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Construction and Demolition Waste Generation Prediction by Using Artificial Neural Networks and Metaheuristic Algorithms

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Abstract: In the actual estimation of construction and demolition waste (C&DW), it is significantly relevant to effective management, design, and planning at project stages, but the lack of reliable estimation methods and historical data prevents the estimation of C&DW quantities for both short- and long-term planning. To address this gap, this study aims to predict C&DW quantities in construction projects more accurately by integrating the gray wolf optimization algorithm (GWO) and the Archimedes optimization algorithm (AOA) into an artificial neural network (ANN). This study uses data concerning the actual quantities of work in 200 real-life construction and demolition projects performed in the Gaza Strip. Different performance parameters, such as mean absolute error (MAE), mean square error (MSE), root mean squared error (RMSE), and the coefficient of determination (R^2), are used to evaluate the effectiveness of the models developed. The results of this study have shown that the AOA-ANN model outperforms the other models in terms of accuracy (R^2 = 0.023728, MSE = 0.00056304, RMSE = 0.023728, MAE = 0.0086648). Moreover, this new hybrid model yields more accurate estimations of C&DW quantities with minimal input parameters, making the process of estimation more feasible.

Keywords: construction and demolition projects; waste estimation; GWO (gray wolf optimization); AOA (Archimedes optimization algorithm); ANN (artificial neural network); Gaza-Palestine

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1. Introduction

The global construction industry is a major contributor to waste generation, due to its production of massive volumes of landfill garbage resulting from consuming considerable amounts of natural resources [1–3]. Construction and demolition (C&D) operations generate over ten billion tons of garbage globally each year [4]. Furthermore, the volume of waste grows each year. For instance, the generation of construction and demolition waste (C&DW) in the United States exhibited a significant increase, reaching 342% between 1990 and 2018 [5]. With continuous urbanization, C&DW generation is predicted to increase [6]. Thus, good C&DW management is critical for sustainable growth.

For effective C&DW management, quantification of C&DW plays a key role, as this estimation is instrumental in the formulation and execution of sustainable waste management plans, enabling contractors and relevant authorities to proactively plan and address waste disposal [7]. Additionally, companies can understand the criticality of waste generated in their projects, and they become more aware of waste management, becoming more eager to develop and employ management plans. By developing effective waste management plans, companies can significantly contribute to achieving sustainable development goals in construction and demolition projects [1].

Moreover, policymakers can gain critical insights from accurate C&DW estimations to create effective regulations and make informed decisions [8]. Furthermore, accurately quantifying C&DW can affect the success of any project, especially given the rising costs associated with waste disposal due to factors such as landfill fees, regulations, and environmental concerns [9]. Thus, companies can use these amounts to prepare their waste disposal budget [10] and plan waste-hauling trucks [11]. As a result, the construction industry demands smart, competent, and precise methods for C&DW management [12]. However, construction companies struggle to effectively manage C&DW due to its large volume and complex composition [13], and attaining a satisfactory level of prediction accuracy for C&DW remains a challenging endeavor due to the intricate nature of the problem and the macro-level socioeconomic impact [14].

There are different efforts made to estimate the C&DW in the literature. Traditionally, companies try to estimate their waste manually; however, manual calculations are impractical since a vast amount of waste data emerge throughout the project, and data on construction waste have been steadily rising as information levels have improved [12]. Therefore, computer-based models are essential for accurate analysis, streamlined processes, and timely project completion. However, existing methods, aside from estimation and prediction techniques, lack the capability to accurately and easily assess waste generated by C&D projects [15]. Gao et al. [12] stated that machine learning can offer solutions to these challenges, providing a solid foundation for decision-making [16], prediction [17,18], and detection [19]. Currently, researchers are focusing on developing optimal strategies that integrate artificial intelligence (AI) models with preprocessing techniques, such as data cleaning, feature selection, and normalization, to enhance forecasting solutions.

In this research study, machine learning methods were applied to improve the precision of generated quantities estimation of C&DW and to assess the effectiveness of these predictive models in determining the most accurate estimation model. In this study, the artificial neural network (ANN) method was chosen to estimate, given the well-documented good performance of ANN in the literature. For instance, Ombres et al. [20] successfully employed ANN to model the bond capacity between steel-reinforced grout composite systems and concrete. Similarly, Umuhoza et al. [21] utilized ANN to predict the quality performance of building construction projects. To enhance the estimation capabilities of the ANN, this study integrates two optimization algorithms: the gray wolf optimization algorithm (GWO) and the Archimedes optimization algorithm (AOA). Additionally, hybrid approaches have been recently explored in the literature, with various studies demonstrating improvements in prediction performance. Consequently, two representative hybrid models, namely AOA-ANN and GWO-ANN, have been proposed toward achieving the above. These models were evaluated using different performance metrics to ensure the robustness and accuracy of the predictive models, providing a thorough assessment of their performance in predicting C&DW generation. The purposes of this study are as follows:

1. Increasing awareness among all construction stakeholders about C&DW management and integrating developed techniques into estimation processes.
2. Proposing hybrid algorithms and comparing their results to identify the most accurate model.

The methodology used in this study is as follows: First, it conducts a literature review to explore existing studies on C&DW estimation, informing the development of a more precise estimation methodology. The methodology deployed for this research is provided through a section summarizing data description and model development. Then, the performance of the proposed models is compared to determine the best model for C&DW estimation. Finally, the study concludes by providing discussions on research limitations and directions for future work and summarizes the most important findings.

2. Literature Review

2.1. Machine Learning Usage in C&DW Estimation

Accurate predictive value in quantitative terms of C&DW is of significant importance with regard to effective waste management. Among the machine learning methods, ANN, Random Forest (RF), Support Vector Machine (SVM), and other commonly used techniques have found remarkable success in application, especially related to data-based decision-making obtained from laboratory and computer simulations [22]. Hence, due to its great utility for prediction, various machine learning and statistical analysis algorithms have been deployed for predicting C&DW.

Akanbi et al. [23] predicted the recoverable tons of salvage and waste material from the buildings before demolition using a deep neural network. After verifying four distinct case study scenarios, it was discovered that their machine learning (ML) approach greatly increased waste estimation accuracy. In the same way, Lu et al. [17] created an ML regression model to calculate the generation of waste in pre-renovation construction projects. They demonstrated significant improvements in the accuracy of waste estimation by comparing their model's performance with the prevailing approach.

ML techniques, particularly ANN, have been extensively applied to predict waste production based on historical data. For instance, Coskuner et al. [24] employed a multi-layer perceptron artificial neural network (MLP-ANN) to predict annual waste generation rates from construction and demolition, domestic, and commercial sources in the Kingdom of Bahrain. This model, trained with data spanning from 1997 to 2016, achieved strong performance metrics, with an R^2 of 0.91, demonstrating its robustness. Similarly, Soni et al. [25] assessed various ML models, including ANN and hybrid models like GA-ANN, for predicting municipal solid waste (MSW) in New Delhi, India. Their findings showed that GA-ANN outperformed other models with an R^2 of 0.87. Additionally, G.-W. Cha et al. [26] compared ANN, support vector regression (SVR), and a random forest autoencoder for forecasting demolition waste using six input parameters and 782 data points in Korea, achieving an R^2 of 0.68. These studies illustrate the effectiveness of ML algorithms in modeling waste generation and highlight their varying performance across different datasets and contexts.

Likewise, a study by Cha et al. [27] developed models using RF and Gradient Boosting Machine (GBM). They could predict demolition waste given a similar dataset. They compared the performance of these methods and found that it was relatively more stable and accurate than the predictions found through GBM. Nagalli [28] compared the performance of construction waste estimation models developed using different combinations of ANN. From these comparisons, the best results were obtained using two neurons in the hidden layer and two training cycles. He concluded that machine learning methods provide better results than linear multiple regression, which is widely used in the literature. More studies using machine learning methods for waste estimation can be found in Gao et al. [12].

2.2. Hybrid Model Approach

Although traditional studies that employ a single machine learning method often yield satisfactory results, currently, a contemporary approach, known as the hybrid approach, has gained widespread adoption in the literature. Ongoing studies aim to enhance forecasting model accuracy through the exploration of various tests that integrate AI models and preprocessing techniques to identify the most effective forecasting solutions. Notably, some studies have highlighted the efficiency of metaheuristic algorithms in prediction models [27]. These algorithms encompass evolutionary methods like the genetic algorithm and AOA, as well as swarm-based approaches such as bee colony optimization, ant colony optimization, and GWO.

In C&DW estimation studies, hybrid modeling has also been employed. Wu et al. [14] innovatively introduced and evaluated an AI predictive standard known as Gene Expression Programming, in addition to multiple linear models and ANN in Hong Kong. The proposed model aims to forecast C&DW using a dataset aggregated from 1991 to 2010. The result showed that gross domestic product proved to be an effective model for prediction. In another study, Lee et al. [9] devised a novel hybrid model that predicts both the cost and amount of construction waste throughout the initial stages of projects of multifamily residential buildings. This innovative approach combines ant colony optimization with ANN. They concluded that their hybrid model provided more efficient and accurate estimates compared to simple ANN. In other words, they recommended hybrid models instead of traditional models.

