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**YILDIZ TECHNICAL UNIVERSITY**
**GRADUATE SCHOOL OF SCIENCE AND ENGINEERING**

# PREDICTING CONSTRUCTION AND DEMOLITION WASTE GENERATION BY USING HYBRID MODELS

**Ruba AWAD**

DOCTOR OF PHILOSOPHY THESIS

Department of Civil Engineering

Constrcution Engineering Program

Supervisor

Prof. Dr. Aslı Pelin Gürgün

Co-Supervisor

Assoc. Prof. Cenk BUDAYAN

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A thesis submitted by Ruba Mohammed AWAD in partial fulfillment of the requirements for the degree of DOCTOR OF PHILOSOPHY is approved by the committee on 30.01.2025 in Department of Civil Engineering, Civil Engineering (English) Program.

| | |
|---|---|
| Prof. Dr. Aslı Pelin GÜRGÜN<br>Yıldız Technical University<br>Supervisor | Assoc. Prof. Cenk BUDAYAN<br>Middle East Technical University<br>Co- supervisor |

**Approved By the Examining Committee**

Prof. Dr. Aslı Pelin GÜRGÜN, Supervisor
Yildiz Technical University _____

Prof. Dr. Hüsnü GÜNAYDIN, Member
Istanbul Technical University _____

Asst. Prof. Gökhan DEMİRDÖĞEN, Member
Yildiz Technical University _____

Assoc. Prof. Kerim KOÇ, Member
Yildiz Technical University _____

Prof. Dr. Gül Polat TATAR, Member
Istanbul Technical University _____

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**Ruba Mohammed AWAD**

Signature

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*I would like to dedicate this thesis*

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# LIST OF SYMBOLS

| | |
|---|---|
| Oi | Amount of Waste (No. of Trucks) |
| P1 | Type of project |
| P2 | Year of project |
| P3 | Location |
| P4 | Duration of project (Month) |
| P5 | Type of building |
| P6 | Total Area of the Building |
| P7 | Site access |
| P8 | Number of floors |

# LIST OF ABBREVIATIONS

| | |
|---|---|
| ACO | Ant colony optimization |
| AD | Automatic differentiation |
| AI | Artificial intelligence |
| ANFIS | Adaptive neuro-fuzzy inference system |
| ANN | Artificial neural networks |
| ANOVA | Analysis of variance |
| AOA | Archimedes optimization algorithm |
| ARIMA | Autoregressive integrated moving average model |
| C&D | Construction and demolition |
| C&DW | Construction and demolition waste |
| CATPCA | Categorical principal components analysis |
| CHAID | Chi-squared automatic interaction detection |
| CW | Construction waste |
| CWM | Construction waste management |
| DL | Deep learning |
| DS | Descriptive statistics |
| DT | Decision trees |
| DWT | Discrete wavelet theory |
| EU | European Union |
| FAST | Fourier amplitude sensitivity test |
| GA | Genetic algorithms |
| GBM | Gradient boosting machine |
| GDP | Gross Domestic Product |
| GEP | Gene Expression Programming |
| GFA | Gross floor area |
| GIS | Geographic information system |

| | |
|---|---|
| GM | Gray model |
| GWO | Gray wolf optimization |
| IMM | Inclusive Multiple Model |
| KNN | k-nearest neighbors |
| LSTM | Long and short-term memory |
| MAE | Mean absolute error |
| MAPE | Mean Absolute percentage error |
| MFA | Material flow analysis |
| MII | Mutual information index |
| ML | Machine learning |
| MLP | Multi-layer perceptron |
| MSE | Mean square error |
| MSW | Municipal solid waste |
| NRSA | Nominal Range Sensitivity Analysis Method |
| POP | Population |
| PSO | Particle Swarm Optimization |
| PWHM | Public Works and Housing Ministry |
| $R^2$ | Coefficient of determination |
| RF | Random forest |
| RM | Resilient modulus |
| RMSE | Root mean squared error |
| RSM | Response surface methods |
| R-value | correlation coefficient |
| SA | Sensitivity Analysis |
| SCA | Sine Cosine Algorithm |
| SD | Standard Deviation |
| SSA | Singular spectrum analysis |
| SVM | Support vector machine |
| SVMR | Support vector machine regression |
| UK | United Kingdom |
| US | United States |
| XGboost | Extreme gradient boost |

| | |
|---|---|
| ΔLOR | Difference in log odds ratio |

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# ABSTRACT

## Predicting construction and demolition waste generation by using hybrid models

Ruba AWAD

Department of Civil Engineering

Doctor of Philosophy Thesis

Supervisor: Prof. Dr. Aslı Pelin GÜRGÜN

Co- supervisor: Assoc. Prof. Cenk BUDAYAN

Construction and demolition (C&D) projects rely on predicting waste generation hence an accurate predicting model assists the scheduling process by saving time, energy, and cost. This research will develop a hybrid model by coupling pre-processing techniques as Archimedes optimization algorithm (AOA), and gray wolf optimization (GWO) algorithm, and a machine learning algorithm such as random forest (RF), and artificial neural network (ANN) to predict the waste generated in construction projects. The study's concept of a hybrid model will be feature selection. AOA and GWO were employed as a feature selection for the hybrid model which select the best input combinations according to minimum error and maximum coefficient of determination ($R^2$). For the development of the model, data on 200 real-life C&D projects from Gaza Strip were used. Demographic and statistical analysis were used for data analysis. The efficiency of the developed models was evaluated using different performance parameters including the mean

absolute error (MAE), the mean square error (MSE), the root mean squared error (RMSE), and the coefficient of determination ($R^2$). The results demonstrated that the AOA-ANN model presented better data modeling than the classical ANN, RF model and hybridized AOA-RF, GWO-ANN and GWO-RF models. The results of testing phase were (e.g., MAE, RMSE, and MSE) (0.0086648, 0.023728, and 0.00056304) and an $R^2$ value of (0.99333) for the AOA-ANN (model 5). This was an attempt to implement the new intelligent techniques in waste management area. Moreover, it can be used to help project managers to control project time, cost and make accurate waste amount predictions.

**Keywords:** Construction and demolition project, grey wolf optimization (GWO), Archimedes optimization algorithm (AOA), random forest (RF), Artificial Neural Network (ANN).

# ÖZET

## Hibrit Modelleri Kullanarak İnşaat ve Yıkım Atıkları Oluşumunu Tahmin Etme

Ruba AWAD

İnşaat Mühendisliği Bölümü

Doktora Tezi

Danışman: Prof. Dr.Aslı Pelin Gürgün

Eş-Danışman: Assoc. Prof. Cenk BUDAYAN

İnşaat ve yıkım (C&D) projelerinde atık oluşumunu tahmin etmek büyük bir öneme sahiptir, çünkü, doğru bir tahmin modeli, zaman, enerji ve maliyet tasarrufu sağlayarak planlama sürecine katkı sağlar. Bu araştırma, Archimedes Optimizasyon Algoritması (AOA) ve Gri Kurt Optimizasyonu (GWO) gibi ön işleme tekniklerini, rastgele orman (RF) ve yapay sinir ağı (ANN) gibi makine öğrenimi algoritmaları ile birleştirerek hibrit bir model geliştirmeyi amaçlamaktadır. Hibrit modelin temel konsepti, parametre seçimi olacaktır. AOA ve GWO, minimum hata ve maksimum determinasyon katsayısına ($R^2$) göre en iyi girdi kombinasyonlarını belirlemek için hibrit modelde parametre seçimi için kullanılmıştır. Modelin geliştirilmesi için Gazze Şeridi'ndeki 200 gerçek C&D projesine ait veriler kullanılmıştır. Geliştirilen modellerin etkinliği, ortalama mutlak hata (MAE), ortalama kare hata (MSE), kök ortalama kare hata (RMSE) ve determinasyon katsayısı ($R^2$) gibi farklı performans parametreleri kullanılarak değerlendirilmiştir. Sonuçlar, AOA-ANN modelinin klasik ANN, RF modelleri ve hibrit AOA-RF, GWO-ANN ve GWO-RF

modellerine göre daha iyi veri modelleme performansı sergilediğini göstermiştir. Test aşamasındaki sonuçlar (örneğin MAE, RMSE ve MSE) sırasıyla (0.0086648, 0.023728 ve 0.00056304) ve $R^2$ değeri (0.99333) olarak belirlenmiştir (model 5). Bu çalışma, atık yönetimi alanında yeni akıllı tekniklerin uygulanması için bir girişimdir. Ayrıca, proje yöneticilerinin proje süresini ve maliyetini kontrol etmelerine ve atık miktarını doğru bir şekilde tahmin etmelerine yardımcı olabilir.

