness of the linear regression model in predicting the Expansion Ratio and Half-life of foamed bitumen. This model can be utilized to optimize the mixture design and enhance the understanding of the influential factors in

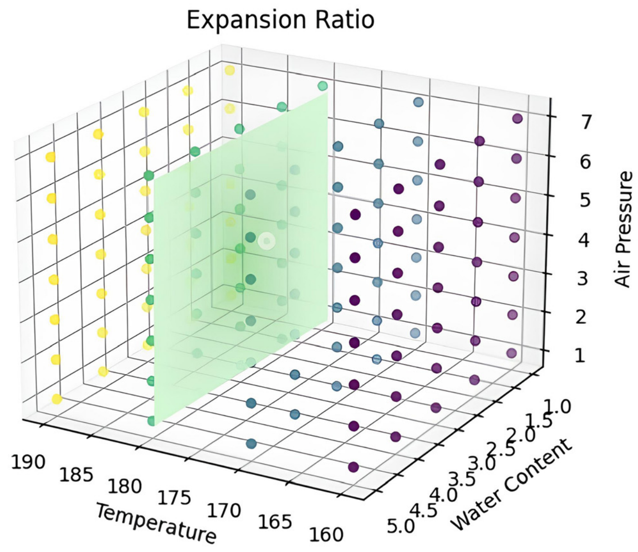



*Fig. 6.* The optimal values using the model

foamed bitumen applications, leading to improved performance and efficiency in this field.

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