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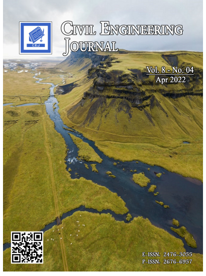

Applications of Nearest Neighbor Search Algorithm Toward Efficient Rubber-Based Solid Waste Management in Concrete

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Abstract

Indeed, natural processes of discarding rubber waste have many disadvantages for the environment. As a result, multiple researchers suggested addressing this problem by recycling rubber as an aggregate in concrete mixtures. Previously, numerous studies have been undertaken experimentally to investigate the properties of rubberized concrete. Furthermore, investigations were carried out to develop estimating techniques to precisely specify the generated concrete's characteristics, making its use in real-life applications easier. However, there is still a gap in the conducted studies on the performance of the k-nearest neighbor algorithm. Hence, this research explores the accuracy of using the k-nearest neighbor's algorithm in predicting the compressive and tensile strength and the modulus of elasticity of rubberized concrete. It will be done by developing an optimized machine learning model using the aforementioned method and then benchmarking its results to the outcomes of multiple linear regression and artificial neural networks. The study's findings have shown that the k-nearest neighbor's algorithm provides significantly higher accuracy than other methods. This kind of study needs to be discussed in the literature so that people can better deal with rubber waste in concrete.

Keywords: Rubberized Concrete; Recycled Aggregate; Concrete Properties; Nearest Neighbour; Machine Learning.

1. Introduction

The tire industry is the primary user of rubber, which yields the most rubber waste; thus, as a result, rubber recycling is frequently referred to as tire recycling [1]. Polymer decomposition is widely recognized to need a long period and has negative environmental consequences. Non-biodegradable waste management is an important and challenging issue for many governments worldwide. Many construction industry researchers have taken on the task of using recycled particles as a partial alternative to natural aggregates in the manufacturing of cement-based products during the last few decades [2, 3]. Currently, throwing away worn rubber tires is a severe environmental issue [4-6]. The great potential for uncontrolled fires and other environmental dangers, as well as several health concerns, are among the most significant risks associated with this technique [7, 8]. According to estimates by the World Business Council for Sustainable Development, around one billion tires worldwide reach the end of their life span annually [9]. In 2015, 4.89 million tons of rubber tires and 2.68 million tons of rubber products were manufactured worldwide. The rubber products industry increased by 2% in 2017, reaching 2.70 million tons, while automobile tire production increased by 1%, reaching 4.94 million tons, resulting in a 1% increase in output [10]. It must be mentioned that the direction of increased manufacture of rubber goods and automobile tires has not been a consistent trend when reviewing prior years; yet, owing to the

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volume of production, management of rubber waste has become a challenge for today's societies. Consequently, using this waste material in building operations has become more popular as a strategy to manage rubber-based solid waste due to the abundance and amount of production of this type of waste substance [3, 11].

Nowadays, various researchers are investigating the feasibility of adding recycled rubber aggregate to concrete to create what is known as "*rubberized concrete*" [11–14]. The benefit of this form of concrete over the traditional one, aside from its environmental advantages, is from rubber's capability to dissipate energy efficiently, which, when employed in structural elements, can favorably impact vibration behavior [15-17]. On the other hand, it has been indicated that substituting natural aggregates with rubber alternatives reduces their mechanical properties substantially [18–23]. This reduction is directly correlated to the amount of rubber aggregates in concrete [24-26]. Marie (2016) [27] observed a reduction of between 14% and 89% when rubber particles replaced 5% to 100% natural aggregates. Aslani & Khan (2019) [28] observed a drop of about 3% to 49% in the splitting tensile strength when replacing the fine aggregates with rubber particles. The drop ratio was later elevated to be between 46% and 73% when the coarse aggregates were substituted. Miller & Tehrani (2017) [29] showed a 50% reduction in the modulus of elasticity of rubberized concrete with 100% rubber particles in the mixture. These decreases are mostly due to replacing a stronger aggregate with a smaller one [23] and the poor bond capacity between rubber aggregates and cement paste compared to natural aggregate [30].

Indeed, much experimental research has been conducted to study the performance of rubberized concrete and the impact of rubber aggregate utilization on concrete. Several previous machine learning models were discussed and investigated in the literature to boost the possibility of recycling this material in the concrete production industry as part of waste management master plans. Topçu & Saridemir (2008) [31] predicted new density and flow table values by applying a feed-forward back-propagation neural network and an adaptive neuro-fuzzy inference system. Cheng & Cao (2016) [32] estimated rubberized concrete's compressive strength and splitting tensile strength using a radial basis function neural network, multivariate adaptive regression splines, genetic programming, and evolutionary multivariate adaptive regression splines. Jalal et al. (2019, 2020) [33, 34] evaluated compressive strength utilizing an adaptive neuro-fuzzy inference system, multivariable nonlinear regression, and a support vector machine. Hadzima-Nyarko et al. (2020) [35] predicted the compressive strength of rubberized concrete using regression trees, a multi-layer perceptron neural network, and random forests. Furthermore, Habib & Yildirim (2021) [36] applied feed-forward back-propagation neural networks and multivariable linear regression to interpolated damping ratio, dynamic modulus of elasticity, and natural frequency of rubberized concrete elements.

Indeed, most of the previous studies have focused on developing either artificial neural networks or multivariable linear regression or both approaches for the compressive strength of rubberized concrete and rarely went into the capability of other techniques and the possibility of predicting other rubberized concrete's properties. Moreover, it can be shown that studies on the applications of k-nearest neighbor for rubberized concrete are limited to the prediction of compressive strength rather than other parameters. Thus, the significant gap in the literature that this study is trying to address is the quality of k-nearest neighbor to predict compressive strength, splitting tensile strength, and modulus of elasticity, which are investigated in this work. Besides, it tries to benchmark and compare the outcomes and accuracy of this method to the most frequently used techniques: multiple linear regression and the artificial neural network approach. The ultimate goal is to address one of the primary challenges in rubber waste management by developing a solid model for estimating rubberized concrete to make its use in the construction sector considerably more productive.

2. Materials and Methods

The mixture of fine (sand) and coarse (either naturally occurring or crushed rock) aggregates and cement paste is referred to as concrete. In contrast, worn tires are considered a severe environmental problem worldwide. Researchers are currently more interested in recycling trash tires and repurposing rubber generated from crushed tires. There have been several suggestions for recycling used tires as part of waste management efforts, for example, putting rubber into concrete as an aggregate alternative in the construction sector, which has been implemented. Figure 1 shows the general methodology applied in this research for evaluating the mechanical properties of rubberized concrete.