**Anahtar Kelimeler:** Inşaat ve yıkım projesi, gri kurt optimizasyonu (GWO), Arşimet optimizasyon algoritması (AOA), rastgele orman (RF), Yapay Sinir Ağı (ANN).

# 1 INTRODUCTION

## 1.1 Background of Research and Motivation

The global construction sector stands out as a major contributor to waste production, utilizing a substantial portion of natural resources and producing vast amounts of landfill waste [1, 2, 3]. Effective waste management holds paramount importance in achieving sustainable development goals [1]. According to Elaish and fellow researchers [4, 5, 6, 7], waste exerts a notable impact on the building industry's performance and the overall economic landscape of a country. This underscores the necessity for construction companies to embrace innovative waste management practices. However, the industry lags in making this transition, hindered by its ingrained culture and a lack of comprehensive waste management plans, processes, and tools [1, 3, 8, 9]. Experts emphasize the pivotal role of waste management solutions in driving this transformative development [1, 10].

Building projects face a notable challenge in managing material waste, a substantial contributor to overall waste production [11]. Construction waste emanates from two main sources: the construction of fresh structures and the demolition of old ones [12]. The scale of construction and demolition waste isn't solely determined by the volume generated but also hinges on the efficiency of its management [13]. Waste produced nonstop correlates with project demands, especially on suburban structures or estates, expansive commercial complexes like hypermarkets, and diverse infrastructure initiatives aimed at enhancing living conditions [4, 14, 15].

Construction waste is a substantial concern worldwide, Palestine included, with the added issue of inefficiently utilizing finite natural resources in the industry. The prevalence of material waste results in diverse project challenges, spanning cost and time overruns, along with environmental and social impacts. The effects of material waste vary across projects and countries [1]. Inaccurate forecasts of waste

generation by contractors can lead to increased waste disposal costs, significantly impacting the project's budget. Recognizing the negative repercussions of heightened construction waste, stakeholders are actively exploring effective strategies to enhance disposal cost projections and secure recyclable materials early in the project timeline, minimizing the risk of cost overruns [16].

Accurately gauging construction waste quantities is vital for the realization of a project, particularly considering all escalating costs associated with waste disposal [16]. Additionally, the intricate nature of the issue and its broader socioeconomic implications make achieving precise forecasting in the construction industry a persistent challenge [17]. Waste estimation provides valuable insights into the amounts and types of waste generated in the course of projects [18]. Elaish [4] highlights the versatility of waste measurement methods, outlining three distinct techniques for quantifying site waste: (1) Measured against the total construction waste; (2) Evaluated in relation to materials acquired; (3) Assessed as a percentage of the overall waste cost.

Scientists have been collecting data on construction project waste to enhance their comprehension of the challenges and formulate effective solutions. The amount of waste from construction that is found in trash yards (by weight) ranges from 13% to 50% in different countries when compared to the total waste generated. **Table 1.1** provides a percentage breakdown of building waste relative to all wastes of various nations [19].

**Table 1.1** Construction waste proportion relative to all construction waste

| References | Country | Waste proportion |
|---|---|---|
| [20] | Australia | 20–30% |
| [21] | Brazil | 50% |
| [22] | Canada | 27% |
| [23] | Denmark | 27% |
| [24] | England | 32% |
| [20] | Finland | 13–15% |
| [20] | Germany | 19% |
| [25] | Hong Kong | 28% |
| [26] | Japan | 20% |
| [20] | Netherland | 28% |
| [20] | United States | 20–29% |

The Palestinian economy heavily relies on the construction industry, as a key figure in developing essential infrastructure. Approximately 16% of the gross domestic product (GDP) stems from this sector, absorbing up to 34% of international donor programs and providing employment for around 22% of the workforce. Despite its economic significance, the Palestinian building industry faces a longstanding issue with waste, with limited research conducted in this domain [27]. Investigations indicate a significant amount of Gaza Strip's building sector excesses, surpassing standard statistics [18]. Utilizing historical data from construction and demolition projects aims to yield accurate waste estimates [16]. Enshassi's study [28] uncovered material losses, stemming from both direct and indirect waste, ranging from 3.6% to 11%, exceeding generally accepted rates (2% to 4.5%) across 86 housing projects in Gaza. Notably, about 11% of construction demolition waste in the Gaza Strip ends up in landfills or on the streets, an inefficient approach to mitigating the environmental impact of waste [28], This method proves ineffective in curbing the antagonistic impacts of building excesses on the surrounding.

Effectively managing waste necessitates precise quantitative forecasting. Estimation includes gauging the past volume of construction waste, while forecast entails projecting impending waste output by leveraging past data. Three main methods for estimating C&DW production include building area estimates, GIS (geographic information system) estimation, and MFA (material flow analysis) [29, 30, 31, 32].

When it comes to estimating construction waste, the building area approach stands out as it considers various stages like construction, demolition, and decorative waste creation, making it the go-to method in the industry. Forecasting the creation and destruction of building waste is accomplished via different methods like autoregressive integrated moving average, linear regression, and gray models [29].

Employing MFA proves beneficial for a methodical exploration of material waste, along with assessing the potential for waste recovery and recycling to inform decision-making in waste management [33]. In the United States, Cochran et al. [32] investigation looked into whether an MFA method could accurately predict the amount and conformation of building waste. Estimations for the debris generated

through demolition activities involve referencing historical consumption statistics and typical lifespan estimates for building materials [29].

Advancements in technology are steering predictive models towards the adoption of artificial intelligence (AI) approaches. In addressing engineering challenges, AI involves computationally constructed methods designed to emulate human reasoning or cognitive abilities. This strategy proves particularly effective in resolving engineering issues characterized by numerous inputs or random variables with unknown correlations between inputs and outputs [34]. The surge in popularity of artificial intelligence approaches in recent decades is attributed to enhanced predictive capabilities based on historical data. Machine learning (ML) methods have demonstrated success across various applications, particularly in decision-making based on data obtained from laboratory and computer simulations. These methods included other methods not mentioned such as support vector machine (SVM), artificial neural networks (ANN), random forests, and other widely employed techniques [35].

Effective waste management strategies greatly benefit from accurate predictions for planning future actions [36]. In construction quantity estimation, various prediction models have been devised, such as SVM, case-based reasoning, and regression analysis [16, 37, 38, 39, 40]. Several prototypes, often applied at national or municipal levels, aim to forecast waste generation. For instance, in Korea, Lee et al. [16] Suggested a combination model that uses ant colony optimization (ACO) with ANN to anticipate both the amount and cost of waste during the initial phases of building projects, as presented by Rimaitytė et al. [41] Proposed an integrated approach employing artificial neural networks (ANNs) and ant colony optimization (ACO) to forecast both the amount and expenses associated with waste in the early stages of construction, as outlined by Rimaitytė et al. [41].

Machine learning offers various prediction models, with ANN and RF emerging as frequently utilized options. Previous studies have highlighted their effectiveness in prediction tasks. While both models serve predictive purposes, distinct differences exist between the two, influencing their performance and suitability for specific applications. **Table 1.2** furnishes a comparative overview of three widely employed machine learning techniques. While both the ANN and RF models excel as

predictors, each comes with distinct strengths and weaknesses. For a quick overview of these key differences, refer to **Table 1.3**.

Currently, ongoing studies aim to enhance forecasting model accuracy through the exploration of various tests. Researchers are actively working on devising an optimal strategy that integrates AI models and preprocessing techniques to identify the most effective forecasting solutions. Notably, certain studies have highlighted the efficiency of meta-heuristic algorithms in extensive global searches [42]. In optimization, we delve into a variety of powerful algorithms. Think of them as problem-solving tools. From the evolutionary powers of genetic algorithms (GA) and the ingenious AOA to the collaborative strategies of bee and ant colony optimization, not forgetting the tenacity of grey wolf optimization (GWO). Each algorithm brings its unique strength to crack intricate problems. Their applications extend to enhancing the waste forecasting capabilities of construction companies. Essentially, a model crafted through these techniques has the potential to deliver dependable predictions concerning construction waste.