Song et al. [18] proposed a model for predicting the quantity of each C&DW component in China. They developed their model by integrating the gray model (GM) and SVR. In their model, the SVR adjusted the residual series, and GM performed the estimation of the discharge of each component based on the outputs of the SVR process. They concluded that the proposed model is effective and provides valuable insight for policymakers.

Cha et al. [29] predicted the rate of waste production during building demolition projects using four models. Two of these models were traditional models developed using ANN and SVR. The remaining two were hybrid models that integrated the ANN and SVR with the Categorical Principal Components Analysis (CAPTCA). By comparing the performance of these models, they found that hybridization significantly improved prediction accuracy. In particular, the CATPCA-SVR model outperformed all other models in terms of prediction ability.

Although the superior advantages of GWO [30] and AOA [31], these metaheuristic algorithms are rarely used in C&DW estimation. Whereas the effectiveness of GWO and AOA with machine learning methods has been examined in the literature. For instance, Ewees and Elaziz [32] introduced a novel approach for predicting Biochar yield. In their model, the GWO and adaptive network-based fuzzy inference system (ANFIS) methods were integrated, and these methods operated in two distinct phases. In the initial phase, GWO was employed to adeptly learn the ANFIS parameters accurately using the training set. Subsequently, the second phase involves the evaluation of the performance of the proposed ANFIS-GWO method by using the testing set. To gauge its effectiveness, three tests were conducted, utilizing six datasets with five inputs. The outcomes of the ANFIS-GWO model were then compared with those of three other algorithms: the original ANFIS, ANFIS-GA, and ANFIS-particle swarm optimization (PSO). Notably, the ANFIS-GWO model outperformed the standard ANFIS and other models by a margin of 35%.

Turabieh [33] explored the effectiveness of combining two computational intelligence methods—GWO and ANN—for predicting heart disease. The study found that the proposed hybrid model, ANN-GWO, achieved high-performance results. Golafshani et al. [34] similarly constructed hybrid models for the prediction of compressive strength in normal and high-performance concretes, employing ANN, ANFIS, and GWO. They stated that the training and generalization capability of both the ANFIS and ANN models improved when they hybridized with GWO. After conducting their study, they concluded that the ANN model with the GWO and LM algorithms had better results when compared with the other models that were developed.

Liang et al. [35] delved into a hybrid model designed to foresee month-to-month municipal solid waste production in seven Iranian megacities. The model integration involved coupling the ANN model with optimization algorithms such as AOA, GA, PSO, and sine-cosine algorithm. Improved gamma testing determined the optimal input combination. The ANN-AOA exhibited a commendable capacity to predict various target variables.

Abo Mhady et al. [36] proposed hybrid models for estimating at-completion (EAC) estimation in construction projects. In their model, they used AOA to optimize the input parameters, and the outputs of this process were used by ANFIS and ANN to estimate EAC. They compared the results of these models with those of traditional estimation models that were separately developed using ANFIS and ANN. They concluded that AOA-ANN outperformed other models, and the accuracy of the estimations increased significantly with the employment of AOA.

Consequently, the hybrid approach can be an innovative approach to overcome the challenges related to the estimation of C&DW. ANNs have proven their efficacy in addressing intricate and challenging problems across various industries and research domains. A substantial body of literature has attested to the robustness of ANN in the C&DW field [9,24]. Furthermore, the AOA and GWO methods provide reliable results in different industries; therefore, they have potential for C&DW estimation. The extensive application of ANN across various research fields underscores the need to evaluate their performance alongside AOA and GWO for future C&DW projections in the construction industry. Therefore, this study develops two hybrid models integrating the ANN with the AOA and GWO methods.

3. Research Methodology

To conduct this study, the methodology involved diving into the relevant literature on waste generation, leveraging machine learning algorithms, and tapping into metaheuristic techniques in construction projects. The research methodology used in this study is shown in Figure 1. The methodology consists of these steps: (1) Literature Review: The aim of this step is to identify and extract the variables used in the C&DW estimation models proposed in the literature (2) Data Collection: A dataset of information for 200 projects, including the amount of waste (no. of trucks), year of construction, duration of project, total area of the building, number of floors, and site access; (3) Preprocessing Step: Improved predictive model performance through the elimination of outliers and normalization of raw data; (4) Feature Selection: Applied feature selection (input combination) based on AOA or GWO, determining the most relevant variables for the models; (5) Model Development: Employed ANN algorithm to estimate C&DW amount; and (6) Model Evaluation: Utilized performance metrics, namely mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), as well as R^2, R (correlation coefficient), for verification and evaluation of the models.

Figure 1. Research methodology.

3.1. Data Collection

Based on a thorough review of relevant studies, it is clear that waste management is a significant and widely recognized issue. Many scientific research efforts have focused on understanding, characterizing, and measuring the waste produced during construction and demolition operations. A literature review was conducted to reveal the variables used in C&DW estimation. Table 1 summarizes eight factors contributing to waste generation identified in studies conducted before 2023 to provide a comprehensive overview. Table 1 also indicates which studies used these variables.

Furthermore, six experts, whose demographic profile is shown in Table 2, discussed the validity of these variables to ensure that these variables are related to C&DW quantity emerging in a project. According to Table 2, the demographic profile of the experts shows that they are experienced and knowledgeable. The identified variables were presented to the experts individually. For each variable, the experts shared their opinions regarding its validity for C&DW estimation, along with their reasoning. If the experts reached a consensus on the validity of a variable, it was accepted as valid. In cases where there was disagreement among the experts, they engaged in discussions until they could arrive at a consensus. At the end of this process, experts verified all variables. Therefore, these variables, or inputs, form the basis for the hybrid model developed in this study.

Two data sources were used in this study: the Ministry of Public Works and Housing, and expert contractors and engineers from Palestinian construction companies. To collect data, a form was developed based on the variables extracted from the literature. In the data collection stage, twenty experts participated. The profiles of these experts are presented in Figure 2 to show that these experts have the required authority to provide data about the variables. Among these participants, thirteen worked as project managers on their projects, while seven were site managers. All participants demonstrated prominent levels of experience in construction projects. Additionally, the study included participants from both public and private organizations to ensure a diverse demographic representation.

Table 1. Identified variables for C&DW.

No	Variable	Description	References
1	Project name	Documented Name	
2	Quantity of waste	The amount of waste: number of trucks that came out of the demolition of the building (a truck that contains a box of size 2.45 m × 6 m × 1.5 m).	
3	Type of project	Construction or demolition project.	[8,27,37]
4	Date (Year)	The starting date of project (2000–2023).	[9,17]
5	Project location	North, Gaza, Medial Area, Khan Younis, Rafah.	[8,9,26,27,37–39]
6	Project duration	The time required to complete the project (months).	[28,38–41]
7	Building use	Only residential, commercial/residential, only commercial, public, infrastructure, and others.	[8,23,26,27,37,38,42]
8	Total building area	The area of all built floors includes the first-floor area and typical floor area (square meters).	[8,9,14,18,23,24,27,37,38,42]
9	Access to the site	There are three levels of access to the site: easy access from the borders and the availability of wide highways; medium ease of access; and difficult access.	[38,42]
10	Number of floors	Number of floors in the construction.	[9,23,42]

Table 2. Demographic profile of experts.

Expert No.	Degree	Position	Year of Experience
01	Associate Prof.	Associate Prof.	25
02	Prof. Dr.	Senior lecturer	10
03–06	Master's Degree	Project manager	8–25

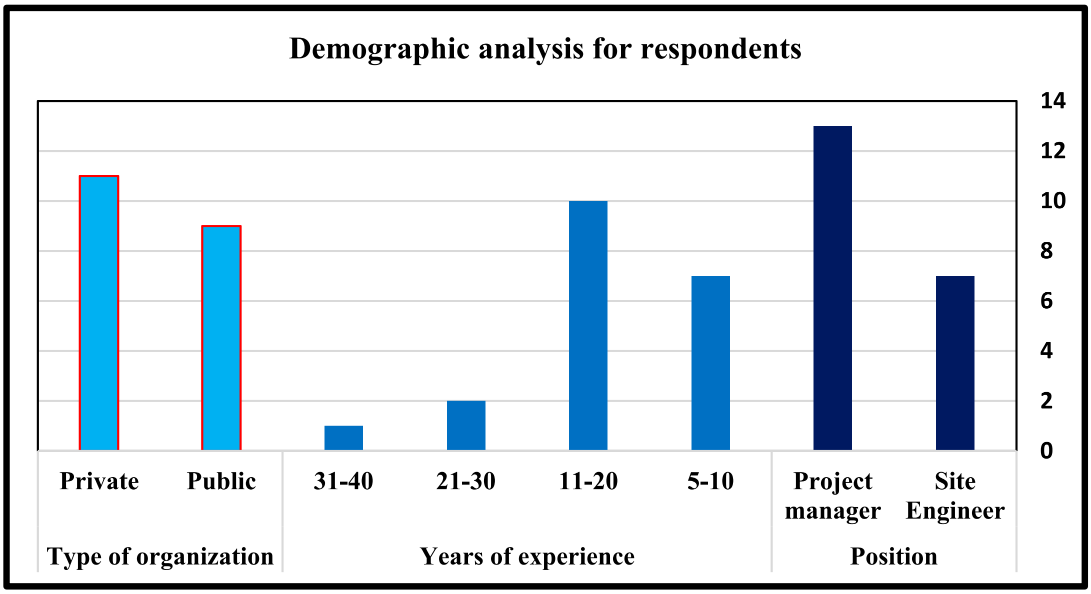


Figure 2. Profile of the participated respondents.