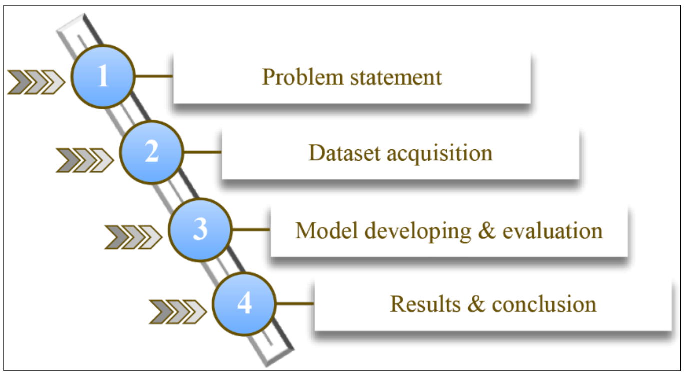


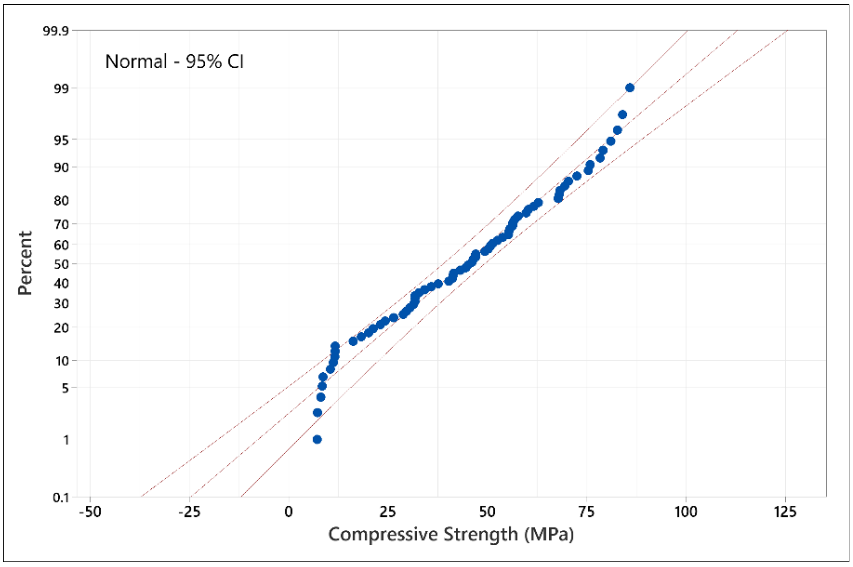
Figure 1. Flowchart of research methodology

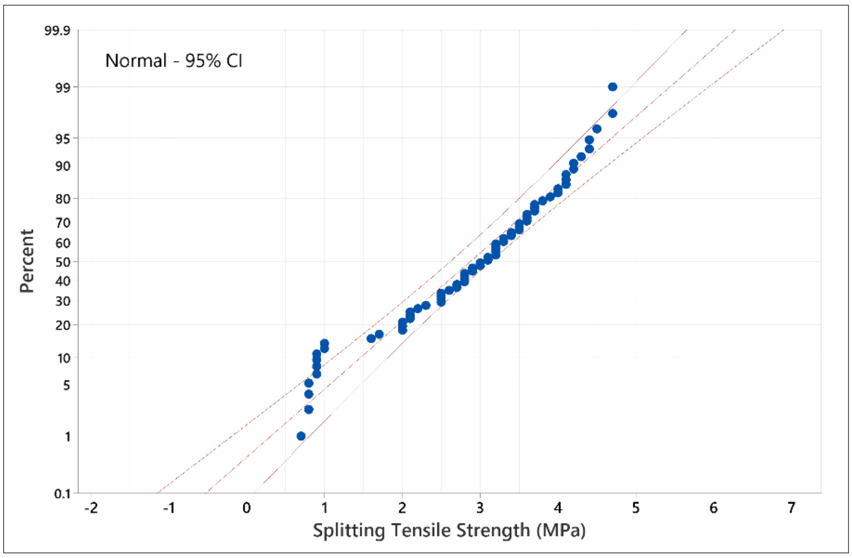
2.1. Dataset Acquisition of Rubberized Concrete Properties

As previously stated, this study aims to gather and reuse existing data from the literature to build some numerical algorithms of rubberized concrete features. The compressive and splitting tensile strengths of rubberized concrete, and its modulus of elasticity, will be determined in this work. The numerical research dataset was captured from earlier experimental results [21] at a broad spectrum of rubber compositions. Table 1 summarizes the illustrative statistics of the data applied to build the estimation algorithms. In addition, Figure 2 indicates a schematic graph of the probability plots of the interpolated component.

Table 1. Summary of statistics information applied in the studied models

Parameters	Statistics	Minimum	Average	Maximum
Inputs	Coarse Aggregates	522.6	898.7	1076.4
	Fine Aggregates	338.4	581.9	697
	Rubber Content	0	95.2	314.1
	Cement	280	360	450
	Silica Fume	0	40	90
	Water	180	195	210
	Superplasticizer	5.25	9.375	13.5
Outputs	Compressive strength	7.1	44.13	85.77
	Splitting Tensile Strength	0.7	2.874	4.7
	Modulus of Elasticity	6.1	27.38	47.5





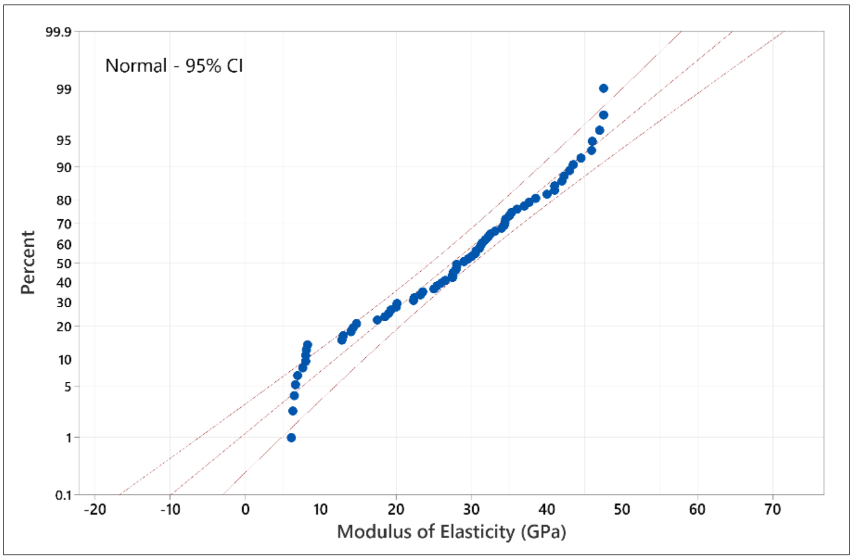


Figure 2. Probability diagram of the predicted parameters

2.2. Machine Learning Methods

2.2.1. Multiple Linear Regression

It has been explained previously that multiple linear regression (MLR) is a statistical technique utilized to construct a linear relationship between two or more independent variables [37]. According to Achen (1982) [38], MLR is described with the help of a mathematical model, as clarified in Equation 1.

$$Y = \beta X + \varepsilon \tag{1}$$

where Y is the dependent variable vector, X is the independent variable, β is the model's coefficients vector to be predicted, and ε is a random error vector.

