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Machine learning in the construction industry: potential of artificial neural networks in estimating construction and demolition waste

Aprendizado de máquina na indústria da construção: potencialidades das redes neurais artificiais na estimativa de resíduos de construção e demolição

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ABSTRACT

The estimation of construction and demolition waste (CDW) generation is essential for sustainable planning and effective waste management on construction sites. However, conventional methods often fail to meet the practical demands of the sector. This study investigated the use of artificial neural networks (ANN) as a predictive tool for CDW quantification. Simulations were performed with samples of 5,000 data points (A) and 10,000 data points (B), followed by validation with a sample of 360 data points (R) collected from construction sites in Curitiba, Paraná state, Brazil. This approach allowed for a comprehensive evaluation of the predictive accuracy and practical applicability of the ANN. The best performance was obtained with sample B, using an ANN configured with two input variables, ten neurons in the hidden layer, and three training cycles. In the simulations, the model presented a coefficient of determination (R^2) of 1.00, a root mean squared error (RMSE) of 6.55 kg, and a mean absolute percentage error (MAPE) of 0.00013%. In the validation, an R^2 of 0.83 was obtained, along with an RMSE of 4,337.69 m^3, and accurate estimates in over 60% of cases (MAPE). The results demonstrated the viability of using ANNs to improve CDW estimation, contributing to decision-making and the development of more efficient waste reduction strategies in civil construction.

Keywords: waste management; data analytics; artificial intelligence; sustainability; simulation method.

RESUMO

A estimativa da geração de resíduos da construção civil (RCC) é essencial para o planejamento sustentável e a gestão eficaz de resíduos em canteiros de obras. No entanto, os métodos convencionais frequentemente não atendem às demandas práticas do setor. Este estudo investigou o uso de redes neurais artificiais (RNA) como ferramenta preditiva para a quantificação de RCC. Foram realizadas simulações com amostras de 5.000 dados (A) e 10.000 dados (B), seguidas da validação com amostra de 360 dados (R) coletados em canteiros de obras em Curitiba, estado do Paraná, Brasil. Essa abordagem permitiu uma avaliação abrangente da acurácia preditiva e da aplicabilidade prática da RNA. O melhor desempenho foi obtido com a amostra B, utilizando uma RNA configurada com duas variáveis de entrada, dez neurônios na camada oculta e três ciclos de treinamento. Nas simulações, o modelo apresentou coeficiente de determinação (R^2) de 1,00, raiz do erro quadrático médio (RMSE, *root mean squared error*) de 6,55 kg e erro percentual absoluto médio (MAPE, *mean absolute percentagem error*) de 0,00013%. Na validação, obteve-se R^2 de 0,83, RMSE de 4.337,69 m^3 e estimativas precisas em mais de 60% dos casos (MAPE). Os resultados demonstraram a viabilidade do uso de RNA para aprimorar a estimativa de RCC, contribuindo para a tomada de decisão e para o desenvolvimento de estratégias mais eficientes de redução de resíduos na construção civil.

Palavras-chave: gestão de resíduos; análise de dados; inteligência artificial; sustentabilidade; método de simulação.

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Introduction

With the advancement of urbanization and the growth of the construction industry, this sector has emerged as one of the largest generators of solid waste globally, with construction and demolition waste (CDW) currently representing the primary waste stream worldwide (Soto-Paz et al., 2023). Inadequate CDW management leads to persistent public complaints regarding local pollution, illegal dumping, and contamination, highlighting the necessity for integrated prevention and control strategies from the project planning phase, which is crucial for promoting environmental sustainability and economic development, particularly in contexts of rapid urbanization (Wu et al., 2024; Sagan and Mach, 2025).

Globally, CDW generation is substantial. Australia recorded a 24% increase in CDW between 2020 and 2021, reaching 29 million tons (Langley et al., 2025). Historically, China and the United States have been major contributors, with China producing over 1 billion tons in 2014 and the U.S. generating approximately 600 million tons in 2018 (Ray et al., 2024). While quantities and compositions vary regionally, China, the United States, and the European Union remain the largest global contributors (Aslam et al., 2020; Kabirifar et al., 2020; Zhang et al., 2022; Zhang et al., 2023). In 2020, the European Union's total waste production was 2,153 billion tons, with 37.5% originating from the CDW sector (Eurostat, 2023). In Brazil, 44,5 million tons of CDW were generated in 2023, underscoring its importance in the national waste profile (ABREMA, 2024). This waste generation poses not only an environmental challenge but also an economic burden, increasing costs for constructors and imposing additional expenses on public authorities due to frequent irregular disposals.

Despite the magnitude of the problem, accurately estimating CDW quantities remains a practical challenge in the civil construction sector. Traditional quantification methods, often based on volume or weight, are time-consuming, labor-intensive, and frequently require detailed project data. In Brazil, Pinto's (1999) pioneering study remains a widely used and influential reference for CDW estimation, proposing a generation rate of 150 kg/m² for new constructions and specific indicators for renovations, demolitions, and informal constructions. The absence of more comprehensive or updated national studies highlights the continued relevance of this foundational work.

The scarcity of detailed data on construction characteristics and waste generation necessitates the development of more efficient, flexible, and accessible estimation models. Artificial neural networks (ANNs) emerge as a promising tool due to their advanced self-learning capabilities and ability to model complex, non-linear relationships without predefined mathematical formulas (Sheekoohiyan et al., 2023).