Communication with experts took place in two stages: face-to-face interactions in which the researcher explained the problem, the data needed, and each variable for the problem. Therefore, the possibility of any misunderstanding could be avoided. Afterward, the researcher sent an Excel sheet for data collection via email. After the data collection stage, a total of two hundred data points from construction and demolition projects were obtained.

3.2. Phase of Preprocessing

This phase prepares the data for developing a prediction model and enhancing its robustness through three primary stages. Initially, data points that had either missing or redundant information were removed, thereby eliminating elements that did not contribute to the model's effectiveness when training on a particular object. Subsequently, the data were split into training and testing groups, with 70% (140 data points) allocated for training purposes and 30% (60 data points) reserved for testing and validation to ensure that the model undergoes substantial training. Lastly, normalizing the dataset is an essential step due to the presence of multiple groups with diverse dimensions in the dataset. This diversity can affect prediction efficiency and accuracy reliability. Additionally, this normalization stage facilitates the establishment of a standardized scale for data parameters without altering variations within the feature range. Specifically, the training, testing, and validation data were independently normalized using the min-max method, as represented by the following formula:

$$N_i = \frac{Y_i - Y_{min}}{Y_{max} - Y_{min}} \tag{1}$$

where N_i is the normalized variable, while Y_i, Y_{max}, and Y_{min} are the original value, maximum, and minimum value of each variable, respectively [43].

3.3. Hybrid Model Development

Improvement strategies have been used in various AI applications. Four principal classifications included a substantial portion of these applications: the selection of features, the training of neural networks, improvement of SVM, and the application of clustering [43]. Among these, feature selection stands out as a crucial process in ML and data mining. The primary objective of feature selection (input selection) is to reduce the number of inputs, retaining the most representative ones while eliminating redundant, noisy, and irrelevant features. However, determining the optimal set of inputs is considered complex and challenging, especially when dealing with severe features [44]. In this study, the estimation model was optimized by integrating two metaheuristic algorithms for selecting features. In this study, feature selection was performed based on two criteria: minimizing RMSE and maximizing R. At the end of this process, the best input combinations were obtained, and these combinations were used by the ANN algorithm's training process to estimate C&DW. The methods used in the development of hybrid models are described as follows.

3.3.1. Gray Wolf Optimization (GWO)

Mirjalili [45] introduced the GWO algorithm. GWO was inspired by the cooperative hunting behavior of gray wolves. Gray wolves are members of the Canadian wolf family, live in groups of 5 to 12 wolves, and are considered the top of the food chain. Typically, these wolf packs have a hierarchical structure defining their social dynamics, and they contain alpha, beta, and omega group members. At the apex of this hierarchy is the alpha wolf, assuming the leadership role within the pack and being responsible for dictating hunting strategies, rest periods, and movement patterns. Following the alphas, the pack has beta wolves, who serve as the support system to the alphas by aiding in making decisions and facilitating group activities. Beta wolves also serve as potential candidates for assuming alpha positions in the future, acting as both alpha assistants and mediators within the group. The omega gray wolves are in the lowest tier, and their role often involves sacrificial acts for the benefit of the pack. Omegas are the last to partake in meals and play a crucial role in maintaining pack cohesion. Wolves that do not fit within the alpha, beta, or omega categories are termed obedient or delta wolves. Delta wolves adhere to the leadership of alpha or beta wolves and oversee the activities of omega wolves, including scouting and sentinel duties [46].

The GWO algorithm was developed with consideration of the social behavior of wolves. In this algorithm, the wolf alpha represents the primary solution, while the wolf beta and the wolf gamma represent the subsequent two best solutions. Other solutions are categorized as omega. As a result, the optimization of the GWO algorithm is driven by alpha, beta, and gamma wolves, with omega wolves aligning with these classifications.

Regarding the gray wolves' hunting behavior, they exhibit a tendency to encircle their prey during hunting. To mathematically model this turning behavior, Equations (2) and (3) are presented [45].

$$\vec{D}_\alpha = |\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}|,\ \vec{D}_\beta = |\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}|,\ \vec{D}_\delta = |\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}| \tag{2}$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha, \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta, \vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta \tag{3}$$

In the given context, the symbol t denotes the repetition count, while A and C denote vector coefficients. Here, P and X represent the position vectors of the prey and a gray wolf, respectively. The determination of vectors A and C follows the calculations outlined in Equations (4) and (5).

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \tag{4}$$

$$\vec{C} = 2\vec{r}_2 \tag{5}$$

As $\vec{a}$ linearly decreases from 2 to 0 over the course of iterations, r_1 and r_2 denote random vectors.

To mathematically emulate the gray wolves' hunting behavior, it is assumed that the alpha (the prime candidate solutions), the beta, and the delta wolves possess sufficient awareness regarding the probable location of the prey. Consequently, the initial three superior solutions are preserved, compelling other search agents (omegas) to adjust their positions relative to the top search agents, as delineated in Equations (6)–(12).

$$\vec{D}_\alpha = |\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}| \tag{6}$$

$$\vec{D}_\beta = |\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}| \tag{7}$$

$$\vec{D}_\delta = |\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}| \tag{8}$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha \tag{9}$$

$$\vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta \tag{10}$$

$$\vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta \tag{11}$$

$$\vec{X}(i+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{12}$$

The ultimate position can randomly occur within a circle defined by the alpha, beta, and delta positions in the search space. Essentially, their positions serve as estimations for the prey's position, prompting other wolves to update their positions in a random manner around the prey.

3.3.2. Archimedes Optimization Algorithm (AOA)

The AOA algorithm serves the dual purpose of determining the optimal initial weight for models and optimizing and adjusting the model parameters. This metaheuristic model, known as AOA, can be applied to solve various mathematical optimization problems, demonstrating its efficiency in reaching global solutions in a shorter period [47]. The AOA method proceeds through seven stages, as stated in Table 3, to discover near-global solutions. Table 3 also represents the calculation and optimization methods for each stage.

Table 3. Stages of hyperparameter tuning process for AOA.

	Stage	Calculation	Optimization
1st	Initiation	Volume	Lower and upper boundaries
2nd	Upgrade volumes and densities	Density	Optimal density
3rd	Transfer operator and density factor	Density factor	Maximum number of iterations
4th	Exploration	Acceleration	Collision
5th	Exploitation	Acceleration	No collision
6th	Normalization Acceleration	Acceleration	Access the percentage
7th	Evaluation	Fitness	Optimal solution

Stage 1—Initiation:

In this stage, a population, including the immersed solution (object), is characterized by density, volume, and acceleration. All solutions are initially placed at random positions beneath the fluid, as expressed in Equation (13), and the fitness value for each solution is assessed.

$$O_i = lb_i + rand(0,1) \times (ub_i - lb_i),\ \forall i\ \in \{1,2,3,\ldots,N\} \tag{13}$$

$$Vol_i = rand(0,1) \tag{14}$$

$$Den_i = rand(0,1) \tag{15}$$

$$ACC_i = lb_i + rand(0,1) \times (ub_i - lb_i),\ \forall i \in \{1,2,3,4,\ldots,N\} \tag{16}$$

In the above equations, O_i represents the i^{th} solution in the population, and N denotes the size of the population. ub_i and lb_i denote the upper and lower limit of the i^{th} solution. Den_i, Vol_i, and ACC_i represent the density, volume, and acceleration of the i^{th} solution, respectively. The term *rand*(0, 1) denotes a randomly selected scalar with a value between zero and one.

Stage 2—Upgrade volumes and densities:

This involves the enhancement of both the volume and density for all solutions.

$$Den_i^{(t+1)} = Den_i^{\,t} + rand(0,1) \times \left(Den_{best} - Den_i^{\,t}\right) \tag{17}$$

$$Vol_i^{(t+1)} = Vol_i^{\,t} + rand(0,1) \times \left(Vol_{best} - Vol_i^{\,t}\right) \tag{18}$$

During this stage, $Deni(t)$ denotes density and $Voli(t)$ denotes the volume of the i-th solution during the t-th iteration. Den_{best} denotes the optimal (best) density, and Vol_{best} denotes the volume of the object comprising the best ability standards.

Stage 3—Transfer operator and density factor:

The algorithm addresses collisions between objects until they reach an equilibrium state. The mathematical expression for this stage can be represented by the following equation:

$$TF = \exp\left\{\frac{t - t_{max}}{t_{max}}\right\} \tag{19}$$

TF denotes the transfer operator, which facilitates the transition of the search process from the exploration to the exploitation stage. t_{max} is the maximum number of iterations.

