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# Determination of Complex Modulus Values of Low-Density Polyethylene Modified Bitumen Obtained by Using Two Different Waste Types with Artificial Neural Networks

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**Abstract**: The present study aims to solve an important environmental problem and improve the performance properties of bitumen by using two types of waste low density polyethylene (LDPE). For this purpose, two types of additives, LDPE (A) and LDPE (B), were added to the pure binder at the rates of 1%, 2%, 3% and 4% to obtain modified binders. Then, Dynamic Shear Rheometer experiments were applied on the binders under different temperatures and frequencies, and their behavior under these conditions was investigated. The complex shear modulus values obtained as a result of the experiment were estimated with Artificial Neural Network models created by training with different training algorithms. Experimental results showed that both additives increased the complex modulus values of the binder, with the LDPE (A) additive having higher complex modulus values compared to the LDPE (B) additive. In addition, it was determined that the model obtained with the Levenberg-Marquardt training algorithm gave the best results and it was concluded that the complex module values of asphalt binders can be successfully estimated using Artificial Neural Networks.

**Keywords:** Waste Materials, Recycling, Asphalt, Modification, Artificial Neural Networks

## Introduction

Waste plastic has been one of the most remarkable materials for the last few years (Y. Huang et al., 2007; Ingrassia et al., 2019). However, the waste plastic recycling rate in the US is quite low compared to other countries that report recycling rates between 30% and 60%. Japan has the highest recycling rate with a value of 78% (Khoo, 2019). Plastic waste mixtures are difficult materials to recycle due to their complex structure and inefficient mechanical recycling processes. Instead of sending waste to developing countries, Australia is taking proactive steps to develop an alternative to using recycled plastic, which contributes significantly to the country's waste generation (Chin & Damen, 2019). In addition, new alternatives are sought for using waste plastics in the USA. In China and India, the import of waste plastics is prohibited (Cockburn, 2019).

Reducing the use of plastic may be the best way to directly reduce waste plastic. For example, a perspective has been proposed to move towards zero waste by banning single-use plastics (Walker & Xanthos, 2018). This prohibition can be difficult to enforce. Therefore, other options should be sought to reduce the plastic waste problem. Researchers and engineers are working to produce wood-plastic composites (Keskisaari & Kärki, 2018), concrete blocks (Meng et al., 2018) and mortars (Makri et al., 2019; Ramli & Akhavan Tabassi, 2012) that can be used in construction infrastructures by evaluating waste plastic materials. Ramli and Tabassi (Ramli



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& Akhavan Tabassi, 2012) found that polymer modified mortars exhibited better engineering properties than conventional mortar mixtures. Arulrajah et al., investigated the possibility of using plastic granules in combination with crushed brick and recycled asphalt pavement (RAP) wastes used as base fill material (Arulrajah et al., 2017) .

Utilizing waste materials in bituminous coatings is an environmentally friendly approach that has gained great importance in recent years. Bitumen is the most commonly used binder in pavement and is derived from a non-renewable resource, petroleum (Ingrassia et al., 2019). On the one hand, researchers make use of various wastes such as waste motor oil, cooking oil, pig manure and coffee grounds within the scope of environmental studies. This can undoubtedly reduce harmful environmental impacts and raw material consumption. Engineers, on the other hand, are hesitant to advocate the use of large amounts of recycled materials unless such a pavement infrastructure with recycled materials is proven to perform as well as those without recycled materials. There are many studies on the use of various waste polymers on roads (Poulikakos et al., 2017; Sangita et al., 2011) . However, there is a gap in the literature to fully understand the performance of asphalt pavements containing various dosages and types of recycled plastics.

Low density polyethylene (LDPE) is often used in bitumen modification to improve rutting resistance at high temperature and significantly reduce temperature sensitivity. In this study, the effect of using low density polyethylene (LDPE) with two different chemical contents on the rheological properties of bitumen binders was investigated. Two different LDPE binders were added to the pure bitumen in 4 different ratios (1%, 2%, 3% and 4%). Dynamic Shear Rheometer experiment was carried out. In addition, Artificial Neural Network models were obtained with two different training algorithms and various neuron numbers, then complex modulus values were obtained through these models.