Recent studies highlight the increasing application of machine learning techniques in CDW estimation, classification, and prediction. Samal et al. (2025) critically reviewed the potential of algorithms such as ANNs, support vector machines, and deep convolutional neural networks (DCNNs) for optimizing waste management processes, noting DCNNs' 94% accuracy in certain applications. A recent review identified 98 studies (2012–2023) applying machine learning algorithms to CDW management, with ANNs, deep learning, and support vector machines being prominent across generation, handling, transport, and final disposal stages (Gao et al., 2024). Specific examples include hybrid models with autoencoders and neural networks for demolition waste prediction (Cha et al., 2023), multilayer perceptron networks for concrete compression strength prediction (Tam et al., 2022), and machine learning-based regression for renovation waste prediction (Lu et al., 2023).

Furthermore, Awad et al. (2024) integrated a metaheuristic approach with ANNs to estimate CDW generation in Gaza, achieving high R^2 values and improved predictive accuracy. Similar results were observed in Bahrain, where multilayer perceptron networks achieved an R^2 of 0.91 for annual civil construction waste prediction (Coskuner et al., 2021). Hu et al. (2021) utilized support vector machines for estimating five types of construction waste, Lu et al. (2021) compared various machine learning models for construction waste quantification, including multiple linear regression, decision trees, gray models, and ANNs, and Gao et al. (2023) proposed an intelligent irrigation model framework based on machine learning. These findings collectively reinforce the viability of predictive models as decision-support tools for sustainable construction waste management.

Despite these advancements, the application of ANNs for CDW estimation in developing countries remains limited. Specifically, there is a dearth of studies focusing on CDW in local contexts, revealing a significant gap in the literature. Validating predictive models with real-world construction site data could enhance their practical applicability and provide more robust tools for waste management (Adeleke et al., 2021; Sheekoohiyan et al., 2023).

Thus, this study aimed to investigate the potential of ANNs in estimating civil construction waste generation, focusing on practical applicability in contexts with limited data and reducing the effort required to obtain accurate information. This proposal sought to contribute through a decision-support tool for waste management, capable of generating reliable estimates and promoting sustainable actions in the construction sector.

Research Method

This study is an exploratory research, utilizing communication media for data collection and employing simulation as a method approach. To apply the simulation, two sources of data were used: the first of a fictitious nature, created using the Microsoft Excel® spreadsheet editor, and the second, of a real nature, with information obtained from construction companies.

In order to run the simulations, two samples were created, labeled Sample A and Sample B, with fictitious data from 5,000 and 10,000 constructions, respectively. Both samples range from 75 to 125,050 m² of total built area, with Sample A having an interval of 50 m² between area data and Sample B having an interval of 25 m² between area data.

The construction waste generation rate of 150 kg/m², proposed by Pinto (1999), was used to obtain the amount of CDW generated in each fictitious project according to the area. Additionally, the demolition waste generation rate of 800 kg/m², proposed by Nagalli (2021a), was used to obtain the amount of demolition waste generated according to the area.

Considering these two waste generation rates available in the literature, all area data from Sample A, which ranged from 75 to 125,050 m², were first multiplied by 150 kg/m², generating the quantities of construction waste for each area data point of the sample. Then, the same Sample A had all its area data multiplied by 800 kg/m², resulting in the quantities of demolition waste for each area data of the sample. The same process was carried out with Sample B, but with 10,000 data points.

A survey of civil construction companies in Curitiba and the metropolitan region in Paraná state was initially conducted to obtain a real database. These companies were then contacted to provide information about the construction areas and the amounts of waste generated. Data were gathered on the total built area and amount of waste of 430 works, from 2006 to 2021, and with an area varying between 906 and 138,824 m²; these data make up Sample R.

In order to remove outliers or "atypical values" from the sample, a box plot diagram was constructed. To this end, the median (Md), first quartile (Q1), third quartile (Q3), and interquartile range (IQR) of Sample R were calculated using Microsoft Excel®. From this, the lower (LI=Q1 - (1.5) * IQR) and higher (LS=Q3 + (1.5) * IQR) limits were calculated. The values between these two limits are called "adjacent values", and the values above the established upper limit or below the lower limit were considered outliers and removed from the sample (Bussab and Morettin, 2017).

The MATLAB® software, version R2022a, was used to verify the applicability of neural networks in the area of construction waste. The neural networks used in this research are classified as feed-forward neural networks, also known as perceptrons. They have only one layer of neurons, where each neuron receives a set of inputs and produces a single output. The input layer receives inputs from the network, the output layer produces the final outputs, and the intermediate layer, also known as the hidden layer, performs data processing.

The data containing the input and output variables were imported into the software to perform the simulations, and then, within the application, the set of samples was randomly divided into three subsets: 70% for training, 15% for validation, and 15% for testing. These percentages are suggested by the software so that the sample is well distributed, but they can be adjusted if necessary. Next, the number of neurons that would be used was adjusted and the algorithm with which the neural network would be trained was selected. After that, the neural network was trained and the training results, including the regression graphs and error histograms, were available in the application. Figure 1 presents the workflow of the simulation steps.

Initially, Sample A with 5,000 data points was imported. The input variables were the waste classification (0 for construction waste, 1 for demolition waste) and the total built area of the project, and the output variables were the quantities of waste calculated with the generation rates presented. Next, the minimum number of training cycles that could be applied was assessed.