Additionally, a reduced density factor (d) plays a role in aiding the AOA to converge toward a global solution.

$$d^{t+1} = \exp\left\{\frac{t - t_{max}}{t_{max}}\right\} - \left(\frac{t}{t_{max}}\right) \tag{20}$$

Stage 4—Exploration:

During the "Exploration" stage, collisions among solutions take place. In this stage, when TF is less than or equal to 0.5, an arbitrary material (mr) is selected, and the acceleration of an object is updated using the following equation:

$$ACC^{t+1} = \frac{Den_{mr} + Vol_{mr} \times ACC_{mr}}{{Den_i}^{(t+1)} \times {Vol_i}^{(t+1)}} \tag{21}$$

In the equation, Den_{mr} is the density, Vol_{mr} is the volume, and ACC_{mr} is the arbitrary material acceleration, respectively [48].

Stage 5—Exploitation:

In stage 5, which is marked by the absence of collisions among solutions, the acceleration of each solution is upgraded when $TF \geq 0.5$:

$$ACC^{t+1} = \frac{Den_{best} + Vol_{best} \times ACC_{best}}{{Den_i}^{(t+1)} \times {Vol_i}^{(t+1)}} \tag{22}$$

While ACC_{best} represents the solution acceleration with optimal fitness.

Stage 6—Normalization acceleration:

Known as "Normalization acceleration", it involves normalizing the acceleration to assess the percentage change:

$$ {ACC_{i-norm}}^{t+1} = g \times \frac{{ACC_i}^{t+1} - \min\{ACC\}}{\max\{ACC\} - \min\{ACC\}} + z\ (19) \tag{23}$$

Here, "g" and "z" represent the normalization range, and ${ACC_{i-norm}}^{t+1}$ is used to determine the percentage by which each agent moves.

Additionally, positions are updated throughout this stage. When the exploration phase exists ($TF \leq 0.5$), the i-th object's position for the coming iteration t plus 1 is determined using Equation (24) [49].

$${x_i}^{t+1} = {x_i}^{t} + C_1 \times randACC_{i-norm}^{t+1} \times d \times \left(x_{rand} - {x_i}^{t}\right) \tag{24}$$

Here, C_1 is a constant equal to two. On the other hand, when an exploitation phase exists ($TF > 0.5$), the objects update their positions using Equation (25).

$${x_i}^{t+1} = {x_{best}}^{t} + F \times C_2 \times randACC_{i-norm}^{t+1} \times d \times \left(T \times x_{best} - {x_i}^{t}\right) \tag{25}$$

Here, C_2 has a value equal to 6, and t is directly proportional to the transfer operator, which increases with time, defined as $t = C_3 \times TF$. T grows over time within the range ($C_3 \times 0.3$, 1), taking a certain rate from the optimal position initially. The initial low rate results in a substantial difference between the current position and the optimal position, which leads to a high step size in the random walk. As the search progresses, this rate increases gradually to reduce the difference between the current and optimal positions, thereby achieving a balance between exploitation and exploration.

The flag F is utilized to alter the motion direction according to Equation (26):

$$F = \begin{cases} +1\ if\ P \leq 0.5 \\ -1\ if\ P > 0.5 \end{cases} \tag{26}$$

Here $P = 2 \times \text{rand} - C_4$.

Stage 7—Evaluation:

In the evaluation stage, fitness values of all solutions are calculated, and a record of the optimal solution is obtained, which leads to the update of the optimal solution (x_{best}), Den_{best}, Vol_{best}, and ACC_{best}.

3.3.3. Artificial Neural Network (ANN)

The concept of the ANN stems from the intricate biological system of the human brain, which is characterized by a vast network of interconnected elements known as neurons. Mathematically, the ANN can be modeled as dynamic systems using a set of combined differential equations [50,51].

A fundamental model of an ANN comprises the input, hidden, and output layers. Each layer contains a varying number of neurons or nodes. The information relevant to a specific problem determines the number of nodes or cells in the input and output layers [51,52].

ANNs endeavor to establish relationships between input-output data pairs and identify the optimal number of nodes in the hidden layers through trial-and-error methods [24,33]. Typically, the collected data undergo randomization and are then considered under three distinct groups: training, validation, and testing. The dataset for training serves as the foundation for teaching the ANN to establish relationships between the input and output pairs through weight and bias adjustments [33]. Numerous traditional training algorithms commence with randomly initialized weights and biases, which progressively converge toward the best solution. However, the application of an ANN generally involves two key calculations: (1) Feed Forward and (2) Back Propagation. In the Feed Forward step, weights, representing the values expressing the impact of the input set, are initially assigned randomly, and the system generates outputs for the given sample. The back-propagation algorithm, which is a widely used ANN training algorithm, adjusts biases and weights originating from the last layer and progresses toward the first layer. To determine the best biases and weights for minimizing differences between predicted and actual values, ANN training is performed [24]. Coskuner et al. [24] summarized many traditional optimization algorithms that can be employed during the training phase of ANN such as Conjugate Gradient [53], Levenberg–Marquardt [44,54], and Gradient Descent, Gradient Descent with Momentum, Gradient Descent with Adaptive Learning Rate, and Gradient Descent with Momentum and Adaptive Learning Rate [55]. Table 4 furnishes a comparative overview of the ANNs.

Table 4. A summary of ANNs based on previous studies.

Methods	ANN
Model Architecture	This model is like a web of interconnected nodes or neurons. Typically, it is organized into three layers: the input, hidden, and output layers [12,56].
Approach	Black box [12,57].
Number of Data	Researchers have suggested that to yield meaningful and dependable results with an ANN, the size of the data should be approximately ten times the number of weights in the network [58].
Advantages	ANN models exhibit remarkable flexibility and are adept at capturing intricate and nonlinear relationships between independent and dependent variables. They are invaluable for modeling a broad spectrum of complex scenarios [12,59]. ANN models exhibit computational efficiency, making them well suited for handling extensive datasets [12]. Training ANN models offers versatility through a range of optimization algorithms, enabling fine-tuning and adjustment of model performance to meet specific requirements [34].

Table 4. *Cont.*

Methods	ANN
Disadvantages	ANN models are prone to overfitting when handling noisy data, which leads to potential shortcomings in generalization performance [12,59]. The black-box structure of ANN models contributes to their reduced interpretability, which poses a challenge in understanding the reasoning behind predictions [12]. Unlike some models, the output of an ANN model is not presented in a readily human-readable form [60].

3.3.4. Hybrid Models

Two hybrid models were proposed in this study. The first model combines GWO with ANN, while the second model combines AOA with ANN. The flowcharts of the proposed algorithms are shown in Figures 3 and 4. The hybrid model is used to optimize the performance of the ANN in terms of input selection and accuracy enhancement. The details of the proposed models are elaborated as follows:

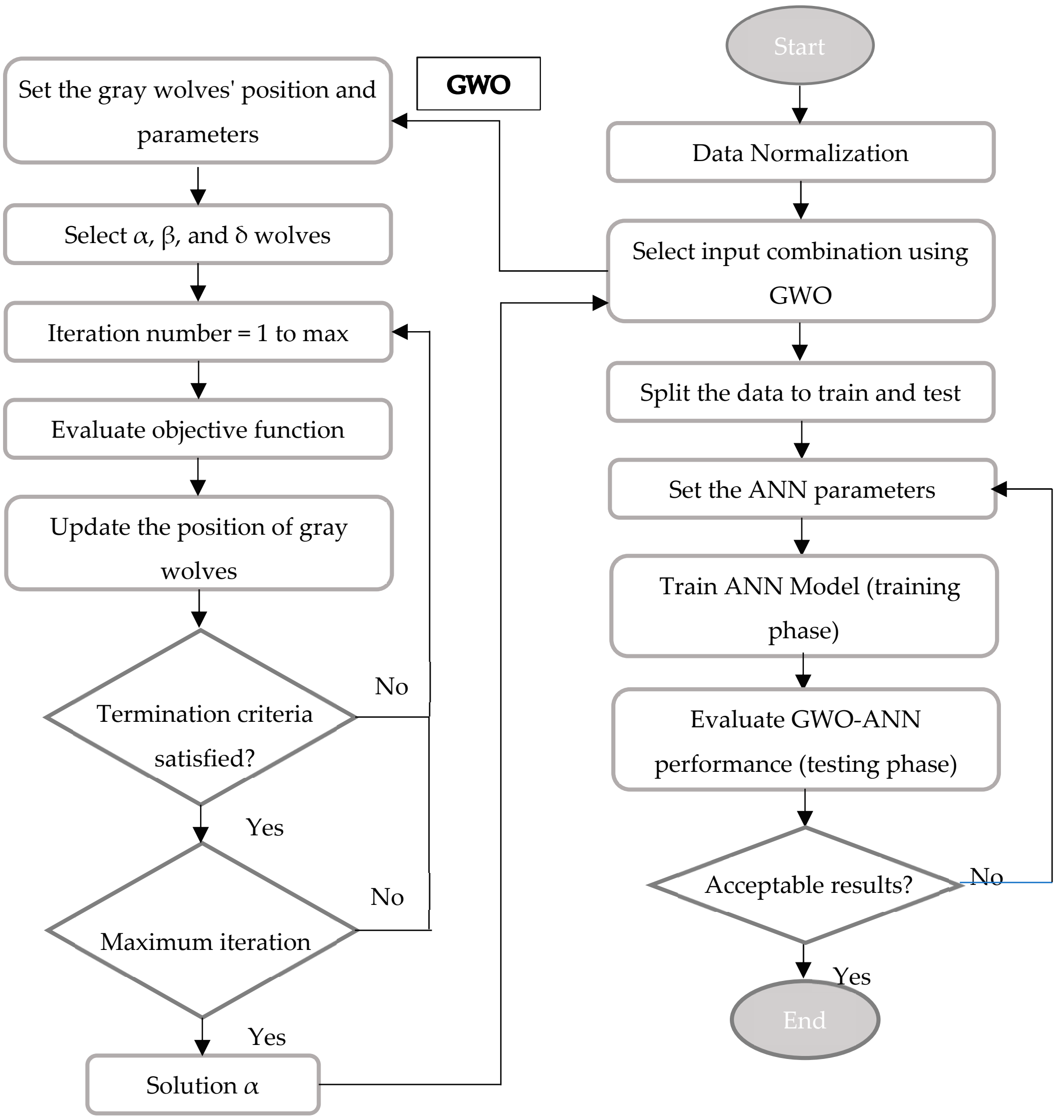


Figure 3. Flowchart of the proposed GWO-ANN algorithm.