## Material

In this study, 50/70 penetration grade pure asphalt binder procured from Batman Refinery by TÜPRAŞ (Turkish Petroleum Refineries Corporation) was preferred. The procured binder was modified with two different low-density polyethylene additives. The physical properties of LDPE (A) and LDPE (B), which are two different additives used, are given in Table 1. The additive rate used for the modification process was determined as 1%, 2%, 3% and 4%.

Table 1. Physical properties of LDPE (A) and LDPE (B)

| Property | LDPE (A) | LDPE (B) |
|---|---|---|
| Specific gravity ($g/cm^3$) | 0.913 | 0.916 |
| Tensile strength (MPa) | 20 | 15 |
| Melting temperature (°C) | 120 | 130 |
| Impact strength ($kJ/m^2$) | 5 | 5 |

## Method

### Dynamic Shear Rheometer (DSR)

The dynamic shear rheometer test is carried out to determine the time-dependent deformation and elastic behavior of asphalt binders at medium and high temperatures. As a result of the experiment, the complex shear modulus (G*), which represents the total deformation resistance of the bitumen binders, and the phase angle (δ), which is defined as the delay between the applied shear stress and the resulting deformation, are obtained.

The frequency scanning test performed with the DSR device can simulate the speed of a vehicle traveling on an asphalt pavement. A loading frequency of 10 Hz corresponds to a speed of 60 km/h, while a loading frequency of 15 Hz corresponds to a speed of 90 km/h. The complex modulus and phase angle values vary significantly with temperature and frequency (W. Huang et al., 2019).

In this study, different temperature and frequency effects were investigated on two different LDPE modified asphalt binders by applying frequency scanning test at 40°C, 50°C, 60°C and 70°C temperatures and in the range of 0.01-10Hz.

**Artificial Neural Network (ANN)**

ANN consists of cells inspired by the working principles of the human brain and are structures that can be programmed for learning with the information given to them. The ANN has structures (neurons) resembling human neurons (Öztemel, 2008). ANN takes information from the available data for the problem to be solved, learns, and uses this information to produce solutions and make predictions (Graupe, 2013).

An ANN structure has a total of five parts: inputs (X1,X2,X3…), weights (W1,W2,W3…), aggregation (addition) function, activation (transfer) function, and output (Y). The inputs enter the neurons together with the weights and pass through the joining function to the activation function. In this study, the Sigmoid (Logsig) Function was used as the activation function.

ANN must be trained to work optimally and produce results. It is important to select suitable algorithms for the training process (Sönmez Çakir, 2019). In this study, ANNs were run in MATLAB environment and two different training algorithms, Levenberg-Marquardt (LM) and Scaled Conjugate Gradient (SCG), were preferred. In the established model, three inputs (temperature, frequency, and additive ratio) were used for both additive types and the complex modulus (G*) values of the asphalt binder were obtained as the output.

70% of the dataset was allocated for training, 15% for validation and 15% for testing. While the number of neurons required in the ANN layers when starting the training can be found by various calculations, this number can be found by trial and error until the desired performance values are obtained. Therefore, for each training algorithm, the model was retested with three different neuron numbers (8,10,12) to obtain the highest accuracy with the lowest error rate. The exemplary architecture of one of the models (with eight neurons) used in the study is shown in Figure 1. Explanation of ANN models given in Table 2.