2.2.2. K-nearest Neighbors

As with other machine learning algorithms, K-nearest neighbors (KNN) are also applied in classification and regression issues. During the prediction phase of the KNN method, feature similarity is typically used, which means that a corresponding value is given to the output based on how close it is to the points in the training dataset. Consequently, the training stage involves defining a similarity metric that assists in determining neighbors with the same class as the target. The k-value specifies the number of neighbors the model searches for when predicting a given value using this method. Additionally, many different functions may also be used in computing the distance between the points, such as Euclidean, Equation 2, Manhattan, Equation 3, and Minkowski, Equation 4.

$$\sqrt{\sum_{i=1}^{k}(x_i - y_i)^2} \tag{2}$$

$$\sum_{i=1}^{k}|x_i - y_i| \tag{3}$$

$$\sum_{i=1}^{k}(|x_i - y_i|^p)^{\frac{1}{p}} \tag{4}$$

The study was able to optimize the nearest neighbor computation by investigating different algorithms such as the brute force algorithm, a ball tree [39], and K-D trees [40].

2.2.3. Artificial Neural Networks

The artificial neural network is extensively used in the civil engineering domain. When using this technique, the training procedure involves optimizing the weights and biases of the model. In this manner, the weighted sums of the inputs can be obtained by Equation 5, and the result of its j neuron may be derived from Equation 6.

$$(net)_j = \sum_{i=1}^{n} w_{ij} x_i + b \tag{5}$$

in which w_{ij} is the weight between i and j neurons, x_i is the output of the i neuron, b is the bias utilized to the algorithm the threshold, and n is the total number of neurons.

$$(out)_j = f(net)_j \tag{6}$$

where; f is an activation function.

As shown in Equation 7, the gradient descent concept is employed to generate the updated weights utilized to adjust the algorithm's error throughout the back-propagation way.

$$\Delta w_n = \alpha \Delta w_{n-1} - \eta \frac{\partial E}{\partial w} \tag{7}$$

where; w is the weight between any two nodes, Δw_n and Δw_{n-1} are the differences in this weight at n and $n-1$ iterations, α is the momentum factor, and η is the learning rate.

As previously stated, extensive research has been conducted on the behavior of this approach in evaluating rubberized concrete attributes; as a result, it was utilized as a benchmark in this investigation to compare it to other models.

2.3. Evaluation of Model Performance

Accurate benchmarking of any numerical model's accuracy is a significant task that should be handled reliably [41]. In this study, multiple measures are employed to investigate the performance of the chosen model. The goal is to first analyze the model's appropriateness to the provided issue by determining the goodness of fit of the model using the whole dataset (both training and testing) and then to evaluate the errors in addressed approaches using just the testing dataset (30 percent of the total sample size). As a result, the determination coefficient, Equation 8, was utilized to determine fit quality. The normalized root-mean-square error (NRMSE), Equation 9, and mean absolute percentage error (MAPE), Equation 10, were used for the error analysis.

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \tag{8}$$

$$\text{NRMSE} = \frac{\sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}}}{y_{max} - y_{min}} \tag{9}$$

$$\text{MAPE} = \frac{100}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \tag{10}$$

where y_i is the actual value, $\hat{y}_i$ is the predicted one, n is the number of observations, y_{max} is the maximum measured value, and y_{min} is the minimum measured value.

3. Materials and Methods

3.1. Parametric Assessment of KNN Properties

In this part, a parametric analysis will be carried out to evaluate the impact of the KNN's hyperparameters on the accuracy of the processed models. Thus, the goal herein is to offer a thorough knowledge of the most critical parameter for the algorithm prediction. Table 2 demonstrates that the nearest neighbors' approach does not influence the model's accuracy in training or testing phases. In contrast, Table 3 illustrates how using a different weight function affects the performance of the KNN method. According to the data provided, the distance weight function produces much higher accuracy when compared to the uniform function in both the training and testing phases. The role of the distance functions in KKN discussed in Section 2.2.2 is shown in Table 4. Clearly, for the given dataset of rubberized concrete, the best distance function was the Manhattan one regarding all of the rubberized concrete properties, where it yielded the maximum value of R^2 and minimum values of NRMSE and MAPE for training and testing scenarios. Finally, Table 5 depicts the impacts of the number of neighbors on the developed KNN related to the number of neighbors. As can be shown there, for the investigated dataset, the optimal number of neighbors is 3, which performed better than other options throughout the testing stage. Additionally, only one neighbor yielded better MAPE values but lower R^2 and NRMSE ones. Moreover, it was concluded that this parameter does not influence the training part of the data.

Table 2. Influence of the nearest neighbors' algorithm on the accuracy of the KNN model

Concrete Property	Nearest Neighbors Algorithm	Training			Testing		
		R^2	NRMSE	MAPE	R^2	NRMSE	MAPE
Compressive Strength	BallTree	1.000	0.000	0.000	0.991	0.025	4.470
	KDTree	1.000	0.000	0.000	0.991	0.025	4.470
	Brute-Force Search	1.000	0.000	0.000	0.991	0.025	4.470
Splitting Tensile Strength	BallTree	1.000	0.000	0.000	0.991	0.027	3.344
	KDTree	1.000	0.000	0.000	0.991	0.027	3.344
	Brute-Force Search	1.000	0.000	0.000	0.991	0.027	3.344
Modulus of Elasticity	BallTree	1.000	0.000	0.000	0.992	0.025	2.851
	KDTree	1.000	0.000	0.000	0.992	0.025	2.851
	Brute-Force Search	1.000	0.000	0.000	0.992	0.025	2.851

Table 3. Influence of the weight function on the accuracy of the KNN model

Concrete Property	Weight Function	Training			Testing		
		R^2	NRMSE	MAPE	R^2	NRMSE	MAPE
Compressive Strength	Uniform	0.991	0.027	4.297	0.987	0.031	6.030
	Distance	1.000	0.000	0.000	0.991	0.025	4.470
Splitting Tensile Strength	Uniform	0.990	0.027	3.826	0.988	0.030	3.823
	Distance	1.000	0.000	0.000	0.991	0.027	3.344
Modulus of Elasticity	Uniform	0.991	0.027	3.577	0.986	0.032	3.984
	Distance	1.000	0.000	0.000	0.992	0.025	2.851

Table 4. Influence of the distance function on the accuracy of the KNN model

Concrete Property	Distance Function	Training			Testing		
		R^2	NRMSE	MAPE	R^2	NRMSE	MAPE
Compressive Strength	Manhattan	1.000	0.000	0.000	0.991	0.025	4.470
	Euclidean	1.000	0.000	0.000	0.984	0.033	5.855
	Minkowski	1.000	0.000	0.000	0.972	0.044	7.054
Splitting Tensile Strength	Manhattan	1.000	0.000	0.000	0.991	0.027	3.344
	Euclidean	1.000	0.000	0.000	0.989	0.029	3.847
	Minkowski	1.000	0.000	0.000	0.979	0.041	5.071
Modulus of Elasticity	Manhattan	1.000	0.000	0.000	0.992	0.025	2.851
	Euclidean	1.000	0.000	0.000	0.992	0.024	3.310
	Minkowski	1.000	0.000	0.000	0.981	0.037	4.267