**Table 1.2** A summary of the two machine learning algorithms ANN and RF

| **Methods** | **ANN** | **RF** |
|---|---|---|
| **Model Architecture** | Picture this model like a web of interconnected nodes or neurons. Typically, it's organized into 3 layers: input layer, hidden layer, and output layer [43, 44] | Random Forest (RF) is an ensemble method that improves prediction by aggregating multiple decision trees, each built on bootstrap samples and considering random feature subsets at each split. Predictions are averaged for regression or determined by majority voting for classification [45, 46, 47] |
| **Approach** | Black-box [44, 48] | black-box [45, 49] |
| **Number of Data** | Researchers suggest that to yield meaningful and dependable results with artificial neural networks (ANN), the size of the data should be approximately ten times the number of weights in the network [50]. | RF does not have a strict requirement for the size of the dataset. |

**Table 1.3** The strengths and weaknesses of ANN and RF

| Method | ANN | RF |
|---|---|---|
| **Strengths** | • ANN models showcase remarkable flexibility, adept at capturing intricate and nonlinear relationships between independent and dependent variables. They prove invaluable in modeling a broad spectrum of complex scenarios. [43, 44, 48, 51].<br>• Artificial Neural Network (ANN) models exhibit computational efficiency, making them well-suited for handling extensive datasets [44].<br>• The beauty of an ANN model lies in its independence from an in-depth understanding of process phenomenology. It operates effectively without requiring intricate knowledge of the underlying processes.[43].<br>• Training ANN model offer versatility through a range of optimization algorithms, enabling the fine-tuning and adjustment of model performance to meet specific requirements [43, 48]. | • Robustness to Overfitting: By aggregating multiple decision trees, RF reduces the risk of overfitting compared to individual decision trees [52].<br>• Handling of Imbalanced Data: RF performs well even when classes are imbalanced, making it suitable for a variety of practical applications [46, 53].<br>• Performance with Large Datasets: It can effectively manage large datasets with high dimensionality and complex interactions among features [53].<br>• Resistance to Outliers: The ensemble nature of RF makes it less sensitive to outliers and noise in the data [52]. |
| Weaknesses | • ANN models are prone to overfitting when dealing with noisy data, leading to potential shortcomings in generalization performance.[44, 48, 51].<br>• The black-box structure of ANN models contributes to their reduced interpretability, posing a challenge in understanding the reasoning behind predictions [44, 48]. An interesting aspect of ANN models is that, unlike certain models, their output isn't immediately presented in a format easily readable by humans.[54].<br>• For accurate learning, ANN models demand a substantial volume of training data. [34]. | • Computational Complexity: RF can be computationally intensive, especially as the number of trees and the depth of trees increase [55].<br>• Model Interpretability: While individual decision trees are easy to interpret, the aggregated model of RF can be complex, making it harder to understand how decisions are made [55].<br>• Memory Usage: Storing multiple trees requires more memory, which can be a concern for very large datasets or models with many trees [55]. |

In this research study, hybrid model development through the application of machine learning methods has been attempted in order 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. Representative AOA-ANN, GWO-ANN, AOA-RF, and GWO-RF models have been proposed for achieving the above. The performance of these models was 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 purpose of this study can be summarized as follows:

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

The study is structured as follows: firstly, it conducts a literature review to explore existing studies on C&D waste 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 will be compared. Finally, the study finishes by providing discussions on research limitations and directions for future work and sums up the most important findings.

## 1.2 Problem Statement

The Gaza Strip grapples with multiple challenges, including a scarcity of natural resources, a declining economic situation, rapid population growth, and the enduring status of being a conflict zone [56, 57]. With the escalating production of waste and the increasing difficulty in securing resources, the imperative to implement innovative strategies becomes paramount [6].

In Palestine, the surge in construction activities, coupled with the absence of suitable dump sites, limited material resources, financial constraints, and a general lack of attention to the issue, has turned construction waste into a significant

problem [58, 59]. The absence of effective tools for waste estimation further exacerbates the challenge, leading project managers to often overlook and struggle to control waste throughout construction projects. Contributing factors to this issue in the Gaza Strip include insufficient qualifications among contractor employees, inadequate material cutting, and improper material handling on construction sites [6].

Unlike the abundance of studies concentrating on waste quantification and source analysis, the discourse around waste management systems has seen a notable gap. While numerous studies address the avoidance or minimization of waste at its source, both academic research and practical project initiatives tend to prioritize waste disposal over waste minimization. Existing waste management studies often lack broad applicability, focusing on specific locations or individual projects. Crucially, there is an evident absence of research dedicated to developing predictive models for the construction industry's waste in the Gaza Strip. Additionally, this research endeavors to bridge the existing gap in the literature concerning hybrid models within construction waste management in the Gaza Strip.

## 1.3 Aim and Objectives of Research

Efficient waste management in construction projects hinges on waste avoidance or minimization at the source. With a noticeable gap in research, especially within the Gaza Strip context, **the main thrust of this study** is to create a hybrid model geared towards predicting the generated waste in building projects and the destruction of old buildings. Emphasizing source control and waste minimization, a comprehensive waste management assessment will be conducted. Past studies have revealed challenges in acquiring waste data in the construction industry, further complicated by geographical and technical disparities among studies. Hence, the study will concentrate specifically on the building of fresh concrete structures as well as the demolition of old structures within the Gaza Strip.

Numerous studies rooted in lean construction principles propose a shift in focus from dealing with generated wastes through recycling or reuse to emphasizing waste reduction or elimination at the source, thereby enhancing waste management systems. Achieving process improvements necessitates a thorough and objective analysis of waste management within the reinforcing construction company.

Consequently, tailoring a waste management and minimization system is imperative, taking into account the specific material and project specifications. In summary, **the study's objectives** can be outlined as follows:

- Taking a deep dive into the current waste management scenario in the Gaza Strip, our goal is to evaluate the quality and effectiveness of waste management practices in various enterprises. The objective here is to pinpoint any obstacles that might impede the smooth execution of efficient waste management.

- Analyzing the origins of C&DW within the Gaza Strip with the goal of establishing a prioritized list highlighting the most prevalent sources of waste.

- Identifying influences contributing to the production of C&DW and evaluating their effect on building projects.

- Developing a hybrid model for predicting the generation of C&DW in the Gaza Strip. This endeavor includes blending the power of metaheuristic techniques like the GWO algorithm or AOA with the prowess of machine learning through ANN and RF.

## 1.4 Research Importance

While the building sector is pivotal in the journey toward sustainability, strides in the formulation of strategies needed for the management of waste have been notably lacking.

This challenge persists due to a lack of comprehensive knowledge among construction enterprises about the origins and reasons behind waste, along with an incomplete grasp of the total waste volume produced.

The escalation of construction activities, coupled with a shortage of suitable dump sites, limited material resources, financial constraints, and a general lack of attention, has turned construction waste into a substantial problem in Palestine.

Our study holds noteworthy importance as it looks to support the progress of a hybrid model solution specifically tailored for waste management in projects that involve strengthening concrete buildings.

## 1.5 Overview of Research Method

In building projects, the hybrid models serve as a predictive instrument, facilitating the estimation of waste generation expressed as a percentage or quantity relative to the total material utilized in the project. The model's formulation will be shaped by various factors linked to construction and demolition waste, encompassing both identified and anticipated elements specific to building projects in the Gaza Strip.

Therefore, by forecasting the potential implications of these factors, a precise and comprehensive estimate of projected waste can be achieved, presented either as a percentage or quantity relative to the total material employed in projects.