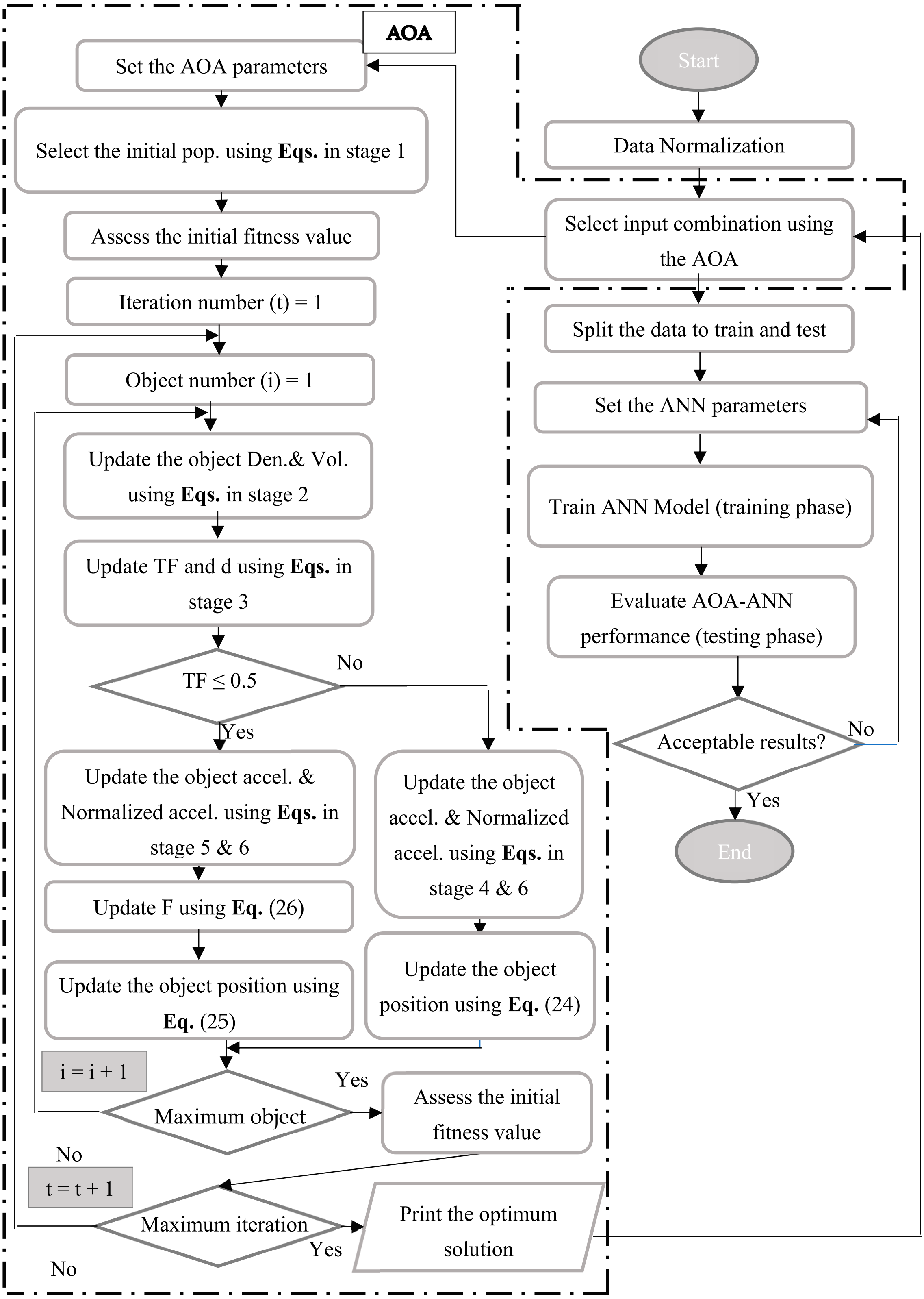


Figure 4. Flowchart of the proposed AOA-ANN algorithm.

The GWO-ANN Hybrid Model Steps are as follows:

Step 1—Data Normalization: Normalize the dataset to ensure uniformity across features.

Step 2—Feature Selection with GWO: Apply GWO to select the optimal input feature combination.

The GWO Optimization Process is as follows:

- Initialize GWO Parameters: Set the initial positions and parameters of the gray wolves.
- Select Leadership Hierarchy: Identify the α (leader), β (second), and δ (third) wolves.
- Iteration Process: Loop through iterations, evaluating the objective function.
- Update Positions: Update the positions of gray wolves based on their interaction with α, β, and δ wolves.
- Termination Check: If termination criteria are satisfied or the maximum number of iterations is reached, obtain the solution α.

Step 3—Data Splitting: Divide the dataset into training and testing subsets.

Step 4—Set ANN Parameters: Configure the architecture and parameters of the ANN.

Step 5—Train ANN: Train the ANN model using the training data.

Step 6—Evaluate Performance: Test the model on the test data and evaluate the results.

Step 7—Result Check: If the results meet the required criteria, end the process. If not, return to the GWO optimization process.

The AOA-ANN Hybrid Model Steps are as follows:

Step 1—Data Normalization: Normalize the input data for consistency.

Step 2—Feature Selection with AOA: Use the AOA to select the optimal input feature combination.

Step 3—Data Splitting: Split the data into training and testing sets.

The AOA Optimization Process is as follows:

- Initialize AOA: Set AOA parameters and select the initial population.
- Fitness Assessment: Evaluate the initial fitness of the population.
- Update Objects: Update object density, volume, TF, distance, acceleration, and position based on AOA equations.
- Check TF: Depending on the TF value, update forces and object positions.
- Iteration Loop: Repeat object updates until the maximum iteration or population size is reached.
- Optimum Solution: Print the final optimized solution.

Step 4—Set ANN Parameters: Define the ANN structure and parameters.

Step 5—Train ANN: Train the ANN model using the training data.

Step 6—Evaluate Performance: Test the ANN on the test set and evaluate its performance.

Step 7—Result Check: If the results are acceptable, end the process. Otherwise, return to AOA for further optimization.

3.4. Performance Evaluation of Models

It is recommended that different performance metrics be employed for the evaluation of the performance of the developed models [22]. Additionally, in this study, to gauge the efficacy of the created models, diverse performance parameters, namely MAE, MSE, $RMSE$, and the R^2 were utilized, with their corresponding equations as shown in Table 5.

The Taylor diagram and scatter chart are valuable tools for evaluating machine learning models; thus, they are used for comparing predictions related to C&D waste. These diagrams provide a clear visual summary of how well different models capture data variability and correlation. They help analysts assess the strengths and weaknesses of each model comprehensively [61]. The Taylor diagram specifically uses performance metrics such as standard deviation, RMSE, and R^2 to gauge how closely estimated values align with experimental results [34]. Meanwhile, the scatter chart employs various performance metrics, including MAE and MSE, to evaluate model performance.

Table 5. The equations of performance criteria used in model evaluation.

Performance Metric	Min	Max	Equation
MAE	0	$+\infty$	$MAE = \frac{1}{n}\sum_{i=1}^{n} \lvert A_{pi} - A_{ai} \rvert$
MSE	0	$+\infty$	$MSE = \frac{1}{n}\sum_{i=1}^{n} \left(A_{ai} - A_{pi}\right)^2$
$RMSE$	0	$+\infty$	$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} \left(A_{pi} - A_{ai}\right)^2}$
R^2	0	1	$R^2 = \left(\frac{\sum_{i=1}^{n}\left(A_{ai}-\overline{A_a}\right)\sum_{i=1}^{n}\left(A_{pi}-\overline{A_p}\right)}{\sqrt{\sum_{i=1}^{n}\left(A_{ai}-\overline{A_a}\right)^2\sum_{i=1}^{n}\left(A_{pi}-\overline{A_p}\right)^2}} \right)^2$

Important Note: In the provided equations, A_a represents the actual value, A_p represents the predicted value, and $\overline{A_a}$ and $\overline{A_p}$ denote the averages of the actual and predicted values, respectively. The variable 'n' represents the total number of data points. The model(s) with the highest R^2 and lowest MAE, RMSE, and MSE values should be chosen as the optimal model(s).