Table 5. Influence of number of neighbors on the accuracy of the KNN model

Concrete Property	Number of Neighbors	Training			Testing		
		R^2	NRMSE	MAPE	R^2	NRMSE	MAPE
Compressive Strength	1	1.000	0.000	0.000	0.986	0.032	4.116
	2	1.000	0.000	0.000	0.985	0.032	5.135
	3	1.000	0.000	0.000	0.991	0.025	4.470
	4	1.000	0.000	0.000	0.986	0.031	5.343
	5	1.000	0.000	0.000	0.976	0.040	6.360
Splitting Tensile Strength	1	1.000	0.000	0.000	0.964	0.053	4.817
	2	1.000	0.000	0.000	0.985	0.035	4.422
	3	1.000	0.000	0.000	0.991	0.027	3.344
	4	1.000	0.000	0.000	0.986	0.034	4.722
	5	1.000	0.000	0.000	0.985	0.034	4.466
Modulus of Elasticity	1	1.000	0.000	0.000	0.952	0.059	4.624
	2	1.000	0.000	0.000	0.989	0.029	3.328
	3	1.000	0.000	0.000	0.992	0.025	2.851
	4	1.000	0.000	0.000	0.992	0.024	3.408
	5	1.000	0.000	0.000	0.992	0.024	4.004

3.2. Compressive Strength

Concrete compressive strength is an essential parameter for designing a mixture with high load-carrying capacity. However, evaluating its reliability requires performing a lengthy experimental procedure that is both time and money-demanding. Previously, various approaches based on soft computing techniques were proposed to the literature for rapid mixture design and characteristics evaluation. Currently, multiple studies can be found on investigating the compressive strength of rubberized concrete. However, the capability of the KNN model is not clearly understood the matter. In this section, the MLR, ANN, and KNN will be evaluated and compared to understand better the influence of KNN quality on predicting the outcomes and determine which algorithm is more appropriate for estimating the compressive strength of rubberized concrete, as demonstrated in Figure 3. The residual diagram, Figure 4, indicates the KNN is much better than both the MLR and ANN, which refers to KNN may be employed to precisely build rubberized concrete mixes, and no trials are necessary to achieve the desired compressive strength. When comparing the algorithm's quality using the fitting rate, Figure 5-a, demonstrates that the coefficient of determination can be significantly improved by about 0.89 in MLR to 0.99 in KNN. Also, the NRMSE values shown in Figure 5-b highlight a considerable drop in error, roughly 85%, when the KNN technique is utilized compared to the MLR model. Also, the MAPE results in Figure 5-c show more than a 90% percent reduction when the KNN is used compared to the MLR model. On the other hand, comparing the performance of the KNN to the ANN, it can be seen that the KNN achieved 12.5 and 60% lower values of NRMSE and MAPE, respectively. Nevertheless, the ANN and MLR results follow Habib and Yildirim's observations [36] about predicting the dynamic properties of rubberized concrete.

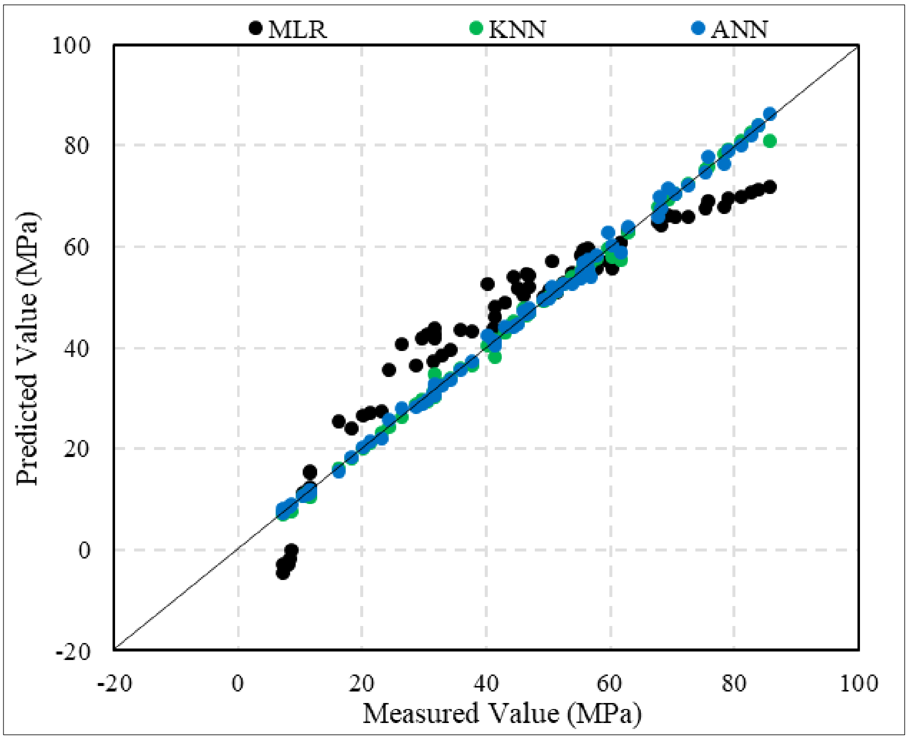


Figure 3. Predictive models for compressive strength of rubberized concrete based on experimental results