The research will unfold in the following sequence:

1. To commence, an extensive review of all preceding studies will be undertaken.
2. Subsequently, a comprehensive compilation of C&DW factors pertinent to building projects will be curated based on insights garnered from past research.
3. A meticulous comparison between the resultant list and the factors identified by experts as contributors to construction and destruction waste generation in the Gaza Strip will be executed. This will be achieved through the utilization of an identification and verification questionnaire (datasheet).
4. A data collection sheet will be designed for the acquisition of information on construction and the destruction of existing structures.
5. The subsequent step involves the compilation of data on new construction and demolition activities spanning the last decade from the Public Works and Housing Ministry (PWHM) and contractor companies in the Gaza Strip. This dataset encompasses companies categorized as first category (the construction companies classified as first, second, third, fourth, and fifth categories).
6. The ensuing stage involves the hybrid model improvement tailored for forecasting construction and demolition waste generation in the Gaza Strip. Illustrative examples from a selected sample of projects will be utilized to estimate hybrid model validity. This model will combine a metaheuristic technique with various machine learning (ML) methods, including RF and

ANN. The model will be employed for predicting waste generation in construction and demolition buildings, drawing on data obtained from prior projects.

7. Rigorous performance evaluations will be applied to the generated models, elucidating the substantial impact of each model input on the outcomes.
8. Finally, this study will culminate in the formulation of conclusive research insights and actionable recommendations, serving as valuable contributions to future research endeavors and studies.

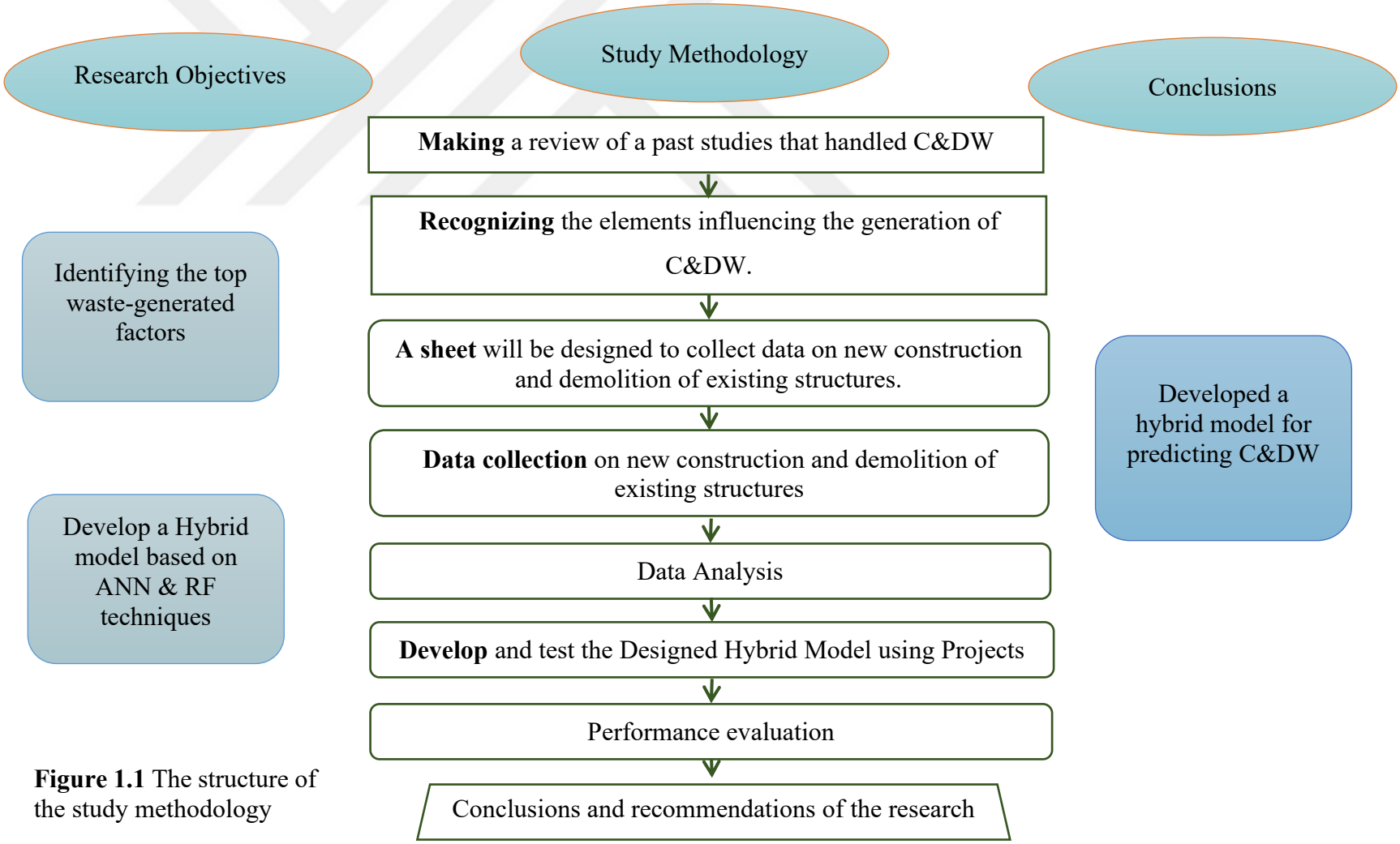



**Figure 1.1** The structure of the study methodology

# 2
# LITERATURE REVIEW

## 2.1 Introduction

A comprehensive review of scholars stands as a pivotal step in the research procedure. Its primary objective is to cultivate a profound understanding of the focal subject, namely, "forecasting building and destruction waste generation utilizing hybrid models."

## 2.2 Waste in Construction

Building and demolition waste garners global recognition for its adverse environmental impact, given the substantial consumption of raw materials, and energy in construction activities [60]. Unlike municipal waste, C&DW emerges from the building, renovation, modification, and destruction of structures like roads and buildings. Hong Kong categorizes construction waste into 2 main groups: inert construction waste, primarily comprising materials like concrete, asphalt, soil, and stone fragments that can be repurposed on-site; and non-inert construction waste, constituting twenty percent of the total, encompassing items such as packaging, plants, wood, bamboo, and other organic materials. Certain materials have the potential for recycling, yet others are simply discarded and transported to designated landfills [19].

### 2.2.1 The Concept of Waste in the Construction Industry

Understanding the concept of waste in the construction industry involves delving into various definitions provided by previous studies Luangcharoenrat et al. [19] characterized C&DW as the impaired and excess supplies and products arising from construction, repair, destruction, and other related activities. Waste can be categorized as any inadequacy leading to the unnecessary consumption of labor, supplies, tools, or funds, resulting in quantities surpassing what is essential for building construction. Examples of waste include the execution of superfluous labor

and the incidence of material damages, incurring extra expenses without contributing value to the final outcome [18, 61]. Building litters encompass byproducts generated and discarded during destruction, renovation, and building activities or projects, as indicated by Poon et al. [62] and Rahmani Mirshekarlou [63].

In waste definition, researchers offer a more comprehensive view, highlighting that waste incurs costs—both direct and indirect—stemming from activities that fail to contribute value to the end product as perceived by the client [18, 64, 65, 66]. A simple definition of waste, in essence, refers to "anything that can be removed from a process without diminishing the overall value perceived by the consumer", encompassing actions, properties, or procedures [7, 18]. Construction material waste as explained by Shen et al. [67], Bardalai et al. [68], and Rahmani Mirshekarlou [63] refers to the inconsistency between the volumes of resources delivered at construction sites and those properly consumed according to procedures and project measurements. Waste in construction projects is a ubiquitous challenge, making it evident that inefficiencies can crop up at any phase of the building process—from the initial design stages to actual construction and the ongoing operation of the completed structure [4].

Current research underscores the importance of delving into waste generated by the Construction Industry [4, 68]. Given the industry's relatively low production efficiency and environmental impact, waste reduction emerges as a major concern [4, 69]. Al-Moghany [18] breaks down CW into 2 main groups: material and time waste. Expanding on this, waste can be broadly understood as any losses—whether material, time, or monetary—arising from operations that never contribute meaningfully or advance the final product and can be eliminated with no diminishing client value.

### 2.2.2 Construction Waste Causes

Waste generation during construction and demolition is shaped by a myriad of factors. These factors can be singular or a combination of various elements. While several studies have delved into waste sources in construction across different countries, these inquiries commonly concentrate on traditional building processes [4]. As highlighted by Ikau et al. [5], inadequate storing leading to rework, the

acquisition of materials not meeting qualifications, and an ignorance or experience in managing construction waste are substantial contributors to waste generation. Furthermore, the absence of robust regulations, enforcement, and guidelines in Malaysia's construction industry exacerbates the issue of construction waste growth.