Based on the study by Nagalli (2021b), it was decided to run three training cycles for three, five, and ten neurons, and for each algorithm available in the software. For example, for the Levenberg-Marquardt algorithm, three training cycles were carried out using the neural network configuration with three neurons, three cycles with the configuration with five neurons, and three cycles with the configuration with ten neurons.

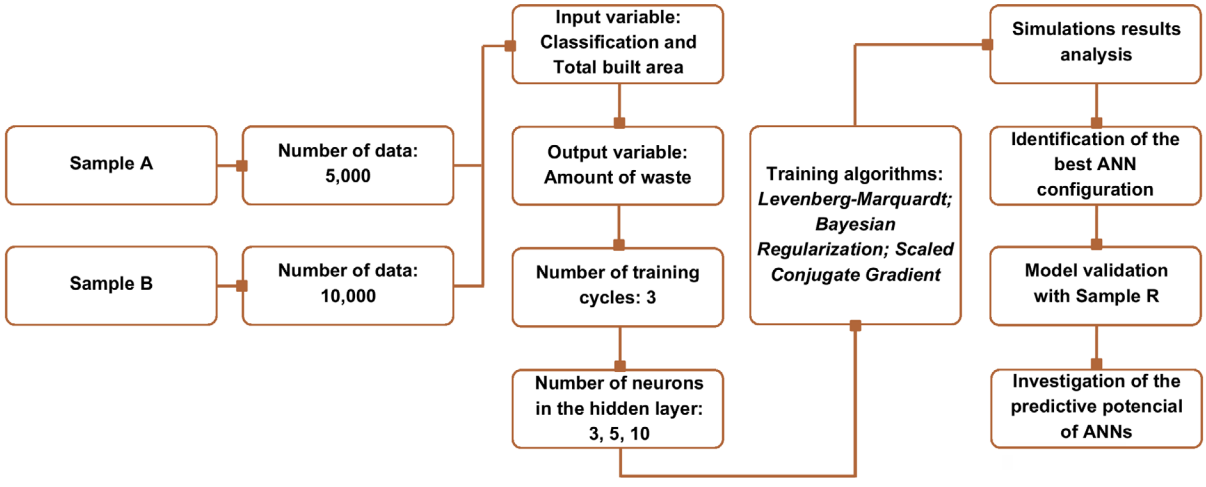

Figure 1 – Workflow of the artificial neural network simulation process for samples A, B, and R.

For the Bayesian Regularization and Scaled Conjugate Gradient algorithms, the same procedure was followed.

Subsequently, simulations were conducted with Sample B with 10,000 data points, which also included two input variables, namely waste classification (0 construction waste, 1 demolition waste) and the total built area of the work, as well as an output variable, which is the amount of waste. For Sample B, three training cycles were also performed for three, five, and ten neurons, with the three algorithms available in the application (Levenberg-Marquardt, Bayesian Regularization, and Scaled Conjugate Gradient).

To evaluate the performance of the neural networks, the results of the simulations of samples A and B were analyzed based on the parameters R^2, root mean squared error (RMSE), and mean absolute percentage error (MAPE). From the analysis of the simulation results, the best neural network configuration was identified, that is, the number of training cycles, the number of neurons in the hidden layer, and which training algorithm had the best performance.

In order to validate the model, the best neural network configuration obtained in the simulations with samples A and B was applied to Sample R, composed of real data on the total built area and quantities of waste generated. After this simulation, the use of the neural network model was validated, and a sensitivity analysis of the model was carried out regarding its predictive performance in relation to one or two input data points in the software, the nature of the data points, and the size of the samples. Furthermore, the output variables, which were the amounts of waste calculated by the neural network, were compared with the actual amounts of waste provided by the companies.

Results and Discussions

Simulations with sample A

In simulations performed with Sample A, which used two input variables (waste classification and total built area) and one output (quantity of waste), it was observed that the Levenberg-Marquardt training algorithm presented the most unsatisfactory performance in waste estimation. Its R^2 value was only 0.13 in the first training cycle with five neurons, indicating a very limited ability to explain data variance. Figure 2 illustrates the R^2 values for the Levenberg-Marquardt, Bayesian Regularization, and Scaled Conjugate Gradient algorithms in Sample A, highlighting performance disparities.

In general, the Bayesian Regularization algorithm demonstrated remarkably consistent performance, with an R^2 value equal to 1.00 in all tested neural network configurations. The waste quantities predicted by this algorithm were consistently very close to the targeted quantities. Furthermore, it was observed that increasing the number of neurons to five and ten resulted in an improvement in predictive capability and a reduction in the mean absolute percentage error. The MAPE values for this algorithm ranged between 0.0076 (third cycle with three neurons) and 0.0030% (first cycle with ten neurons), with the lowest MAPE of 0.0003% verified in the first cycle with ten neurons.

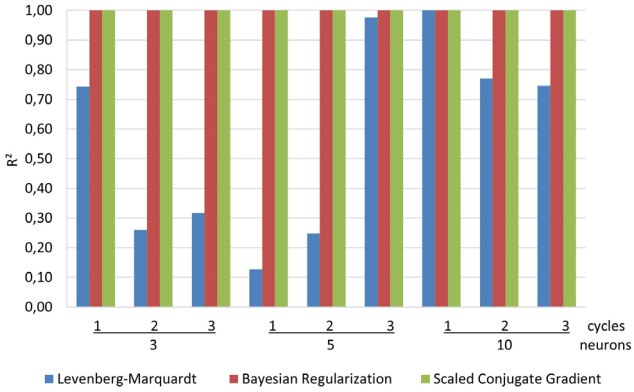

Figure 2 – Coefficient of determination (R^2) results for the three training cycles with three, five, and ten neurons, using Levenberg-Marquardt, Bayesian Regularization, and Scaled Conjugate Gradient in Sample A.