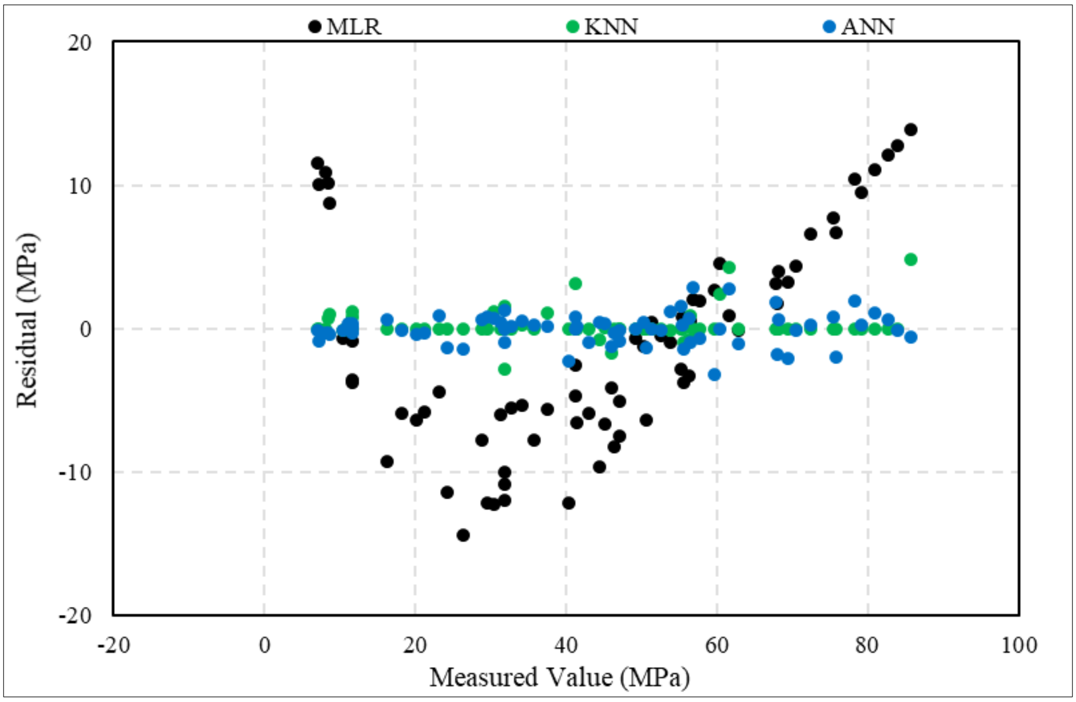
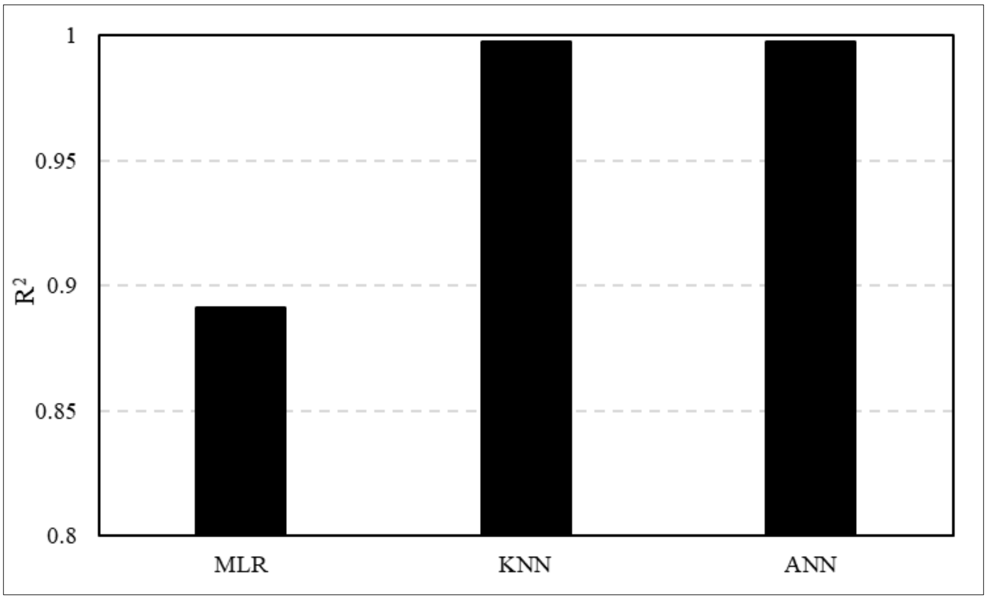
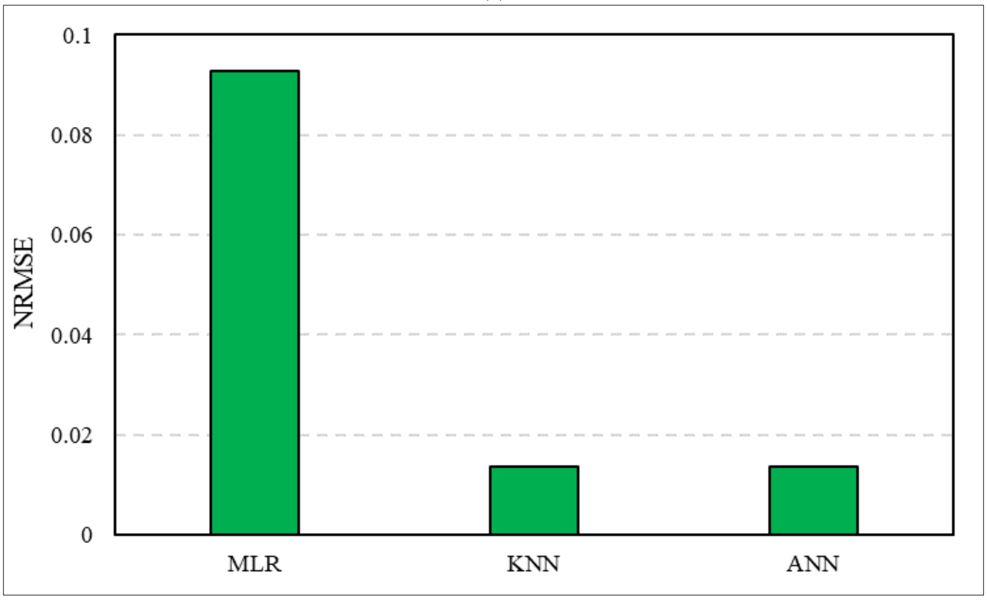


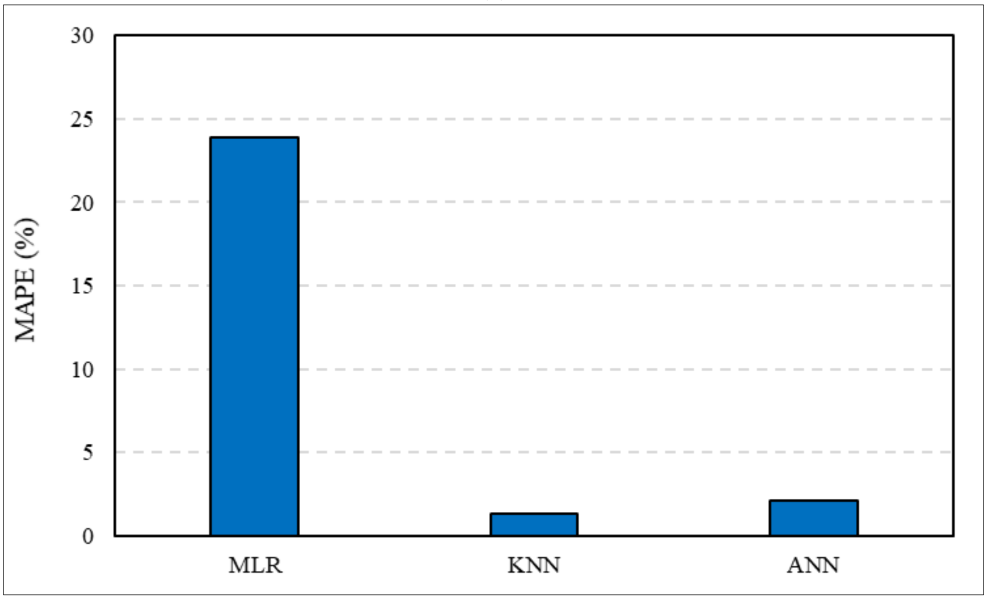
Figure 4. Residual diagram of the compressive strength prediction techniques for rubberized concrete