Udawatta et al. [70] and Li et al. [71] have compiled the primary reasons for building waste, summarized in **Table 2.1**. Additionally, Bossink et al. [20] undertook an extensive examination of the origins of construction waste in the Netherlands, categorizing them into six primary groups and identifying 31 specific sources of waste, as outlined in **Table 2.2.** Their findings highlighted that the main contributors to waste are material supply, design issues, and deficiencies in transit and storage handling.

**Table 2.1** Main causes of building waste summary

| Group | Causes |
|---|---|
| **Decision making** | Poorly allocating tasks to labor |
| | Inefficient distribution of personnel |
| | Inadequate supervision |
| **Data** | Data unavailability. |
| | Unfortunate data quality |
| | Untimely data delivery |
| **Planning** | Insufficient workspace |
| | Overcrowded work areas |
| | Poor work conditions. |
| **Methodology** | Insufficient plan of work groups. |
| | Deficient methodology |
| | Deficient help for work procedures |
| **Resources** | Materials: an absence of materials at work, inappropriate circulation of materials, and insufficient transportation implies. |
| | Equipment: non-availability; improper utilization; insufficient materials for building requirements. |
| | Labor: individual perspectives of laborers; the resistance of laborers |
| **Quality:** | Poor work execution. |
| | Damages to work already finished. |

**Table 2.2** Construction waste causes and sources in the Netherlands [20]

| Source | Cause |
|---|---|
| **Design** | Contract records were fragmented at the initiation of development |
| | Contract documents mistakes |
| | Decisions about product details |

**Table 2.2** Construction waste causes and sources in the Netherlands [20] (continued)

| Source | Cause |
|---|---|
| **Design** | Design changes |
| | Absence of impact of project workers and absence of information about development |
| | Absence of impact of project workers and absence of information about development |
| | A selection of used products in sizes and of low quality |
| **Procurement** | Requesting blunder, over-requesting, under-requesting, etc |
| | Utilization of materials that don't fit |
| | Pool of conceivable outcomes to arrange small amounts |
| **Handling of materials** | Improper capacity prompts harm or crumbling |
| | Destroyed during transportation to site/nearby |
| | Expendable bundling |
| | Unloaded materials |
| **Operation** | Gear breakdown |
| | A blunder by a merchant or worker |
| | Mishaps |
| | Severe Weather conditions |
| | Utilization of wrong material, requiring substitution |
| | Harm brought about by ensuing exchanges |
| | Data about types and sizes of items that will be utilized shown up later than expected at the worker for hire |
| | The necessary amount of item is obscure because of defective preparation |
| | Strategy to establish the groundwork |
| **Residual** | Off slices from slicing material to length |
| | Transformation squanders from cutting uneconomical shapes |
| | Packing |
| | Squander from the application interaction |
| | Overblending of materials for wet exchanges because of an absence of information on prerequisites |
| **Other** | Criminal waste because of harm or burglary |
| | Absence of location squander the executives' plans and materials control |

Polat et al. [7] conducted a survey involving consultants and contractors in Turkey to assess the prevalence of 14 waste causes categorized into six groups. The sources of time waste are detailed in **Table 2.3**, while **Table 2.4** delineates the 14 material waste sources in construction**.**

**Table 2.3** Primary factors contributing to time waste in Turkish construction projects [7]

| Source | Causes of Material Waste |
|---|---|
| **Design** | Delay in approval of drawing |
| | Inconsistency in plan records |
| | Mistake in data about sizes and types of materials on plan records |
| | Absence of data about sizes and types of materials on plan records |
| | Rework due to plan changes and revisions |
| | Interaction between various specialists |
| **Procurement** | Delay in transportation and/or installation of equipment |
| | Receiving materials that are defined on design documents, do not fulfill project requirements, and waiting for replacement |
| | Delay in material supply |
| **Operation** | Mishaps because of the absence of wellbeing |
| | The decision of wrong development strategy |
| | Absence of coordination among teams |
| | Waiting for design documents and drawings |
| | Scarcity of equipment |
| | Rework due to workers' mistakes |
| | Unrealistic master schedule |
| | Scarcity of crews |
| **Others** | Acts of God |
| | Unpredictable local condition |
| | Bureaucracy and red tape |
| | Severe weather conditions |
| | Irregular cash flow |

**Table 2.4** The primary sources of trash in Turkish buildings [7]

| Source | Causes of Material Waste |
|---|---|
| **Design** | Assurance of aspects and sorts of material disregarding waste |
| | Mistakes in the data of the sizes and kinds of materials recorded in plan reports |
| | Configuration changes and corrections |
| | Insufficient information in the design documentation regarding the sizes and types of materials |
| **Procurement** | Under- or over-ordering as a result of a lack of coordination between the construction crews and the warehouse |
| | underordering or Overordering because of a mistake in quantity surveys |
| | materials Ordering does not fulfill project requirements defined on the design document |
| **Handling of Material** | Harm of materials because of lacking amassing and treatment of materials |
| **Process** | Damage caused by subsequent trades |
| | Workers' mistakes |
| | Imperfect planning of construction |
| **Residual** | Change squander from cutting uneconomical shapes |

**Table 2.4** The primary sources of trash in Turkish buildings [7] (continued)

| Source | Causes of Material Waste |
|---|---|
| **Others** | Unavailable waste management plans |
| | Unavailable on-site materials control |

**Table 2.5** summarizes 10 significant findings from a concentration on the development of construction waste in Egypt's structure industry [72]. Improper handling of materials, inadequate certification of contractor employees, and poor coordination among Gaza Strip construction sites are major contributors to waste issues [6]. Furthermore, the closure-related scarcity of materials, coupled with the absence of a robust quality control system and communication lapses on construction sites, exacerbates waste concerns [4], [73]. As noted by. Enshassi et al. [27] material waste in the Gaza Strip is primarily attributed to factors such as poor performance, low-quality timbers, replastering, exceeding allowable aggregate quantities, manufacturing defects, incompatible paints, and excessive asphalt mixture thickness. Enshassi [28] has detailed the specific instances of construction material waste on Palestinian construction sites, as outlined in **Table 2.6**.

**Table 2.5** The causes that contribute to construction waste in Egypt [72].

| No. | Causes of waste |
|---|---|
| 1 | Damage during transportation |
| 2 | Changes to design |
| 3 | Poor technology of the equipment |
| 4 | Work not done |
| 5 | Untrained labor |
| 6 | Unnecessary people move |
| 7 | Poor control |
| 8 | Inadequate information |
| 9 | Uncompleted design |
| 10 | Late information |

**Table 2.6** Construction waste resources in Palestine sites [28]

| No. | Resources |
|---|---|
| 1 | Poor project information |
| 2 | Transport and handling of materials |
| 3 | Site stacking and storage |
| 4 | Misuse and damage |
| 5 | Training |
| 6 | Indirect waste |

### 2.2.3 Classification of Waste in Construction

Efficient management of waste in the building sector necessitates a thorough grasp of diverse waste classifications, considering the diverse nature of waste in different industries and working methodologies [74]. Al-Moghany [18] introduced a classification based on source, loss, resource depletion, and nature. Waste is further categorized as avoidable or unavoidable based on its nature. Waste is categorized as avoidable when the expense of waste is substantially lower than the prevention cost. On the other hand, waste is deemed unavoidable when the cost of its reduction surpasses its economic value. The volume of waste generated varies across companies and regions, influenced by technological advancements. Loss-induced waste can be either direct, involving the actual material loss or replacement, or indirect, arising from factors like human error, neglect, or unclear contract terms [68]. Waste can likewise be arranged in light of its source or the stage in the materials' life cycle, encompassing design, manufacturing, material supply, planning, and construction processes [68, 75].