The consistency and low MAPE values of Bayesian Regularization indicate superior robustness in modeling Sample A data, suggesting that this algorithm is more suitable for waste prediction in this context.

On the other hand, the Scaled Conjugate Gradient algorithm presented inconsistent estimates, with quantities significantly higher or close to those expected, in a random manner. This variability was observed in all neuron configurations (three, five, and ten) and in all three training cycles. Although an R^2 value of 1.00 may indicate that the adjusted linear regression perfectly explains the variation in the data, this does not guarantee estimation accuracy. The occurrence of overfitting is a real concern here, where the model may have overfitted to the training data (70% of the sample), failing to generalize to other data, resulting in inaccurate estimates.

The neural network configuration with the Scaled Conjugate Gradient algorithm that presented the lowest MAPE value (1%) was the first cycle with ten neurons, where the R^2 was 0.99. However, the average percentage of absolute errors ranged between 1% and 11% for the three training cycles, using three, five, and ten neurons in the hidden layer. These MAPE values, although low, may indeed confirm the occurrence of overfitting, indicating that the model performed well on the training data, but failed to generalize to the test and validation sets (15% each). In other words, the neural network achieved a good estimate with the training data, which constituted the majority of the sample, resulting in a low mean absolute percentage error, but with little generalization capability. Figure 3 presents the error histogram for the model evaluation using one training cycle, ten neurons, and the Bayesian Regularization algorithm, which demonstrated the best performance in training this sample, as verified by the lowest MAPE value.

As illustrated in Figure 3, the error histogram exhibits outliers, which are data points where the fit is significantly worse than the majority of the data. This typically occurs when the sample has a non-linear characteristic. In the case of Sample A, the highest bar, close to the orange line,

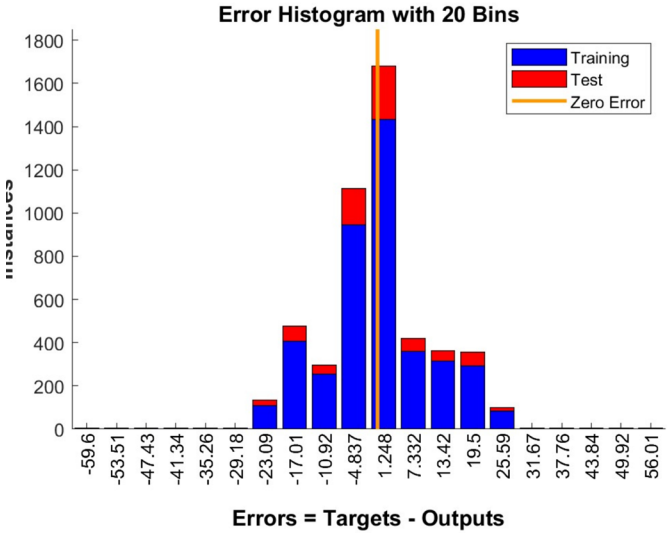

Figure 3 – Error histogram for the first training cycle of the neural network with ten neurons, using the Bayesian Regularization algorithm in Sample A.

indicates that most errors are very close to zero, with few distant errors. This reinforces the idea that the model, despite some deviations, could effectively capture the central tendency of the data for most instances. The presence of few significant errors, represented by the "outliers", can be attributed to data anomalies or inherent limitations in the model's ability to capture all nuances of a complex non-linear relationship.

Regarding the mean squared error (MSE), another metric used to evaluate the ANN model, it was noted that the MSE decreased rapidly as the network was trained, reaching the best performance in the training samples around time 1,000. It is important to emphasize that the error of the training set and the test set presented similar characteristics, evidenced by the overlap of the blue and red lines. This overlap is a positive indication that the model is not suffering from severe overfitting, as the performance on the training data is consistently reflected in the test data, suggesting good generalization capability.

During training with the Levenberg-Marquardt and Scaled Conjugate Gradient algorithms, it was observed that when there was a change in sample classification (from 0 for construction waste to 1 for demolition waste), the neural network failed to correctly estimate waste quantities in the half of the sample where this change occurred. This difficulty suggests that these algorithms may be sensitive to discontinuities or abrupt changes in input data characteristics. Therefore, for these two types of algorithms, it is recommended to create two separate models: one to predict construction waste and another to predict demolition waste. In contrast, the Bayesian Regularization algorithm proved to be more robust to this variation, as its predictive capability was not altered by the change in waste classification. This resilience of Bayesian Regularization makes it a more versatile option for datasets that may present such variations.

Simulations with sample B

For simulations using Sample B, which also employed two input variables (waste classification and total built area) and one output (quantity of waste), the Levenberg-Marquardt training algorithm again demonstrated the lowest performance in waste estimation, with R^2 values ranging between 0.03 and 1.00. Figure 4 illustrates the R^2 values for the three training cycles with three, five, and ten neurons, using Levenberg-Marquardt, Bayesian Regularization, and Scaled Conjugate Gradient in Sample B.