(a)



(b)



(c)

Figure 5. Quality of the rubberized concrete's compressive strength estimation algorithms in the testing stage

3.3. Splitting Tensile Strength

Currently, minimal information regarding the estimation of splitting tensile strength of rubberized concrete can be found in the literature. Accordingly, this section is intended to evaluate, analyze and compare the potential of the MLR, ANN, and the KNN, aiming to realize the effect of KNN accuracy on the prediction results and specify which model is more suitable for estimating the splitting tensile strength of rubberized concrete. Figure 6 and Figure 7 indicate that the KNN results are better than MLR, which can precisely develop rubberized concrete mixes to achieve the desired splitting tensile strength without trials. In contrast, an inspection of the model's performance by fitting rate, Figure 8-a, reveals that the determination coefficient can be significantly enhanced from approximately 0.95 for MLR to 0.99 for the KNN. Furthermore, when the KNN technique is utilized instead of the MLR one, the normalized root mean square error depicted in Figure 8-b shows a significant reduction of error around 70%. Identically, as seen in Figure 7-c, the mean absolute error percentage declined by more than 85 percent. Similar to the compressive strength results, the KNN provided better performance than the ANN model in terms of the NRMSE and MAPE metrics, as shown in Figures 8-b and 8-c, respectively.

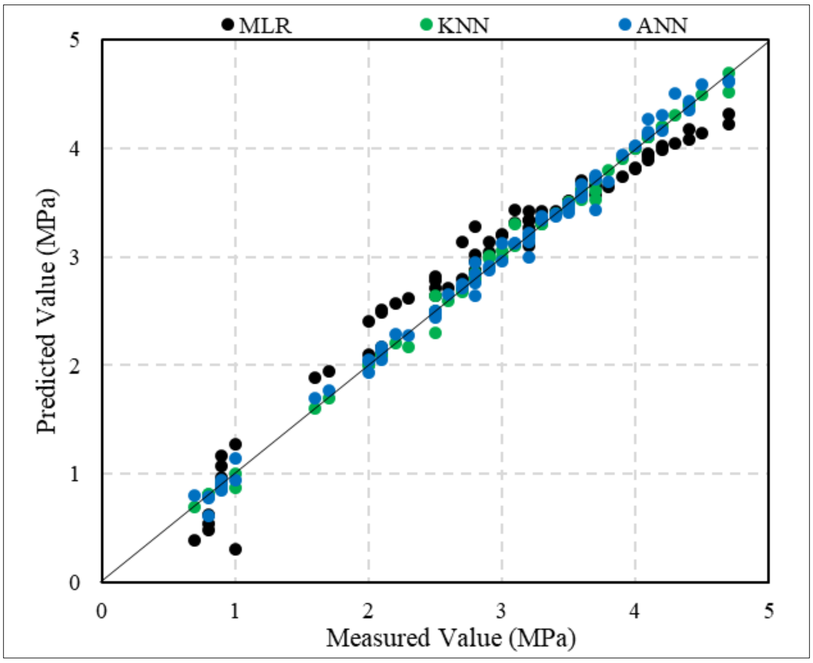


Figure 6. Splitting tensile strength estimation technique for rubberized concrete

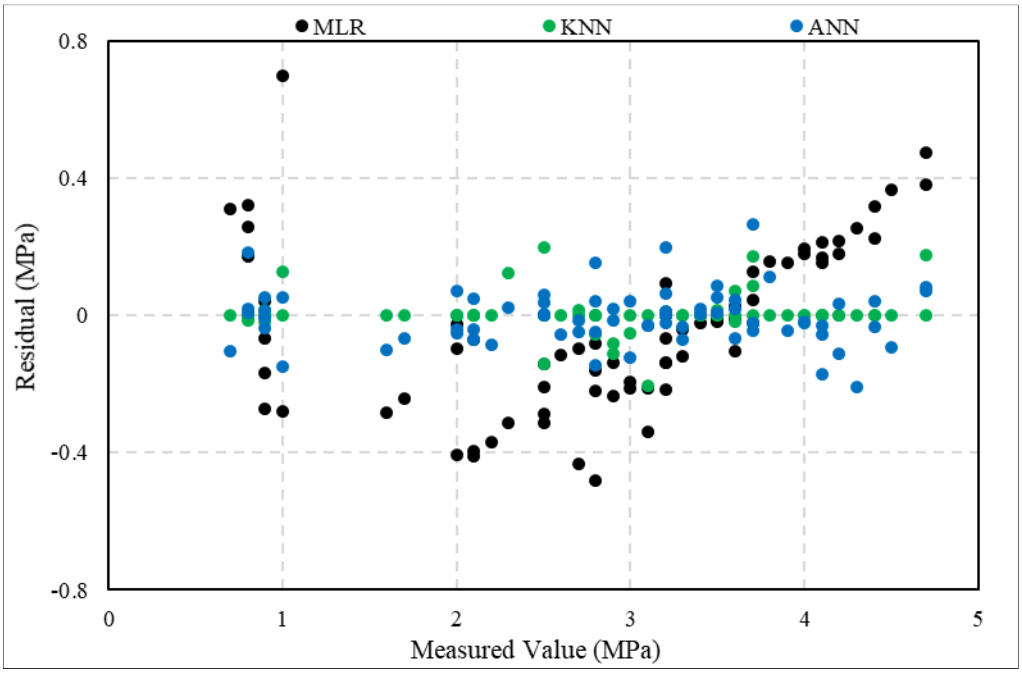


Figure 7. Residual diagram of splitting tensile strength prediction algorithm for rubberized concrete