4. Results and Discussion

4.1. Analysis of Data

In the first step, the collected data were analyzed using descriptive statistical analysis, which was performed using Microsoft Excel, to reveal its characteristics. Descriptive statistics can provide an overall perspective. The results of these analyses are presented in Table 6 and Figure 5. The quantity of waste (in terms of trucks) was identified as the model's output and given the abbreviation Oi; the remaining variables were identified as the model's inputs and given the names P1, P2, P3, P4, P5, P6, P7, and P8.

Table 6. Descriptive statistics of continuous variables.

Item	Symbol	Min	Mean	Max	Stand. Deviation	Variance
Amount of Waste (No. of Trucks)	Oi	1	80	810	167.05	27,906.83
Starting year of the project	P2	2010	2018	2023	3.78	14.28
Duration of project (Months)	P4	0.5	10	36	6.09	37.11
Total building area	P6	200	5245	27,000	4949.11	24,493,672.28
Number of floors	P8	1	4.63	17	3.22	10.34

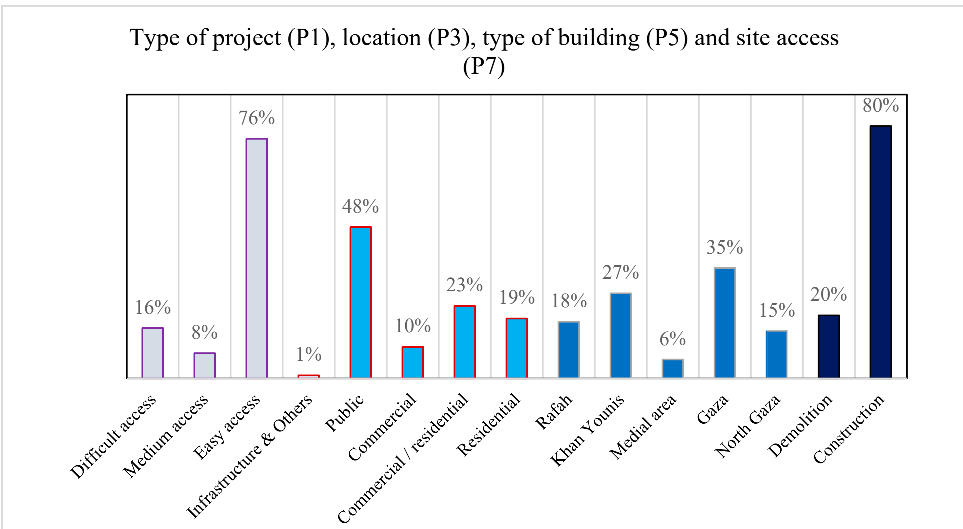


Figure 5. Frequency analysis of categorical variables.

To mitigate the disproportionate influence of the Year of Construction (P2) and Total Building Area (P6) due to their wide ranges compared to those of other variables, these variables were scaled. This involved converting the original values (2010, 2011, 2013, 2014, 2015, . . ., 2023) and (200, . . ., 27,000) to a scaled range of (1, 2, 3, 4, 5, . . ., 13) and (0.2, . . ., 27.00), respectively.

In the context of AI, categorical variables must be encoded into numerical data to be processed by AI models. This encoding process entails assigning a unique numerical value to each category. For example, in this study, geographical locations were encoded as follows: North was represented by the value 1, Gaza by 2, Medial Area by 3, Khan Younis by 4, and Rafah by 5. Similarly, building usage categories were encoded with the values 1, 2, 3, 4, and 5, representing only residential, commercial/residential, only commercial, public, infrastructure, and other categories, respectively.

4.2. Required Parameters for Each Technique

A model for predicting the waste produced by construction and demolition projects in the Gaza Strip was developed using the MATLAB R2021a program. Before using GWO, AOA, and ANN for prediction, it is essential to comprehend them. For this situation, each strategy required a rundown of data to begin demonstrating. The essential boundary settings of each calculation are presented in Table 7.

Table 7. Initial parameters of the metaheuristic and machine learning algorithms.

Algorithm/Model	Parameter's Settings	Value
GWO	Number of agents	30
	Maximum iteration	10
AOA	Population size	30
	Maximum iteration	10
ANN	Number of inputs	8
	Number of hidden layers	1
	Number of outputs	1
	Number of nodes in hidden layer	10
	Algorithm for training	Levenberg–Marquardt back-propagation algorithm
	Maximum iteration	1000
	Transfer function type for hidden and output layers	Sigmoid and linear function

4.3. Results of Stand-Alone Predictive Models

The stand-alone proposed ANN with ten and seventeen nodes in the hidden layer was applied to the data. Table 8 presents the performance prediction indicators using all the chosen inputs. It is observable that the ANN with ten nodes outperformed the ANN with seventeen nodes in terms of prediction skills (minimum error). The ANN with ten nodes achieved the following performance metrics: MAE, RMSE, and MSE of 0.012322, 0.034859, and 0.0012152; and R^2 of 0.98615 in quantitative terms. A scatter plot was included to illustrate the variation between the actual and predicted waste generation amounts for the stand-alone ANN models. Please refer to the two scatter plots in Figure 6. After analyzing the model, it was found that the best number of hidden nodes was different from the number of hidden nodes used in previous studies [62,63], which is twice the number of inputs plus one.

Table 8. Evaluation of ANN models during the testing modeling phase.

Model	MAE	MSE	R^2	RMSE
ANN with ten nodes	0.012322	0.0012152	0.98615	0.034859
ANN with seventeen nodes	0.036166	0.003871	0.96064	0.062217

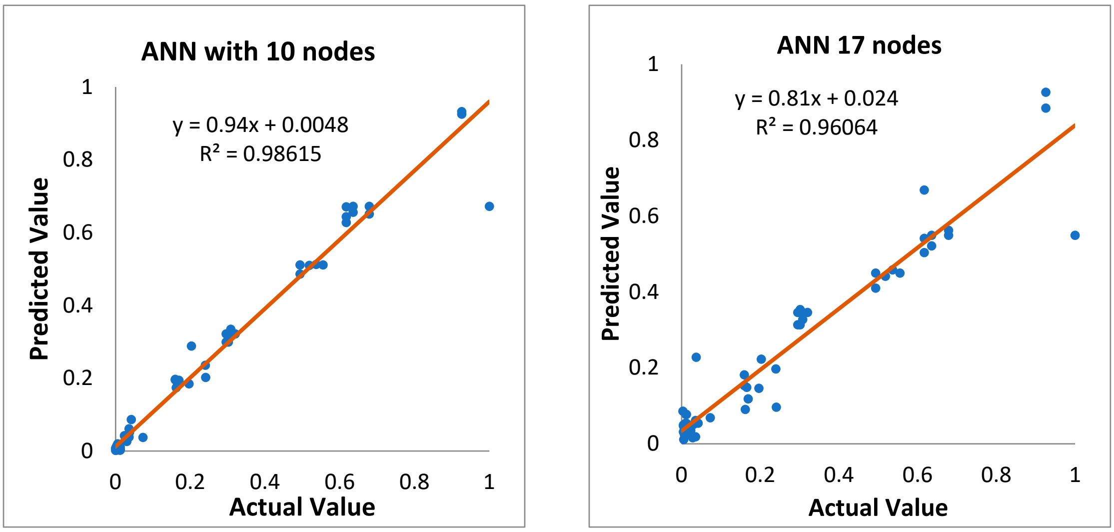


Figure 6. The scatter plot graphical visualization for developed ANN models with different nodes.

4.4. Results of Hybrid Predictive Models

This study uses a systematic approach to optimize prediction accuracy by selecting the most optimal input combinations for the seven hybrid models. To achieve this, GWO and AOA were employed, which can identify the most influential input variables for accurate C&DW prediction. These optimization techniques select the combinations based on two criteria: minimizing the root mean squared error (RMSE) and maximizing R^2.

Table 9 presents the combination of inputs and prediction skill outcomes of the hybrid models (GWO-ANN and AOA-ANN). The results of hybrid models are presented in Table 10. Model 5 (AOA-ANN with five inputs) was found to be the most accurate in terms of predicting waste generation. Quantitatively, model 5 achieved better results, with MAE, RMSE, and MSE values of 0.0086648, 0.023728, and 0.00056304 respectively, and an R^2 value of 0.99333. Traditional ANN, on the other hand, had lower prediction indicators with values of 0.012322, 0.034859, 0.0012152 and 0.98615. The proposed data-intelligence model 5 showed significant improvement in performance. To visually represent the variation between actual and predicted waste generation, scatter plots were created for both the stand-alone AOA-ANN and GWO-ANN models.

Figure 7 shows scatter plots with Cartesian coordinates illustrating the relationship between predicted waste generation (y-axis) and actual data (x-axis). Blue points in the plots represent the correlation between predicted and actual data for the test cases in this study.