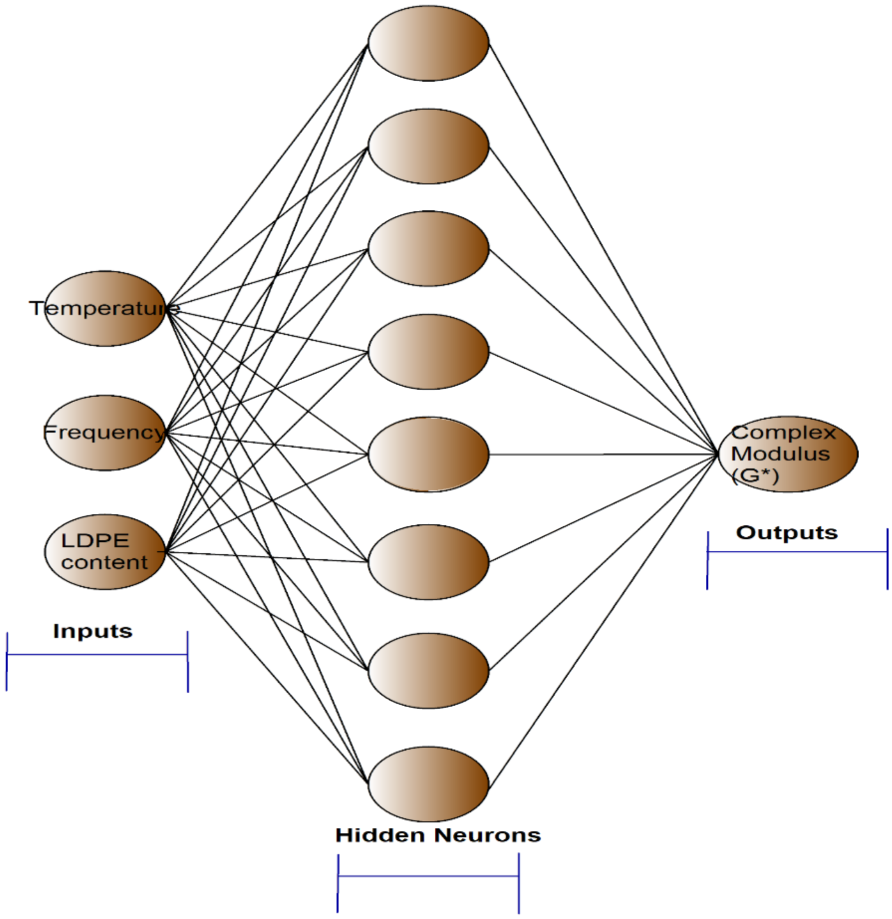


Figure 1. ANN architecture

Table 2. Explanation of ANN models

| Model Name | Explanation |
|---|---|
| Lev-8_A | Levenberg-Marquardt training algorithm with 8 neurons / LDPE (A) |
| Lev-10_A | Levenberg-Marquardt training algorithm with 10 neurons / LDPE (A) |
| Lev-12_A | Levenberg-Marquardt training algorithm with 12 neurons/ LDPE (A) |
| Sca-8_A | Scaled Conjugate Gradient training algorithm with 8 neurons/ LDPE (A) |
| Sca-10_A | Scaled Conjugate Gradient training algorithm with 10 neurons/ LDPE (A) |
| Sca-12_A | Scaled Conjugate Gradient training algorithm with 12 neurons/ LDPE (A) |
| Lev-8_B | Levenberg-Marquardt training algorithm with 8 neurons/ LDPE (B) |
| Lev-10_B | Levenberg-Marquardt training algorithm with 10 neurons/ LDPE (B) |
| Lev-12_B | Levenberg-Marquardt training algorithm with 12 neurons/ LDPE (B) |
| Sca-8_B | Scaled Conjugate Gradient training algorithm with 8 neurons/ LDPE (B) |
| Sca-10_B | Scaled Conjugate Gradient training algorithm with 10 neurons/ LDPE (B) |
| Sca-12_B | Scaled Conjugate Gradient training algorithm with 12 neurons/ LDPE (B) |

A total of three statistical methods, namely Coefficient of Determination (R2), Mean Square Error (MSE) and Root Mean Square Error (RMSE), were used to evaluate model performance and errors.

$Y^{experimental}$ = Experimental data,

$Y^{predicted}$ = Estimated data and n is the number of experimental data:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (Y_i^{predicted} - Y_i^{experimental})^2}{\sum_{i=1}^{n} (Y_i^{experimental})^2} \tag{1}$$

$$MSE = \frac{\sum_{i=1}^{N} (Y_i^{predicted} - Y_i^{experimental})^2}{n} \tag{2}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (Y_i^{predicted} - Y_i^{experimental})^2}{n}} \tag{3}$$

## Results and Discussion

### Dynamic Shear Rheometer (DSR) Results

In the study, dynamic shear rheometer test was applied on pure and modified binders at four different temperatures, 40°C, 50°C, 60°C and 70°C, at ten different frequencies in the range of 0.01-10Hz. The complex modulus values obtained at different frequencies as a result of the experiment are given in Figure 3 for LDPE (A) and Figure 4 for LDPE (B).