Researchers have proposed diverse models for categorizing construction waste based on its source, characteristics, or state, considering factors such as construction and demolition, energy conversion, household waste, emission treatment, processing, nuclear, hazardous, combustible, biodegradable, liquid, solid, or gaseous [76]. Adewuyi et al. [77], noted significant efforts to classify building waste based on properties like process, location, quantity, and type. Additionally, waste can be arranged by its source, recognizing the stage where its underlying drivers start. In their research, Viana et al. [78] explored three waste categories: specific types like rework and accidents, non-esteem adding exercises as cycle waste, and development material waste, incorporating physical and non-physical (non-actual) waste [78, 79]. Also, Khaleel et al. [80] highlighted the two primary categories of construction debris as physical trash and non-actual waste, depicted in **Figure 2.1** below

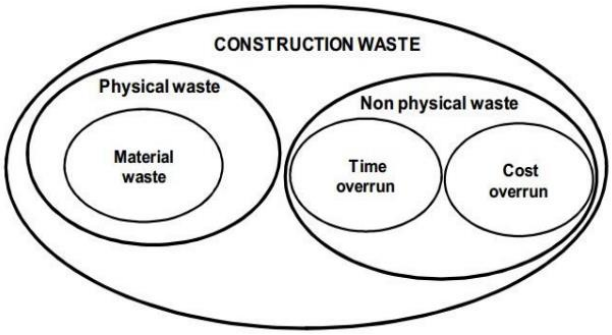



**Figure 2.1** Construction waste classification [80]

Luangcharoenrat et al. [19] provided an overview of construction waste categorization in the US, the EU, and the UK. In the US, development waste is separated into fifteen classes, including black-top-related materials, soil-related materials, electrical-related materials, protection-related materials, blocks and-cement related materials, steel-related materials, paint-related materials, paper-related materials, oil-related materials, material related materials, vinyl-related materials, gypsum-related materials, wood-related materials, wood-containing-pollutants related materials, and different classifications. The European Association arranges development waste into eight gatherings, covering block, concrete, ceramic, tile, glass, wood, plastic, coal, black-top, metals, soils, protection materials, asbestos-containing materials, development materials (counting gypsum), and other development squander. In Britain, development squander is arranged into eleven classifications, like pastes and fillers, paint and covering materials, tile, earthenware, concrete, gypsum, soil, debased soil, stone, dig soil, metals, black-top, oil, coal, bitumen, wood, glass, plastic, cement, block, and protecting materials [33].

### 2.2.4 Effect of Waste on Construction

Waste poses a dual challenge, impacting both the overall economy of a country and the operational efficiency of the construction industry [4, 5, 6, 7]. The issue of C&DW has become a significant environmental concern in major cities worldwide [14]. Mitigating waste in construction yields various advantages, such as the protection of economic assets and diminished reliance on primary materials for construction material production. This translates into cost savings related to reduced construction material quantities and waste disposal expenses [19, 81]. The essential

decrease of waste not only upgrades the seriousness of partners in the development business, including land designers, general project workers, and subcontractors, but also brings about additional benefits. These include a decrease in carbon dioxide ($CO_2$) emissions, diminished health risks for both nearby residents and workers, an extension of landfill life, and an overall decrease in the costs of projects [19, 82].

Hossain et al. [83] conducted a comprehensive evaluation of the overall environmental consequences associated with waste generation across various building stages, encompassing construction, renovation (with building effect), and end-of-life considerations. They recognized a few effect classes, incorporating respiratory inorganics, ozone layer consumption, earthbound and sea-going fermentation potential, oceanic eutrophication potential, an unnatural weather change prospect, and nonrenewable power use.

The environment is significantly impacted by the construction industry. For instance, waste materials, vehicle emissions, noise, and the discharge of toxins to the atmosphere, ground, and water are significant potential sources of pollution from building activities [84]. Environmental impacts, as classified by Boussabaine et al. [85] are categorized into atmospheric and resource impacts. Atmospheric impacts include the greenhouse effect and ozone layer reduction, while resource impacts encompass contamination of air, water, and soil. The environmental consequences of construction span a wide range of activities, broadly classified as offsite, onsite, and operational. Offsite activities involve material extraction and manufacturing, material transportation, land acquisition, and project definition and design. Onsite activities, including resource consumption, site-related traffic issues, construction waste generation, lack of recycling, and biodiversity loss, can lead to air, water, and ground pollution [84].

The ecological effect encompasses several significant types [86]:

- Using both renewable and nonrenewable resources, including metals, water, and wood, during the creation of building supplies and machinery, potentially leading to biodiversity loss.
- Air, water, and land pollution brought on by manufacturing and transportation.

- Deforestation, the loss of agricultural land, urbanization with its attendant transportation and social challenges, increased demand for water, electricity, and other services, and biodiversity loss may all be exacerbated by the commitment of land for new facilities.
- Project goals' choices impact the plan, development, and activity of offices concerning asset use, inside ecological quality, traffic concerns, recycling, waste management, facility maintenance and lifespan, and the social environment.

Construction projects grapple with a notable challenge – waste. The repercussions of waste are profound, impacting project productivity, material conservation, and completion timelines, ultimately leading to substantial financial losses. Moreover, the surge in construction waste production has given rise to an alarming issue of illegal dumping in Malaysia [87, 88].

The building sector's environmental and social impacts have been systematically examined across different academic domains, with a particular focus on life cycle assessment and social impact assessment literature [89]. To shed light on the environmental repercussions of the construction industry, **Table 2.7** offers a concise overview of the various types of waste that warrant consideration in these assessments.

**Table 2.7** A summary of the environmental implications.

| Waste | Description |
|---|---|
| **Air pollution** | Incorporating all air-emitted gases with the potential to influence the environment or human health is crucial [90]. This envelops a scope of models like Earth-wide temperature gases (CFC-12, CFC-11, NO2, CH4, CO2, N2O), substances adding to stratospheric ozone consumption (CFC-113, CFC-12, CFC-11), those engaged with photochemical ozone creation (NOx and VOC), and supporters of fermentation (SO2 and NOx). |
| **Solid Waste** | Taking into consideration undesirable or superfluous resources is integral. Industrial waste, for example, encompasses municipal waste, which includes home, commercial, and demolition, along with unsafe waste [91]. |
| **Wastewater** | Water accounts envelop some water whose quality has been unfavorably impacted by human movement. This can happen as a result of activities at home, at work, in a business, or in |

**Table 2.7** A summary of the environmental implications (continued)

| Waste | Description |
|---|---|
| **Wastewater** | agriculture, as well as surface runoff or stormwater and sewer intake or infiltration [89]. |
| **Noise disturbance** | Sound and vibration accounts for any audible or perceptible vibrations that have the potential to disturb or annoy individuals with normal sensitivities, create a detrimental effect on public health and welfare, pose a danger or cause harm to people, or threaten personal or real property. This category is often referred to as noise nuisance [92]. |
| **Over Illuminating** | This class represents the presence of light power higher than ideal for a particular action [89]. |
| **Excessive soil usage** | This classification represents the usage of soil in the built climate, thus forestalling its utilization as a creature living space [89]. |

### 2.2.5 Construction Waste Management Strategies

The cornerstone of effective waste management in construction projects lies in the Waste Management Plan. This detailed on-site strategy serves to comprehend and actualize the waste management objectives of the project [78]. Detecting and making waste transparent to all parties involved is crucial for waste elimination or reduction [74]. While complete elimination of waste may be challenging, the emphasis should be on managing practices within the local industry to minimize waste [6].

Efforts to minimize waste should align with the waste hierarchy depicted in **Figure 2.2**. As such, the first phase in establishing effective processes is to formulate strategies that adhere to this guiding philosophy [1].

The most efficient and effective method in waste management is reduction, as it not only decreases trash production but also reduces expenses associated with waste transportation, recycling, and disposal [93]. Reusing materials in construction entails employing the same material multiple times, whether it's for its original purpose (such as using formwork in a structure) or adapting it for a different role (for instance, utilizing stone fragments as road base material or repurposing steel bars with cut for shelves corners) [94]. Waste materials that cannot be reused are directed towards two primary paths: recycling for integration into new construction or disposal in landfills. In the spectrum of waste management strategies, reuse takes

precedence after reduction because of its minimal processing and energy requirements [95]. If reduction and reuse prove challenging, the next viable option is recycling. Recycling allows for the conversion of waste materials into valuable resources for new construction endeavors [96].