According to Figure 4, the lowest R^2 value (0.03) was observed in the third training cycle with three neurons in the hidden layer. However, by increasing the number of neurons to five, the neural network showed significant improvement in its performance, reaching an R^2 of 0.99 in the third training cycle. With ten neurons in the hidden layer, in the second training cycle, the neural network achieved an R^2 of 1.00 and superior estimation results, confirmed by MAPE values of 0.003%, indicating that the estimated waste quantities were very close to expected. This progression in performance with an increasing number of neurons suggests that model complexity is a critical factor for capturing relationships in Sample B data, and that an insufficient number of neurons can lead to underfitting.

In simulations with the Bayesian Regularization algorithm, the three training cycles, with three, five, and ten neurons in the hidden layer, consistently presented R^2 values equal to 1.00 and predictive results very close to expected. With the increase in the number of neurons to five and, subsequently, to ten, the estimation capability improved, and the mean absolute percentage error decreased, reaching a remarkably low value of 0.00013%. This extremely low MAPE reinforces the high precision of the estimates, indicating that the predicted results were in excellent agreement with the actual values. The robustness and precision of Bayesian Regularization in Sample B are consistent with the performance observed in Sample A, consolidating it as the most effective algorithm for waste prediction in this study.

For the Scaled Conjugate Gradient algorithm, the three training cycles, with three, five, and ten neurons in the hidden layer, presented R^2 values between 0.99 and 1.00. However, the neural network demonstrated an inability to predict waste quantities from the beginning of the sample. This initial prediction failure, despite high R^2 values, again suggests the occurrence of overfitting. It is likely that the neural network overfitted to the training set data (70% of the sample), resulting in low mean absolute error percentages (ranging between 2 and 21%) for these data, but compromising its generalization capability for unseen data. The discrepancy between the high R^2 and the initial prediction failure of the sample is a strong indication that the model did not learn the underlying relationships but rather memorized the patterns of the training set. Figure 5 presents the error histogram for the neural network configuration with three training cycles, ten neurons in the hidden layer, and the Bayesian Regularization training algorithm, considering its best performance verified based on MAPE.

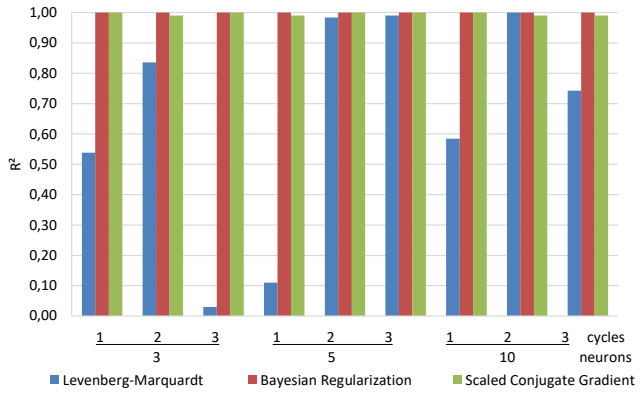

Figure 4 – Coefficient of determination (R^2) results for the three training cycles with three, five, and ten neurons, using Levenberg-Marquardt, Bayesian Regularization, and Scaled Conjugate Gradient in Sample B.

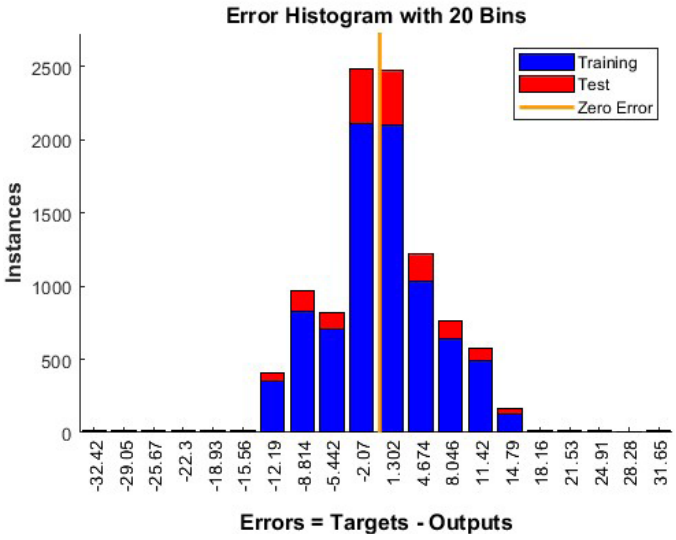

Figure 5 – Error histogram for the third training cycle of the neural network with ten neurons using the Bayesian Regularization algorithm in Sample B.

As shown in Figure 5, the highest bars in the histogram, close to the orange line, indicate that most errors are very close to zero, with few distant errors. However, it was observed that the number of negative error values was slightly higher than the number of positive errors. This implies that the waste quantities estimated by the neural network were, on average, slightly higher than the target quantities. This tendency to overestimate, although small, is an important point to consider in interpreting the results and may indicate a slight bias in the model. Detailed analysis of the histogram allows identifying not only the magnitude of errors but also their distribution and trends, providing valuable insights into model behavior.