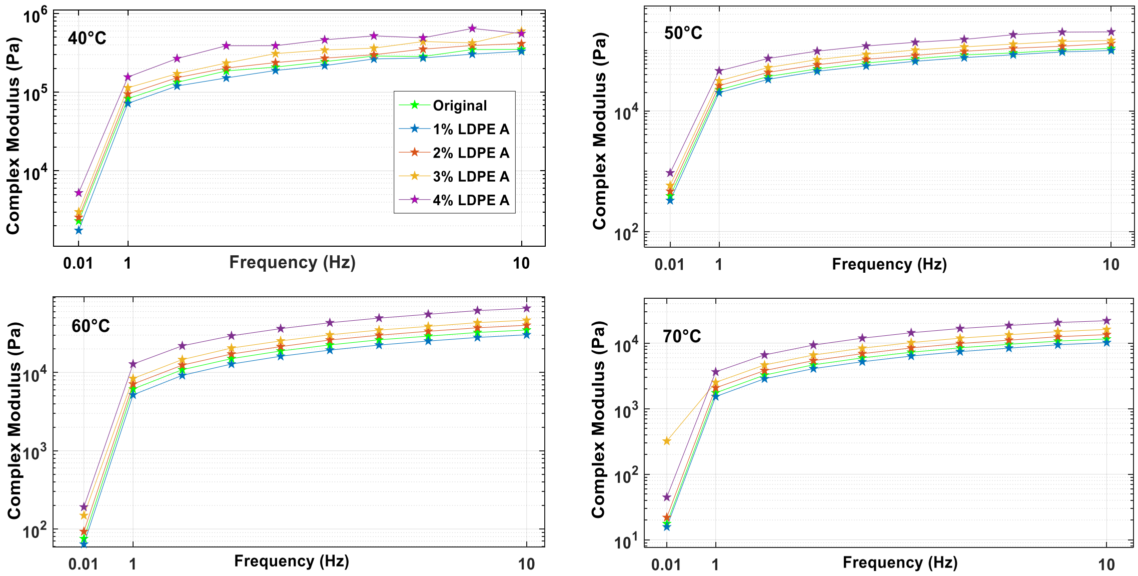


Figure 3. Complex module results for LDPE (A)

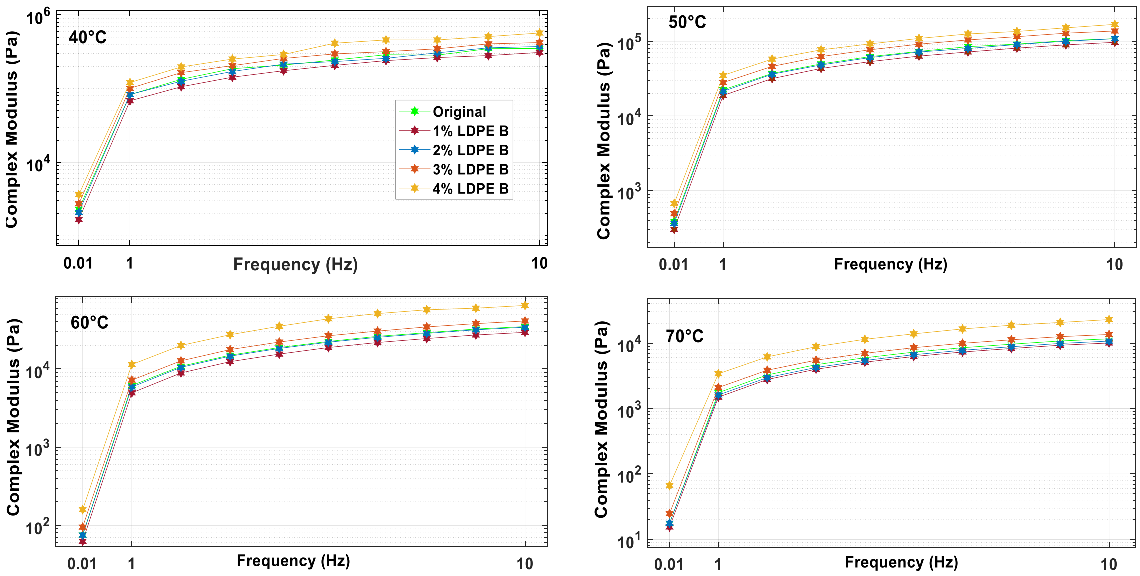


Figure 4. Complex module results for LDPE (B)