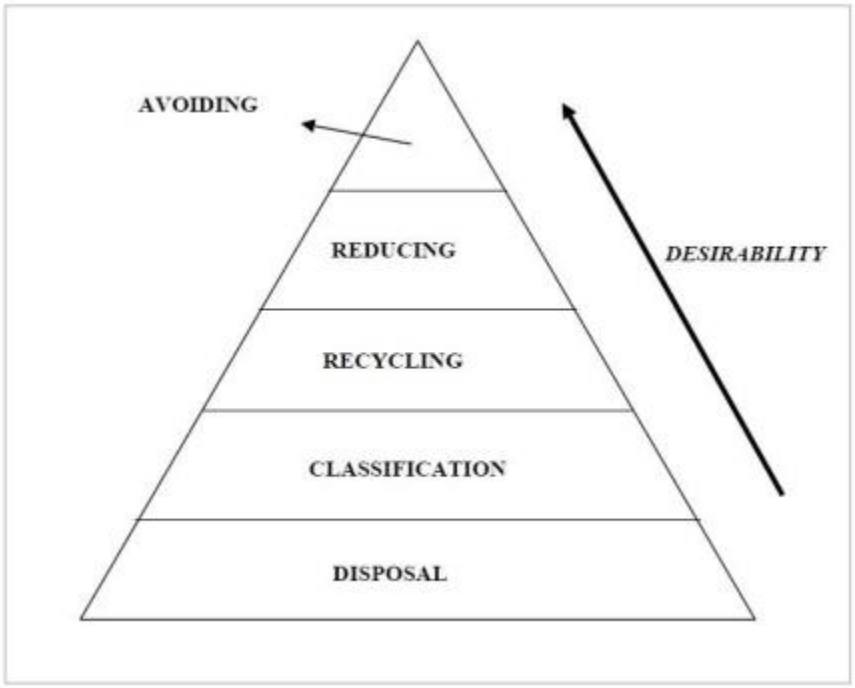



**Figure 2.2** Construction waste management hierarchy [1]

Create initiatives focused on enhancing public awareness, attitudes, and behaviors regarding waste sorting. Implementing public counseling programs can effectively transform individual and community perspectives, fostering a heightened environmental consciousness. An individual with a genuine concern for the atmosphere possesses the information, approach, and conduct needed to contribute to comprehensive solutions for both personal and societal waste management challenges [97].

Strategically, there are seven key approaches to address construction waste management (CWM) challenges in Shenzhen:

- Creating a process to determine the obligation of various involved departments.
- Implementing a system to monitor the strategies' implementation.
- Developing a system to evaluate the effectiveness of the strategies.
- Proclaiming important and complete CWM guidelines.

- Exploring the volume of development squander in Shenzhen and arranging waste offices likewise.
- Incorporating CWM all through the existence pattern of development projects.
- Executing an experimental run program for the use of reused development materials.

Additionally, it is proposed to establish a research institute for construction waste in Shenzhen and raise awareness of CWM through educational and public relations efforts [9].

The Australian study highlights several waste management solutions, including team development and supervision, extensive planning and documentation, imaginative waste control choices, and lifecycle control [70]. Reducing waste through adequate material storage, precise ordering, and worker training and awareness are the top three measures identified for waste reduction. This approach is widely favored by businesses, emphasizing the preference for waste deterrence over mere waste management [76]. Similarly, it is crucial to take into account the environmental consequences of the generation of waste and proactively prevent waste formation in the early stages of construction projects [98].

Gavilan et al. [99] identified key sources of waste generation in construction, including design, handling of material, procurement, implementation, and site remnants. **Figure 2.3** gives an outline of the different stream examples of development materials, specifying their excursion from the mark of supply to the building site until their definitive arrangement. Consumables in development allude to materials that are coordinated into the last structure, like bricks, concrete, and building-up steel. Conversely, "non-consumable" materials include concrete forms, scaffolding materials, and provisional holding barriers, among others, but are not directly incorporated into the final structure.

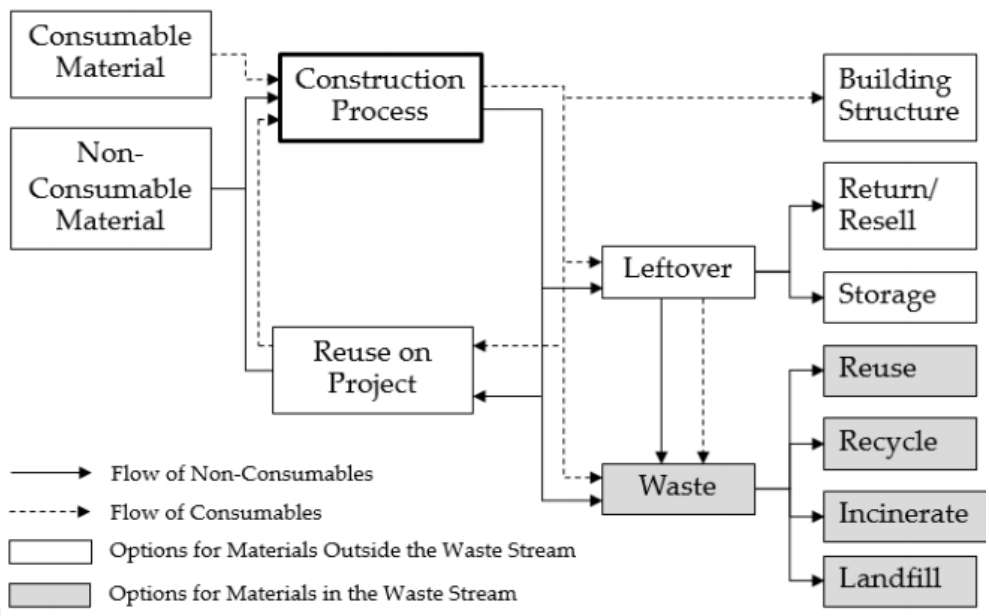



**Figure 2.3** Generic Material Flow Pattern at the Site of Construction [99].

### 2.2.6 Important Of Construction Waste Management

Upon effectively implementing waste management within the outlined framework, a multitude of advantages can be realized throughout the entire waste cycle, spanning from its creation to eventual clearance [100]. The financial well-being and sustainability of the construction sector play a pivotal role in a nation's capacity to attain sustainable economic growth. In the contemporary landscape, construction companies engage in global competition, demanding a relentless pursuit of minimal costs and maximal performance levels [63].

The management of C&DW demands special attention because of the small area for disposal in lands and the presence of numerous hazardous substances. If not handled appropriately, these substances could pose significant risks to both the environment and people's health [101].

Haggar [102] suggests that effective construction waste management can lead to economic benefits by reducing project costs through the proper execution of a waste control plan. In addition to the financial benefits, waste control can have a positive impact on the following areas [100, 103, 104, 105, 106].

1. Expense reduction and profit maximization: Putting more focus on waste control can lead to cost savings and various positive outcomes. Opting for

old or recycled materials instead of purchasing new construction materials can cut down on additional expenses. Moreover, producing less waste from construction projects not only lowers disposal costs and landfill fees but also contributes to an overall reduction in project expenses. Ultimately, these cost savings have the potential to enhance project profitability.

2. Receding claim for Dumping Ground: Decreasing how much waste is sent to dump yards can reduce the interest in dump yard space and moderate negative ecological effects, including noise, discharges, emissions, and deposits from fire.
3. Improved handling of resources: Efficient waste control comprises strategic arrangement and coordination of project materials to minimize waste generation. This means that by minimizing waste, we can also optimize the overall effectiveness of resource management for the project.
4. Building a Positive Image: Incorporating waste management practices into an organizational policy can be a strategic move for businesses aiming to enhance their public image. Being recognized as an "environmentally friendly" business not only contributes to a positive perception among clients but also aligns with the growing emphasis on corporate social responsibility.
5. Boosting Efficiency and Quality: Streamlining processes and minimizing the need for reordering and repurchasing due to wasted materials can significantly enhance overall productivity. Opting for durable and high-quality materials not only contributes to the longevity of a facility but also reduces the likelihood of generating waste during its life cycle compared to the use of lower-quality materials.

### 2.2.7 Navigating Construction Waste Management Challenges

It is essential to comprehend and address the main waste control issues in structure building and destruction. It doesn't just permit leaders to get a handle on these obstructions yet it frames the reason for investigating procedures to improve waste control productivity. Identifying and tackling these challenges head-on are pivotal steps in the quest for more operational building debris control practices [96].