The MSE of this sample decreased rapidly as the network was trained, reaching the best performance in the training samples, with a value of 43.04 kg^2 (RMSE equal to 6.55 kg) at time 1,000. When comparing the results of samples A and B, it is possible to note that larger samples tend to present better estimates. This aligns with the principle that neural networks, as machine learning models, use data to learn the relationship between input and output variables: the more data available to the model, the more information it will have to adjust its weights and learn this relationship more precisely. However, sample size is not the only factor to consider when choosing a model or evaluating its performance. Other factors, such as data quality, variable selection, and the choice of hyperparameters, can also significantly influence model performance. The discussion about the influence of sample size should be complemented with the caveat that data quality and representativeness are equally, if not more, important than mere quantity.

Validation of the neural network model with Sample R

The validation of the neural network model was performed with Sample R. Initially, the median, quartiles, and interquartile range were calculated to identify and remove outliers. As a result, 70 data points that exceeded the calculated upper limit were removed from Sample R, which then had 360 data points. This preprocessing step is crucial to ensure data quality and prevent extreme values from distorting model training and validation.

After data processing, Sample R was simulated based on the best neural network configuration identified previously, using the evaluation parameters R^2 (1.00), RMSE (6.55 kg), and MAPE (0.00013%), obtained from training Sample B. This configuration consisted of a feed-forward neural network with three training cycles, ten neurons in the hidden layer, and the Bayesian Regularization training algorithm. The validation results in Sample R showed an R^2 of 0.83, an RMSE of 4,337.69 m^3, and a MAPE of 38.35%. Figure 6 presents the linear regression graph, one of the evaluation parameters of this neural network configuration.

According to Figure 6, the R^2 value for the training and test data set was 0.83. This value is comparable to those obtained in previous studies, such as Cha et al. (2022), who reported an R^2 of 0.90 using neural networks with a sample of 160 data points, and Coskuner et al. (2021), who obtained an R^2 of 0.91 for construction waste prediction. Considering that Coskuner et al. (2021) used a smaller sample (20 data points, two input variables, and 180 simulations), it can be inferred that Sample R, with 360 data points, performed well with just three training cycles. Furthermore, the R^2 of 0.83 obtained in this research surpassed the value of 0.458 reported by Cha et al. (2023) for the use of neural networks in a sample of 782 data points from demolition works with six input variables, which was also higher than the R^2 of 0.72 obtained by Soni et al. (2019). These contextual comparisons are crucial for positioning the relevance and contribution of the results obtained in this study.

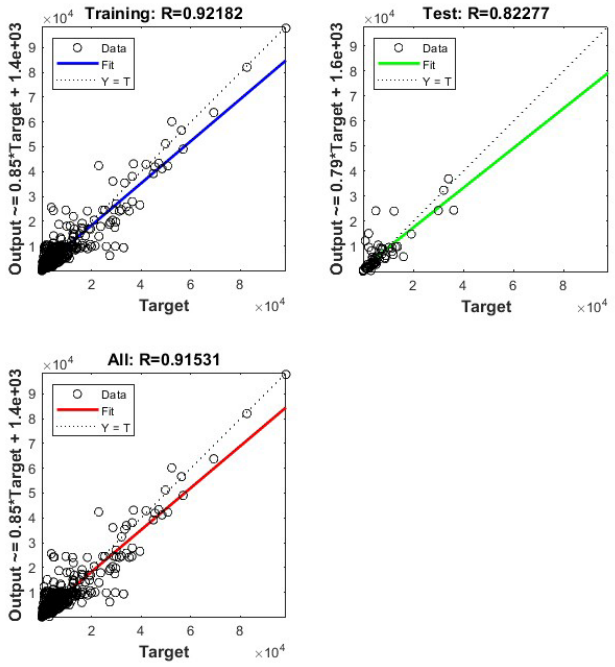

Figure 6 – Linear regression chart for the first training cycle of the neural network with ten neurons using the Bayesian Regularization algorithm in Sample R.

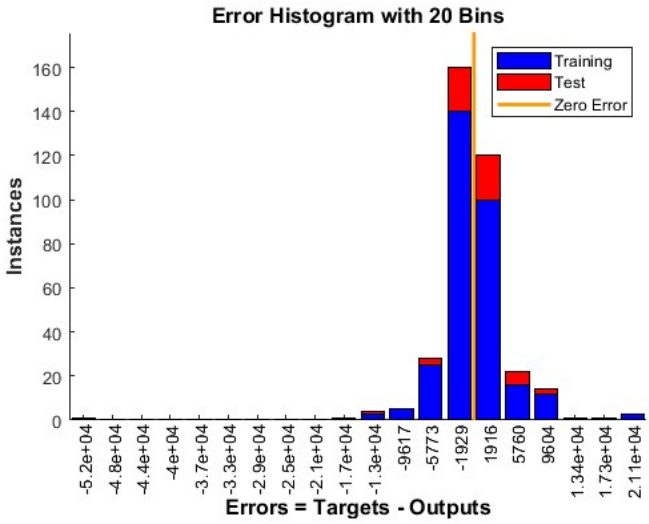

Figure 7 – Error histogram for the third training cycle of the neural network with ten neurons using the Bayesian Regularization algorithm in Sample R.

It is possible to verify that the neural network performed better on the training data set, as the data were better distributed along the regression line and the R value (0.94) was higher, compared to the R (0.85) of the test set. As observed by Nagalli (2021b), training set data tend to present better results, with R^2 values ranging between 0.94 and 0.96, while for test set data, R^2 values ranged between 0.75 and 0.91. This performance difference between training and test sets is common and expected, but the magnitude of this difference can indicate the degree of model generalization.