The figures clearly show that the complex modulus values increase with the increase in frequency (loading rate). It was determined that the complex modulus values of the binders increased as the amount of waste additive used as a modifier in asphalt binders increased. Also, the difference in complex modulus values became more pronounced with increasing LDPE content. The LDPE (A) additive produced greater changes in complex modulus values compared to the LDPE (B) additive. It was observed that LDPE (A) modified binders had lower complex modulus values compared to LDPE (B) modified binders.

## Artificial Neural Network (ANN) Results

The R2, MSE and RMSE results obtained to evaluate the performances of the created ANN models are given in Tables 3 and 4, respectively, for each contribution type. Considering the performances of the models created for LDPE (A), the highest R2 value was obtained with the Lev-8_A model (0.9878), while the lowest R2 value was obtained with the Sca-12 model (0.6424). Table 3 shows that the Lev-10_A model gives the results with high accuracy (98%) and the lowest error (30.122). Considering that the G* values are between 102 and 104, the RMSE, that is, the distance between the actual and predicted values as 30.12, indicates that the model performance is quite high. In Table 4, it is clear that the Lev-10_B model performs better than other models.

Table 3. Error values for LDPE (A)

| *LDPE A* | R2 | MSE | RMSE |
|---|---|---|---|
| Lev-8_A | 0.98788978 | 498806.5327 | 706.2623681 |
| Lev-10_A | 0.98662916 | 907.3571236 | 30.12236916 |
| Lev-12_A | 0.968757957 | 300146.9421 | 547.8566802 |
| Sca-8_A | 0.957851173 | 14815431.44 | 3849.081895 |
| Sca-10_A | 0.904859996 | 4283121.59 | 2069.570388 |
| Sca-12_A | 0.642444886 | 16581287.09 | 4072.012658 |

Table 4. Error values for LDPE (B)

| LDPE B | R2 | MSE | RMSE |
|---|---|---|---|
| Lev-8_B | 0.996919861 | 6998.412564 | 83.65651537 |
| Lev-10_B | 0.996004047 | 5153.020205 | 71.78454015 |
| Lev-12_B | 0.987051443 | 91855.23165 | 303.0762802 |
| Sca-8_B | 0.955447955 | 11135010,8 | 3336,916361 |
| Sca-10_B | 0.979690252 | 509762.3127 | 713.976409 |
| Sca-12_B | 0.972448819 | 6982088.272 | 2642.364145 |

The performances of the model, which has ten neurons and obtained by using the Levenberg-Marquardt training algorithm, in the training, validation and testing stages are given in Figure 5 and Figure 6 for LDPE (A) and (B), respectively.