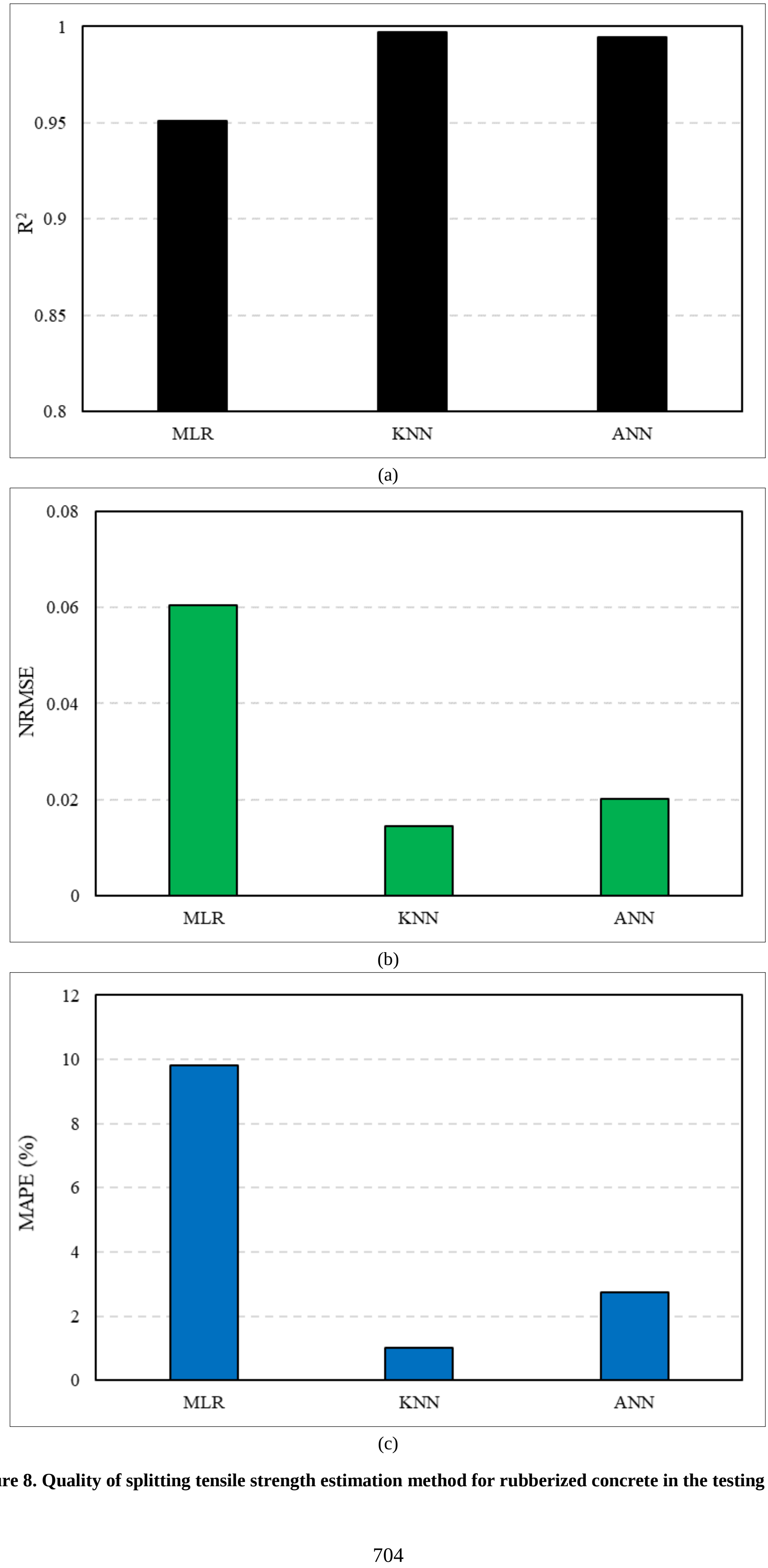


Figure 8. Quality of splitting tensile strength estimation method for rubberized concrete in the testing stage

3.4. Modulus of Elasticity

The modulus of elasticity of rubberized concrete is a considerably important parameter that needs to be evaluated for designing reinforced concrete structures. Therefore, reliable prediction of this parameter is a significant task for structural engineers. The estimation model results for the modulus of elasticity are illustrated in Figure 9, and Figure 10 depicts the residual plot of the analysis. Indeed, it can be observed that the KNN model is much better than that of the MLR and was marginally superior to the ANN technique. It means that KNN may be utilized to design rubberized concrete mixtures more precisely without the need for any trials to reach the required modulus of elasticity level. Figure 11 illustrates a comparison of the model's performances based on the fitting rate. Figure 10-a reveals that the coefficient of determination is significantly improved from about 0.91 in MLR to 0.99 in KNN and ANN. In addition, the normalized root mean square error shown in Figure 11-b describes a considerable drop in the error of about 70% when the KNN is used compared to the MLR approach. In parallel, as shown in Figure 11-c, the mean absolute error percentage was reduced by more than 92 percent. The KNN model outperformed the ANN method in terms of the NRMSE measure and produced a much lower MAPE value than the ANN approach.

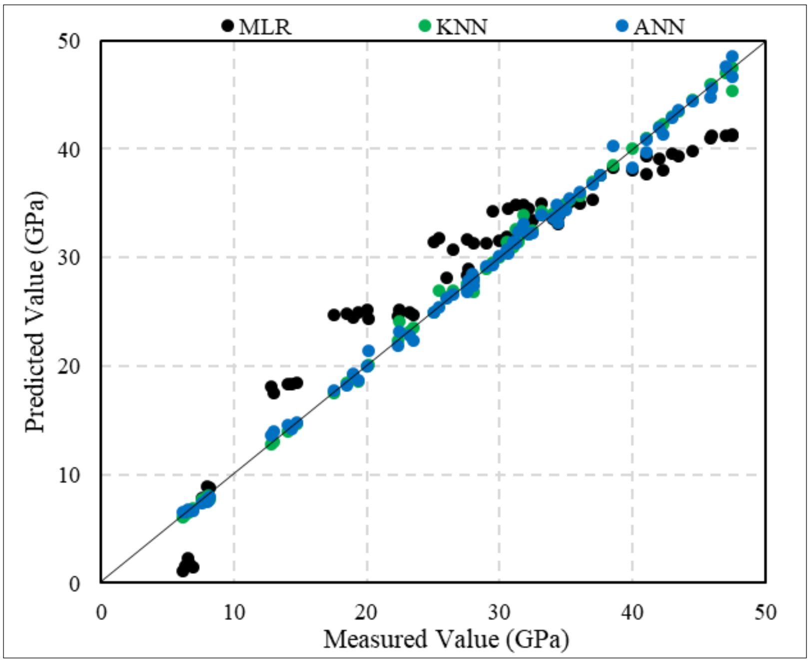


Figure 9. Output of modulus of elasticity estimation algorithm for rubberized concrete