Regarding the MSE, it is common to use it to compare models or evaluate improvements in model performance across samples of different sizes. For example, the RMSE of Cha et al. (2022) was 100.80 kg, while in this study, it was 4,337.69 m^3. Compared to the use of the support vector machine algorithm in the study by Cha et al. (2023), the RMSE value was 1,020.30 for a sample of 782 data, and in the study by Abbasi et al. (2013), using a support vector machine, the RMSE value was 2.070. Figure 7 presents the error histogram of this neural network configuration.

Based on the histogram in Figure 7, it is possible to verify that the training set presented more positive and close to zero (orange line) error values at the height of the blue bars, confirming superior performance relative to the test set. This neural network configuration did not present results very close to zero when compared with the histograms of samples A and B. This can be justified by the fact that Sample R contains varied values and does not follow an increasing scale like samples with fictitious data. The distribution of errors in Sample R, although not as concentrated at zero as in synthetic samples, still demonstrates that most errors are within an acceptable range, indicating that the model has reasonable predictive capability for real-world data, which are inherently more complex and noisier.

The mean absolute percentage error of Sample R indicates that, on average, the difference between predicted and actual values is equivalent to 38.35%. Although this value may seem high compared to the MAPEs of samples A and B, the estimates still have manageable imprecision and can be considered reliable for practical applications, especially considering the complexity and variability of real data. The best neural network configuration proposed by Nagalli (2021b) also used Bayesian Regularization as a training algorithm; however, with two neurons and two training cycles, the ANN presented a MAPE of 56.7%. This demonstrates that the optimized configuration in this study (ten neurons, three cycles) resulted in a significant improvement in accuracy.

Most of the sample data showed absolute error percentages of up to 30%. The difference between the amount of waste calculated by the neural network model and that reported by construction companies was less than or equal to 30% in 210 cases (58.33% of the sample), and in 69 data points (19.17% of the sample), the difference was less than or equal to 10%. Compared to the study by Kern et al. (2015), who used a linear regression model to predict waste quantities in 18 buildings, obtaining a difference between actual and estimated quantities less than 30% in about 83% of the sample, and less than 5% in 5 buildings, it can be stated that the neural network model developed in this work per-

formed excellently in the criterion of difference between actual and estimated quantities and sample size. However, it is fundamental to emphasize that this analysis is restricted to this sample, and it is important to consider that the amount of data and the methodology used in the two studies are different, which prevents a direct and absolute comparison. Figure 8 presents the actual waste quantities and the estimated quantities using the feed-forward neural network with ten neurons in the hidden layer, three training cycles, and the Bayesian Regularization training algorithm.

When analyzing the blue (actual quantities) and red (estimated quantities) lines in Figure 8, it is possible to note that the actual quantities exhibit large fluctuations, indicating significant variations in waste quantities. In contrast, the line representing the estimated quantities suggests that the estimation model captured a general trend in the data, as the estimates are increasing, even though Sample R was simulated with randomly arranged data. This increasing trend in prediction, in the face of random real data, may be an indication of overfitting, where the model may be excessively fitted to the training data, creating a prediction that, although it appears to perfectly match the real values at some points, is not generalizable to other situations. This can lead to an increasing prediction even when the real data are random, which is an important limitation to be discussed. The model's ability to capture the general trend, despite fluctuations, is a positive point, but the lack of sensitivity to random variations may limit its applicability in dynamic scenarios. Table 1 presents a summary of the best results obtained for the R^2, RMSE, and MAPE parameters in simulations with samples A, B, and R, and with the three training algorithms used. This table serves as a visual consolidation of the main findings, facilitating comparison between different configurations and algorithms.

The model proposed in this study has similar configurations to that proposed by Nagalli (2021b), who also used the Bayesian Regularization algorithm and ten neurons in the hidden layer. Comparing these studies with the research by Lu et al. (2021) it is possible to verify that the Bayesian Regularization training algorithm works better with larger samples, since Lu et al. (2021) used the Levenberg-Marquardt algorithm on a sample with 43 data sets and the best result obtained for R^2 (0.92) was achieved with 15 neurons in the hidden layer and 35 training cycles. The use of the Bayesian Regularization algorithm provides good predictive results with a smaller number of neurons and fewer training cycles.

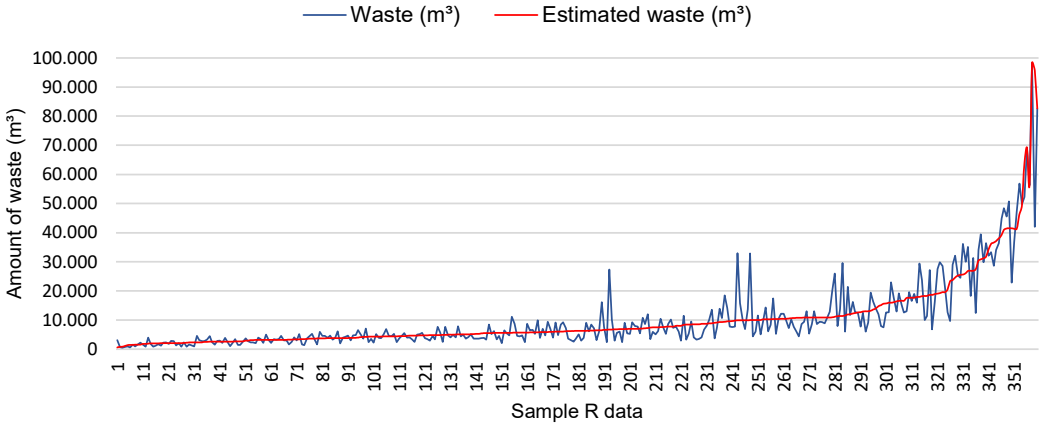

Figure 8 – Real waste quantities and the estimated quantities using the feed-forward neural network with ten neurons in the hidden layer, three training cycles, and the Bayesian Regularization training algorithm.