Figure 8 presents the Taylor diagrams for the top-performing models assessed on the dataset. The diagrams reveal that the hybrid ANN model with AOA algorithms provides the most accurate predictions, with AOA-ANN model 5 showing the highest performance among the models. Additionally, among the hybrid ANN models using GWO algorithms, GWO-ANN model 7 exhibits the best predictive ability compared to the other GWO-ANN models. Figure 8 provides a comprehensive comparison of various models, including the traditional ANN and the best-performing models utilizing the GWO-ANN and AOA-ANN techniques. The evaluation is based on three performance metrics: MAE, RMSE, and MSE. The figure clearly illustrates that the AOA-ANN model significantly outperforms the other models for all these metrics. This indicates that the AOA-ANN (model 5) approach delivers superior accuracy and reliability in predictions compared to both the standard ANN model and the GWO-ANN models.

Table 9. The combination of input used in the hybrid models.

No.	Models	Input/Variable GWO-ANN	Input/Variable AOA-ANN
1	Model 1	P5	P4
2	Model 2	P6, P2	P6, P1
3	Model 3	P4, P8, P5	P8, P1, P3
4	Model 4	P5, P2, P1, P4	P8, P6, P7, P1
5	Model 5	P7, P8, P6, P1, P2	P6, P1, P5, P2, P8
6	Model 6	P7, P3, P2, P8, P4, P5	P5, P1, P3, P2, P6, P7
7	Model 7	P5, P2, P4, P8, P6, P3, P1	P1, P7, P3, P6, P8, P4, P5

Table 10. The evaluation for the hybrid models through the testing modeling phase.

	Model	MAE	MSE	R^2	RMSE
GWO-ANN	Model 1	0.019014	0.0014154	0.98331	0.037622
	Model 2	0.02301	0.0020101	0.97686	0.044834
	Model 3	0.014414	0.0012981	0.98495	0.036029
	Model 4	0.028611	0.002881	0.96748	0.053675
	Model 5	0.015772	0.0014574	0.98409	0.038177
	Model 6	0.03422	0.0039633	0.95306	0.062955
	Model 7 [1]	**0.012154**	**0.00085292**	**0.99033**	**0.029205**
AOA-ANN	Model 1	0.023863	0.0020703	0.97805	0.045501
	Model 2	0.018417	0.0014887	0.9825	0.038583
	Model 3	0.015966	0.00121	0.98669	0.034785
	Model 4	0.011764	0.0012868	0.98605	0.035871
	Model 5 [2]	**0.0086648**	**0.00056304**	**0.99333**	**0.023728**
	Model 6	0.013769	0.00089333	0.98958	0.029889
	Model 7	0.013227	0.00077767	0.99104	0.027887

[1] This model shows superior performance compared to other GWO-ANN models. [2] This model shows superior performance compared to other AOA-ANN models.