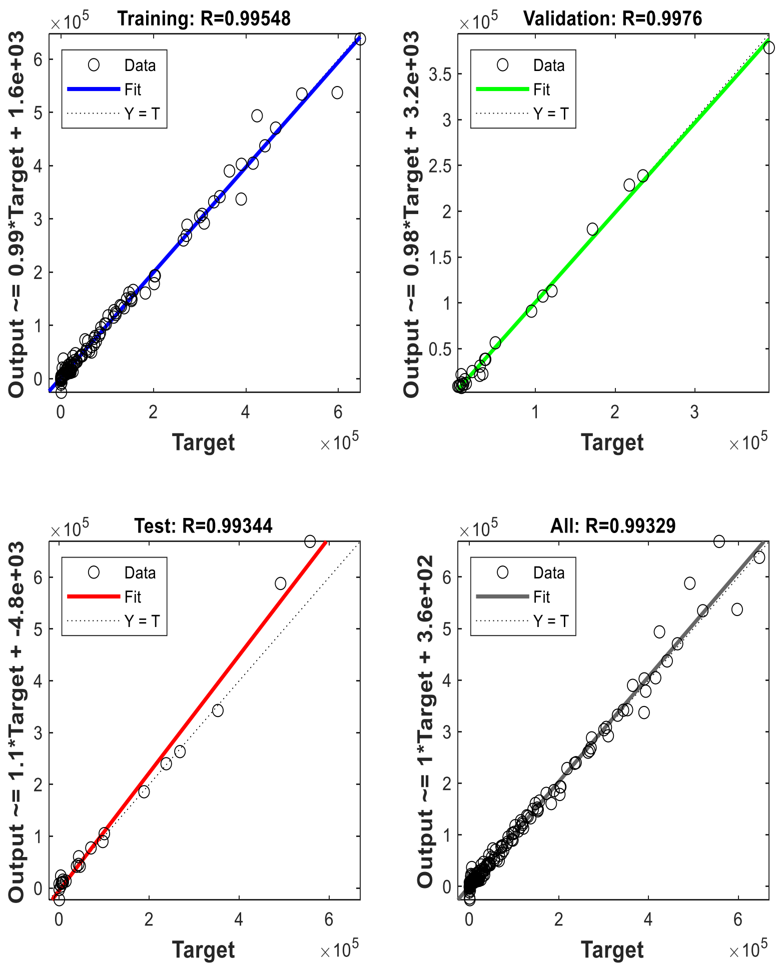


Figure 5. Training, validation and testing performances of the Lev-10_A model

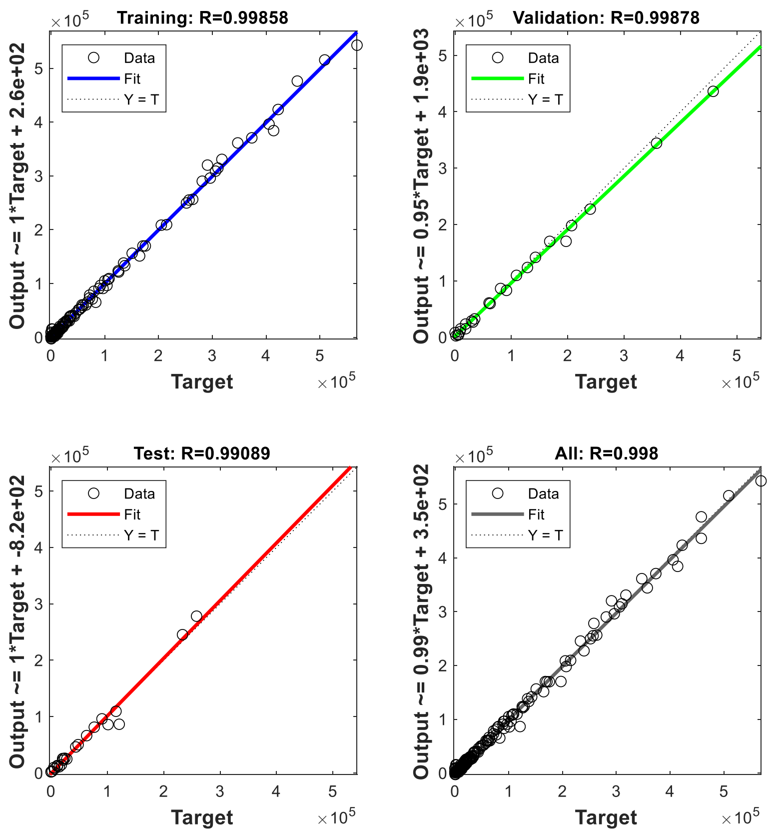


Figure 6. Training, validation and testing performances of the Lev-10_B model

Figures 5 and 6 show that Lev-10_A and Lev-10_B models are quite successful in both training, validation, and testing phases. The correlation ratio between predicted and experimental values is quite high. Comparison of the best and worst neural network models for LDPE (A) is presented in Figure 7. When Figure 7 is examined, it is seen that the Lev-10_A model successfully predicts the complex modulus values of the modified bitumen binder. It is clearly seen in the graph that the most unsuccessful model, Sca-12_A, cannot provide high accuracy rates and its prediction performance is low.