Table 1 – Summary of the best results obtained for the R^2, RMSE, and MAPE parameters in simulations with samples A, B, and R, and with the three training algorithms used.

Sample	Algorithm	Configuration (Cycle / Neurons)	R^2	RMSE	MAPE (%)
A	Bayesian Regularization	1 cycle / 10 neurons	1.00	11.56 kg	0.0003
A	Scaled Conjugate Gradient	1 cycle / 10 neurons	1.00	—	1.00
A	Levenberg-Marquardt	1 cycle / 10 neurons	1.00	—	0.003
B	Bayesian Regularization	3 cycles / 10 neurons	1.00	6.55 kg	0.00013
B	Levenberg-Marquardt	2 cycles / 10 neurons	1.00	—	0.003
B	Scaled Conjugate Gradient	3 cycles / 3 neurons	1.00	—	2.00
R	Validation (Bayesian Regularization)	3 cycles / 10 neurons	0.83	4,337.69 m^3	38.35

R^2: coefficient of determination; RMSE: root mean squared error; MAPE: mean absolute percentage error.

Regarding the parameters used to evaluate neural network models, the value of R^2 equal to 0.83 in this research was considered satisfactory for estimation models, being above the value obtained by Hu et al. (2021), R^2 equal to 0.75, in their research with neural networks using data from 206 works, equal to the value obtained by Abbasi and El Hanandeh (2016), R^2 of 0.83 for data from the training set and close to that obtained by Cha et al. (2022), R^2 equal to 0.90 for training with backpropagation neural networks.

Although the R^2 value was satisfactory, indicating that the neural network can explain 83% of the variations in waste quantities, the RMSE value of 4,337.69 m^3 was above the values obtained by Abbasi et al. (2013) and Abbasi and El Hanandeh (2016) using the support vector machine algorithm (RMSE 2,070 kg and RMSE 300.70 kg, respectively), and neural networks (RMSE 498.43 kg). This discrepancy in RMSE can be attributed to differences in units of measurement (m^3 *vs*. kg), the nature of the data (construction waste *vs*. other types of waste), or the scale of the problems addressed. It is fundamental that future comparisons consider the standardization of units and contextualization of data for a more precise analysis of model performance.

In this study, the MAPE value was 38.35%, which means that the proposed neural network model is capable of estimating the amount of waste accurately in more than 60% of cases. This value was lower than that obtained by Nagalli (2021b) of 56.7%, and higher than the values achieved by Abbasi and El Hanandeh (2016) of 0.07% for data from the training set, and Hu et al. (2021), of 8.22% for simulations with neural networks, 5.37% for simulations with a support vector machine, and 10.31% for the linear regression model. The MAPE value was acceptable compared to other studies, indicating that the model presents a low percentage variation in relation to real data.

From this research, it appears that improvements in predictive capacity can be achieved by increasing the sample size to at least 5,000 data points. Although the results obtained are restricted to the samples analyzed, ANNs demonstrated potential for application in waste estimation. Furthermore, the perspective is that with the expansion of the database, even considering different input variables and maintaining the treatment of sample data, in order to remove outliers, the neural network will improve its ability to estimate quantities of waste. The continuous collection of data and the refinement of models are crucial steps to improve the accuracy and applicability of ANNs in this field.

Conclusions

This study aimed to evaluate the potential of ANNs to estimate CDW generation, using synthetic and real data. The results demonstrated that ANNs are efficient tools for predicting CDW quantities, provided they are used under appropriate training conditions. To ensure more robust predictions, it is recommended to use sufficiently large and homogeneous databases (≥5,000 records) with relevant input variables.

The study's limitations include its reliance on a relatively small real-world dataset (Sample R), the use of only two input variables, and the absence of cross-validation in different geographical contexts or construction typologies. Although the ANN showed good overall performance, the MAPE of 38.35% on real data suggests that variations may be associated with local practices, data noise, or unconsidered factors such as construction methods, material types, and project timelines.

Future work should aim to expand the real-world dataset, incorporate more input variables (such as construction typology, project duration, and material composition), and test the models in different regions and realities. Additionally, comparative studies with other machine learning techniques (such as decision trees, ensemble models, or deep learning architectures) could offer new perspectives on the most suitable methods for CDW estimation. Finally, the development of applied computational tools, based on trained models, is recommended to support planning and decision-making in waste management within the construction sector.

Authors' Contributions

Recalcatti, S.: Conceptualization, Data Curation, Formal Analysis, Funding Acquisition, Investigation, Methodology, Resources, Software, Visualization, Writing – Original Draft. **Carvalho**, K.Q.: Validation, Writing – Review & Editing. **Kern**, A.P.: Validation, Writing – Review & Editing. **Nagalli**, A.: Conceptualization, Methodology, Project Administration, Resources, Supervision, Validation, Writing – Original Draft, Writing – Review & Editing.

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