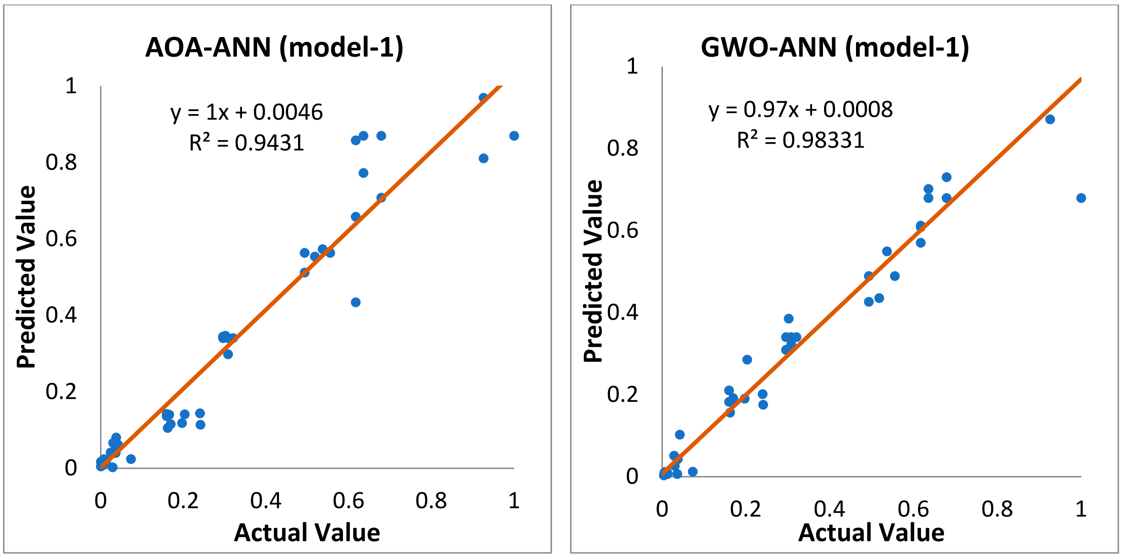


Figure 7. *Cont.*

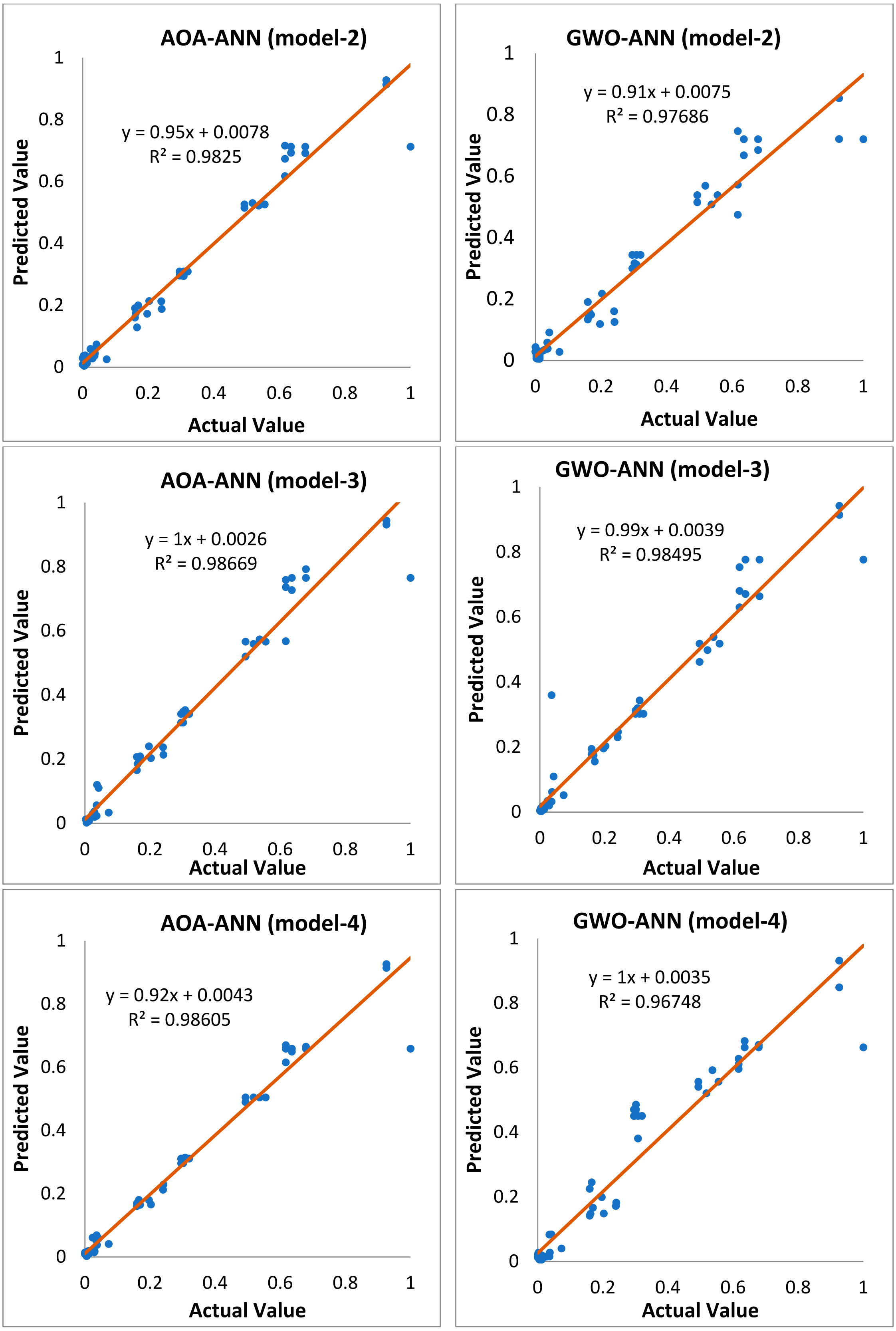


Figure 7. *Cont.*

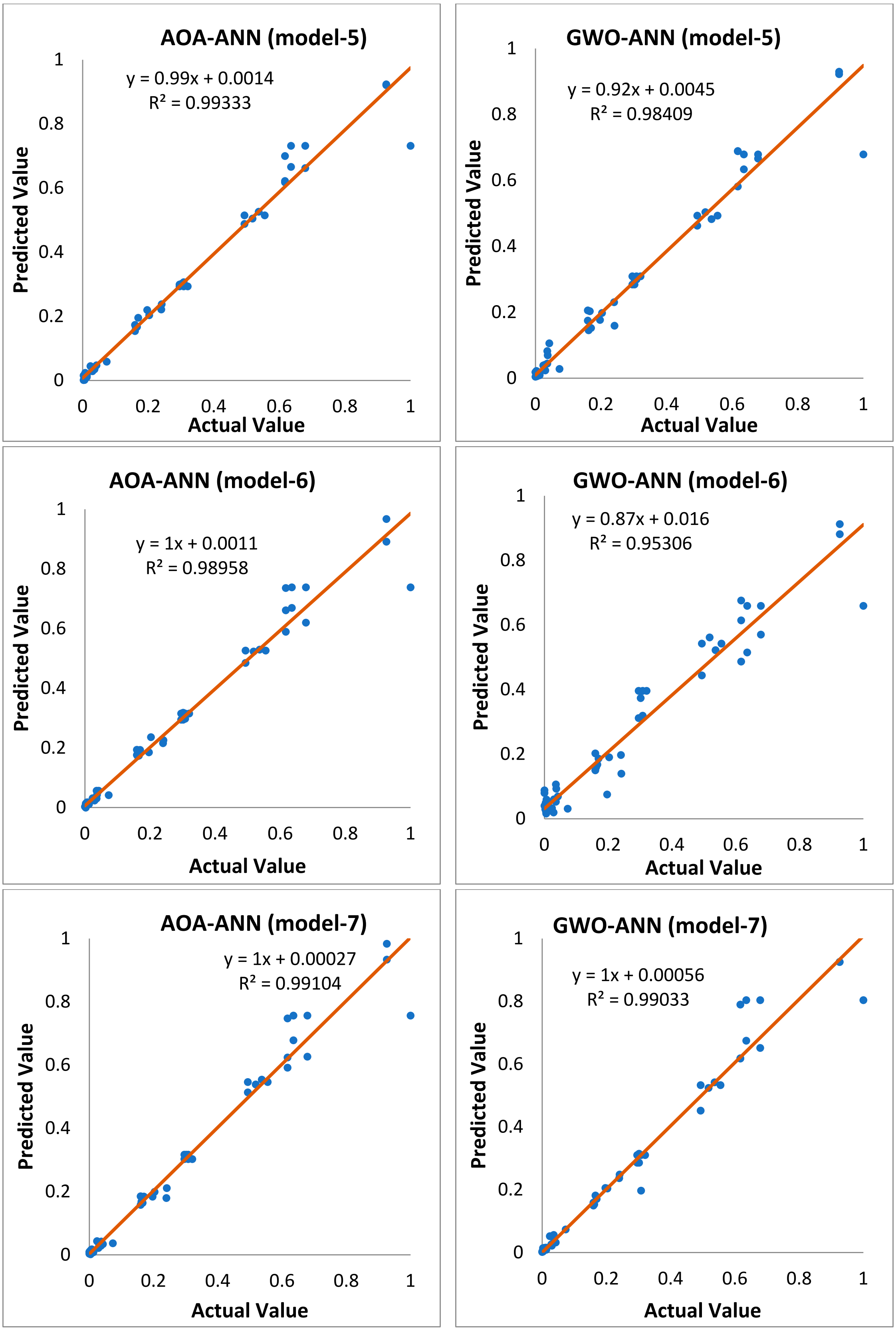
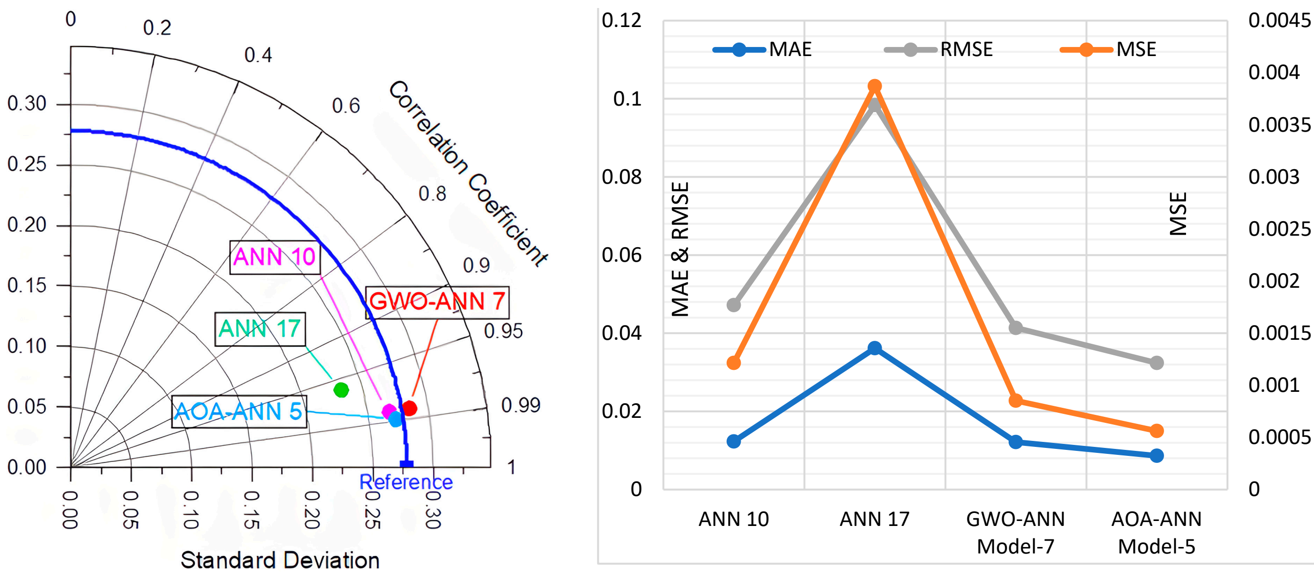


Figure 7. The scatter plot graphical visualization for the different developed models for testing datasets.



(**a**) (**b**)

Figure 8. Comprehensive performance analysis of the best models: (**a**) the Taylor diagram and (**b**) scatter chart for the best developed models for testing datasets.

5. Research Shortcomings and Future Work

This study also has some limitations and can be summarized as follows:

Firstly, collecting data in C&DW studies is a challenging stage, as it requires extensive document and bill review due to the site engineers' limited involvement in waste management. However, in Palestine, the widespread reuse of waste, due to limited access to new materials, facilitated data collection. For collecting this data, which is not available online, personal and professional connections were used. All data were collected by connecting with the professionals personally, ensuring its reliability.

Another critical limitation is that this study is based on Palestinian data. Due to the complex structure of the developed models, they may have limitations in their applicability to other regions. Due to variations in construction practices and data availability, it is difficult to generalize the findings of machine learning waste estimation models [17]. To address this, the models should be reevaluated for other regions of the world, and the required modifications should be performed before the implementation of the models.

While the study provides an estimate of total C&DW, it does not offer a detailed composition of the waste. Nevertheless, this information can still be valuable for construction companies in planning waste disposal budgets and hauling coordination. Additionally, general composition proportions from existing research [11,64] can be used to approximate the weight of individual components.

Finally, the number of the data points can be another issue; however, several C&DW estimation studies have employed a similar number of data points. The primary goal of this research was to demonstrate the effectiveness of hybrid models in waste prediction, and the promising results highlight their potential in civil engineering. However, it is important to note that the accuracy of the models may improve with a larger dataset.

6. Conclusions

A substantial portion of all waste generated comes from C&D projects. In the construction industry, finding solutions to reduce C&DW is a significant challenge. This study aims to enhance our understanding of waste produced at construction and demolition sites through the application of AI modeling techniques. By leveraging AI, we seek to develop insights and predictive models that can help identify patterns, optimize resource allocation, and ultimately minimize waste generation in construction activities. For this purpose, the study included two main parts: data collection and hybrid model development. The main findings of this study are as follows:

- The hybrid models, GWO-ANN and AOA-ANN, demonstrate superior accuracy in predictions while requiring fewer parameters compared to the stand-alone ANN. The application of metaheuristic techniques, specifically AOA and GWO, plays a pivotal role in selecting optimal input combinations for the ANN machine learning algorithm, thereby enhancing the accuracy of the estimations.
- In this study, the best model was selected based on the higher R^2 with minimum MAE, MSE, and RMSE among the proposed C&DW prediction models. The results showed that AOA-ANN achieved the best performance by incorporating five variables: total building area, type of project, type of building, starting year of the project, and number of floors. This model provided the lowest MAE (0.0086648), RMSE (0.023728), and MSE (0.00056304) with the highest R^2 value (0.99333) compared to the models based on other input combinations.
- The GWO-ANN yielded the best result with a combination of seven variables: type of building, starting year of the project, duration of project, site access, total building area, location, and type of project. This model achieves MAE, RMSE, and MSE values of 0.012154, 0.029205, and 0.00085292, respectively, with an R^2 value of 0.99033.
- Notably, AOA-ANN (model-5) outperformed the GWO-ANN (model-7), albeit with a greater number of features, enhancing its ability to comprehend the internal mapping relationship between predictors and predictions.
- This study demonstrates that hybrid models developed by integrating metaheuristic techniques with machine learning methods can be highly beneficial for C&DW management. Project supervisors can better control project time and cost by estimating waste amounts more accurately using data from fewer parameters.

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