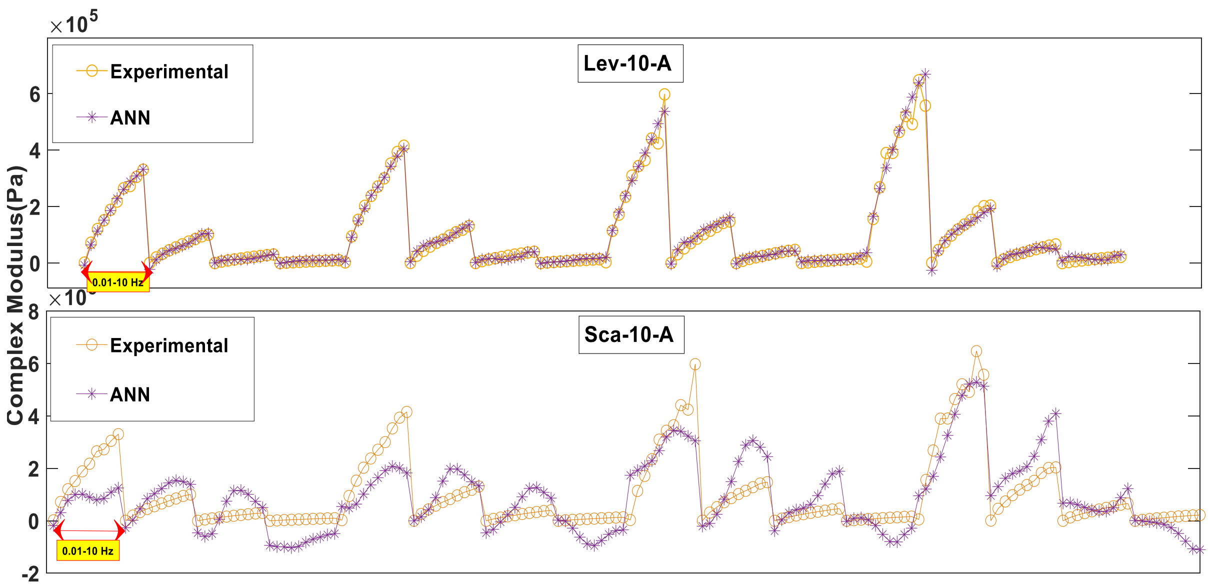


Figure 7. Comparison of the most successful and most unsuccessful neural network models

## Conclusion

In the present study, a Dynamic Shear Rheometer experiment was performed on pure and modified binders by modifying the pure asphalt binder with two different types of waste low density polyethylene (LDPE A, LDPE B). Within the scope of the experiment, the binders were tested at four different temperatures including 40°C, 50°C, 60°C and 70°C and ten different frequencies in the range of 0.01-10Hz and complex modulus values were examined. In addition, Artificial Neural Network models were created with two different training algorithms and various neuron numbers and complex module values were obtained through these models. The results are given below:

- When the complex modulus values were examined, it was determined that the complex modulus values of the asphalt binders increased as the additive content increased, thus contributing to the resistance shown against deformations.

-When LDPE A and LDPE B were compared, it was seen that LDPE A contribution gave more positive results compared to the other contribution.

-It was seen that the artificial Neural Network models created successfully predicted the complex modulus values for both additive types. It was determined that the preferred number of neurons significantly affected the model performance.

-It was seen that the models trained with the Levenberg-Marquart training algorithm obtained more accurate results compared to the Scaled Conjugate Gradient training algorithm and had the lowest error rate when compared to the experimental data. The artificial neural network model trained with the Levenberg-Marquart training algorithm, which has ten neurons with the lowest error rate, gave the most accurate result.

-When the experimental data and the estimation data were compared in general, it was concluded that the complex modulus values of artificial neural networks and asphalt binders could be successfully estimated.

In this study, it was aimed to provide environmental and economic benefits by using two types of waste materials that are harmful to the environment as modifiers in bitumen binders. In addition, a lot of time and materials are spent for experiments performed in laboratories. Predicting possible results using artificial intelligence techniques is quite useful in terms of both time and materials used.

## Scientific Ethics Declaration

The authors declare that the scientific ethical and legal responsibility of this article published in EPSTEM journal belongs to the authors

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