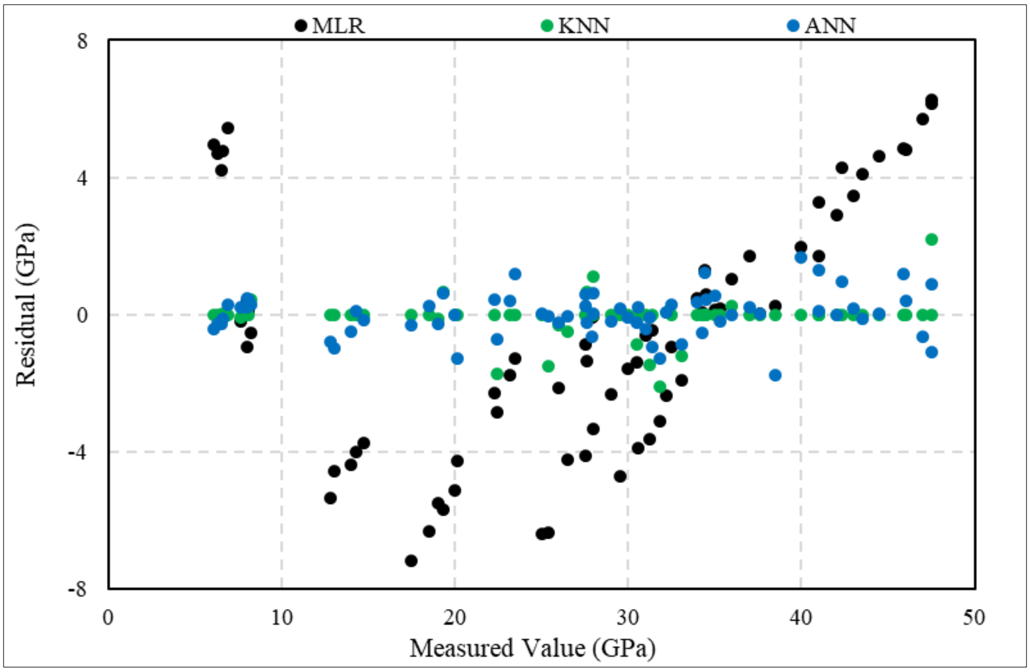
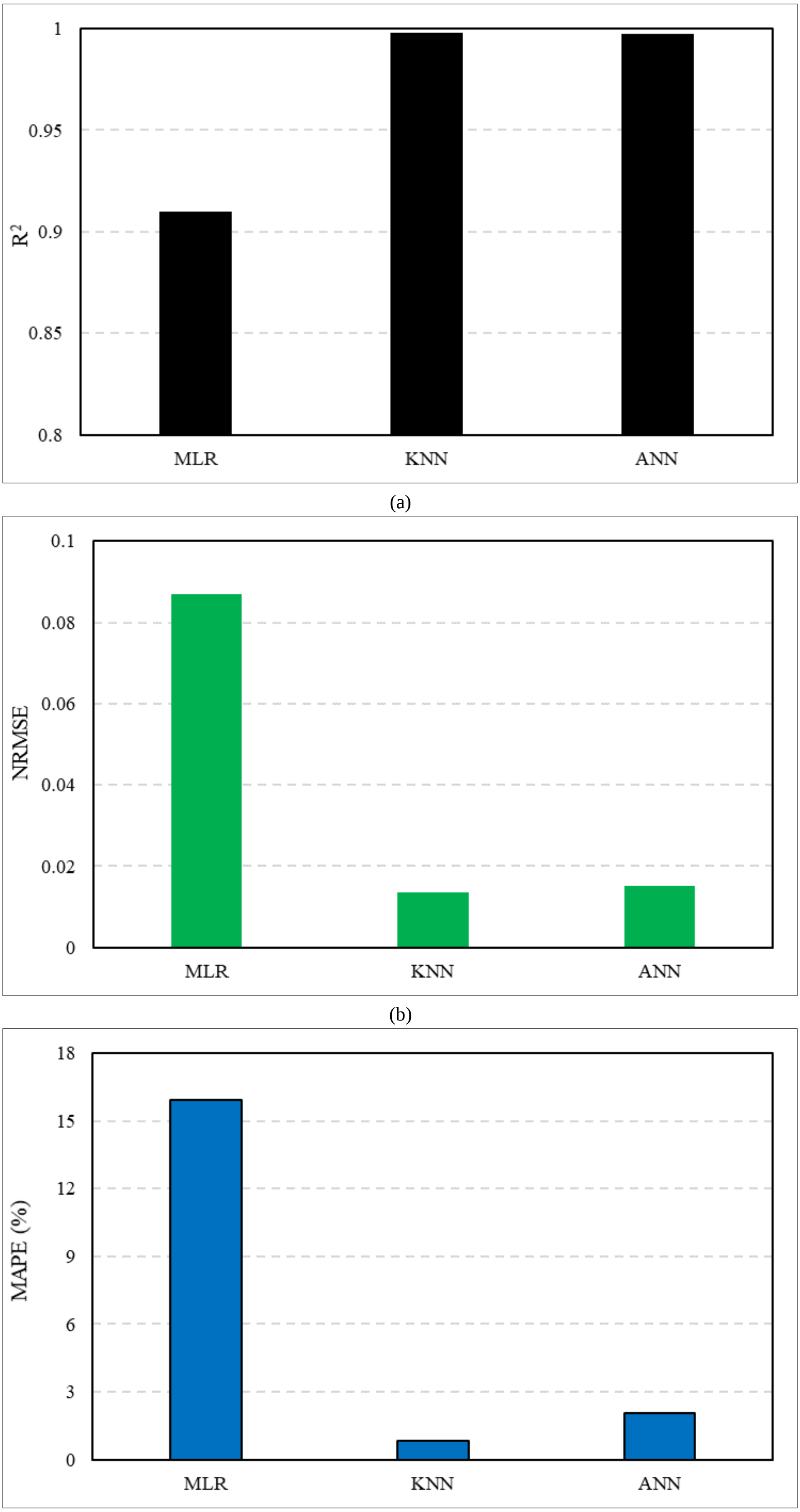


Figure 10. Residual diagram of modulus of elasticity estimation algorithm for rubberized concrete



(a)

(b)

(c)

Figure 11. Behavior of modulus of elasticity estimation model for rubberized concrete in the testing stage

4. Conclusion

Indeed, previous studies focused on estimating the compressive strength of rubberized concrete using ANN and MLR techniques, but they did not go into detail about estimating other properties of this material, nor did they discuss the behavior of k-nearest neighbors or benchmark its accuracy. Accordingly, the purpose of this research was to investigate the possibility of utilizing the nearest neighbor searching method in estimating the characteristics of rubberized concrete. Moreover, it intended to compare the accuracy of this algorithm against the most commonly used techniques, represented by ANN and MLR. Evaluating the effect of each of the KNN parameters was carried out, and the findings were presented in detail. Practically, using the distance weight function in conjunction with the three nearest neighbors provides the best prediction outcomes. On the other hand, when estimating the properties of rubberized concrete by KNN from the mixture's components, good behavior and significantly fewer minor errors are observed compared to the MLR. It also had a much better performance than the ANN model for the MAPE metric case in all of the properties of rubberized concrete.

Generally, the applications of the findings reported in this study would include developing software packages for mixture design of rubberized concrete, which could eventually promote the use of rubber particles in concrete. Additionally, the results presented herein will provide researchers in solid waste management in cement-based materials with some ideas about using soft computing techniques for modeling the characteristics of recycled aggregate concrete. In this case, more research is needed to find out how well other machine learning methods work and how well rubberized concrete attributes work. This will help us learn more about how much recycled rubber can be used in the construction industry as part of waste management and sustainable development initiatives.

5. Declarations

5.1. Author Contributions

Conceptualization, Y.A. and H.A.; methodology, H.A.; software, D.A.; validation, Y.A., H.A. and B.A.; formal analysis, B.A.; investigation, Y.A.; resources, D.A.; data curation, D.A.; writing—original draft preparation, H.A.; writing—review and editing, B.A.; visualization, D.A.; supervision, D.A.; project administration, Y.A.; funding acquisition, B.A. All authors have read and agreed to the published version of the manuscript.

5.2. Data Availability Statement

The data presented in this study are available in the article.

5.3. Funding

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5.4. Conflicts of Interest

The authors declare no conflict of interest.

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