In building projects, unavailable cohesion in processes, particularly within the waste management phase, poses a significant barrier to achieving minimal waste generation through effective waste control. The inherent unpredictability of construction projects, compared to more standardized manufacturing processes, coupled with the diverse and dynamic factors contributing to waste, is a primary culprit behind the inefficiencies observed in waste management operations. Addressing this lack of integration becomes paramount in the pursuit of more streamlined and efficient construction waste control [63].

Yuan et al. [96] delved into the prominent challenges facing the management of C&DW in China. Through ranking analyses, they discerned the relative importance of 16 identified barriers, as outlined in **Table 2.8**. The discoveries feature that the "absence of an advanced waste reusing market," "lacking regulatory backing," and "deficient consideration regarding waste decrease in building plan" are seen as the main three huge obstructions. Conversely, "limited site space hindering effective waste management," "concerns about increased project costs with waste management," and "low disposal costs" are viewed as the three not-so-critical hindrances with regard to building and destruction waste control.

**Table 2.8** Sixteen particular difficulties hinder the compelling execution of C&DW management [96].

| No. | Obstacle |
|---|---|
| **O1** | Insufficient regulation support |
| **O2** | Difficulties in operationalizing existing regulations |
| **O3** | Poor governance in waste management execution |
| **O4** | Potential increases in project costs |
| **O5** | A lack of effective waste management methods |
| **O6** | Entrenched traditional construction culture and behaviors |
| **O7** | A dearth of economic incentives for contractors to adopt waste management practices |
| **O8** | Reluctance fueled by intense competitiveness in the industry |
| **O9** | Insufficient training and education for practitioners |
| **O10** | Low disposal costs hindering waste reduction efforts |
| **O11** | A lack of emphasis on waste reduction in building design |
| **O12** | An underdeveloped waste recycling market |
| **O13** | Weak awareness among operatives regarding waste reduction |
| **O14** | On-site material waste |
| **O15** | Limited space for effective waste management |
| **O16** | Clients' insufficient awareness of C&DW management |

## 2.3 Factor Affecting Construction and Demolition Waste

In C&DW, considering the influences on the production of waste is pivotal for effective waste reduction and management. With the rapid expansion of construction activities due to population growth and urbanization, there's a significant surge in garbage generation globally. While various studies delve into the factors influencing construction waste, there's a notable gap when it comes to predictions. The literature on waste management lacks forecasts for the future production of building and demolition waste, presenting a crucial area for exploration and research [19].

Efforts to curtail construction waste and enhance on-site recycling contribute to the effectiveness of construction management [80]. Keeping the goal of waste reduction in mind, Khaleel et al. [80] systematically identified factors, drawing insights from interviews and comprehensive literature reviews that contribute to waste minimization and management systems in Iraq. Their exploration revealed a range of variables influencing waste production, leading to the categorization of fifteen components based on shared characteristics. These components include aspects like "materials management on site," "materials handling, transportation, and storage," and "site management and practices," as detailed in the organized **Table 2.9.**

**Table 2.9** Waste factor of project construction [80].

| Category | Factor |
|---|---|
| **Materials Management on-Site** | On-site material damage |
| | Production errors |
| | Packing flaws |
| | Stealing and destruction |
| | lacking control of building areas resources |
| | Larger than average structure components due to non-straightness in building project |
| **materials Handling, Transportation, and Storage** | Improper resources management |
| | Warehouse located far from the building location prompting waste during transportation |
| | incorrect storing practices |
| | Multiple material management |
| | Mishaps while handling and transporting materials |

**Table 2.9** Waste factor of project construction [80]. (continued)

| Category | Factor |
|---|---|
| Site Management and Practices | Nonattendance of obligation regarding waste control by the occupant engineer. |
| | The absence of shortcomings of a waste control program |
| | Ineptitude of the worker for hire's dedicated staff |
| | Absence of constructive incentives aimed at waste reduction |

In Hong Kong, Poon et al. [107] identified three key factors shaping the composition and volume of C&DW: the type of structure, its size, and the specific activity being carried out. The overall project size, its location, the materials employed in construction, demolition methods, schedule, and the contractors' "housekeeping" practices are additional elements influencing the nature and volume of C&DW generated. Refer to **Table 2.10** for specific examples corresponding to each factor.

**Table 2.10** The factors influencing both the composition and volume of C&DW in Hong Kong, as outlined by Poon et al. [107]

| Factor | Example |
|---|---|
| Structure type | Residential, commercial, industrial buildings, roads, bridge |
| Structure size | Low-rise, high-rise |
| Performed activity | Construction, renovation, refurbishment, demolition |
| Project Size | custom-built residence versus tract housing |
| Project location | waterfront versus inland, rural versus urban |
| materials used | brick versus wood |
| demolition practices | manual versus mechanical |
| Schedule | rushed versus paced |

Construction waste is often the culmination of various factors rather than a single origin [5]. Researchers like Gavilan et al. [99] and Craven et al. [108] have categorized and grouped construction waste sources into 6 main categories: design, material procurement, material handling, operations, residual, and others. Although classifying construction waste can be challenging, it's crucial to highlight that both human and technical errors stand out as primary contributors to on-site construction waste generation [109]. Inefficient material storage and handling practices emerge as leading causes of building waste production [110]. Most issues related to waste on construction sites can be traced back to poor site management rather than a lack of skills or qualifications among the workforce. Additionally, waste is typically a result of a sequence of events rather than a singular cause. In a similar vein, Poon

et al [62] emphasized that irresponsible handling and utilization lead to the wastage of damaged materials like tiles, ceramics, and plastering materials. Concurrently, Rounce [111] pointed out that critical sources of construction waste manifest during the plan stages, including building plan modifications and variations in the level of plan specifics.

In the Malaysian building sector, Rahman et al. [112] have pinpointed seven clusters of factors encompassing a total of 77 critical elements that play a role in shaping construction waste production. You can peruse the exhaustive list of these 77 factors in **Table 2.11**. The factors are categorized into Design, External, Handling of Equipment and Management, Materials, Procurement and Site Condition, and Workers. Notably, through a PLS model derived from these grouped factors, it was revealed that the procurement category exerted the most substantial influence on the production of building waste.

**Table 2.11** The 77 waste-generating factors listed in Rahman et al. [112] study.

| No. | Factor | NO. | Factor |
|---|---|---|---|
| 1 | Unpredictable local conditions | 2 | Poor site management |
| 3 | Celebration festivity upset works at destinations | 4 | Inadequate controlling |
| 5 | Harms brought about by outsiders | 6 | Inadequate planning |
| 7 | Vandalism at site | 8 | A lot of idle time for laborers |
| 9 | No legal enforcement | 10 | No awareness among the workers |
| 11 | Stealing at site | 12 | Abnormal wear of equipment |
| 13 | Effect of accidents at the site | 14 | The materials' inventory is poorly documented. |
| 15 | Weather impact | 16 | Worker’s no enthusiasm |
| 17 | Waiting for replacement | 18 | Poor workmanship |
| 19 | Inappropriate methods used for estimation | 20 | Inappropriate use of materials |
| 21 | Frequent variation orders | 22 | Shortage of skilled workers |
| 23 | Allowances paid lead to over budget | 24 | Lack of experience |
| 25 | Wrong material delivery procedures | 26 | Insufficient training for workers |
| 27 | Supplier errors | 28 | Damage caused by workers |
| 29 | Surveyors’ mistake | 30 | Employees' negative attitudes |
| 31 | Error in shipping | 32 | Incompetent worker |
| 33 | Items not in compliance with specification | 34 | Workers' mistakes during construction |
| 35 | Ordering errors | 36 | Materials supplied in loose form |
| 37 | Interference with other crews at the site | 38 | Inefficient methods of unloading |
| 39 | Unforeseen ground conditions | 40 | Tools not suitable for used |

**Table 2.11** The 77 waste-generating factors listed in Rahman et al. [112] study. (continued)

| No. | Factor | NO. | Factor |
|---|---|---|---|
| 41 | Hardships for conveyance vehicles getting to building destinations | 42 | Delivery Delay |
| 43 | Holding up because of lighting issue | 44 | Equipment failure |
| 45 | Waiting because of the site's congestion | 46 | Poor quality of materials |
| 47 | Damage caused by poor site conditions | 48 | Damage during transportation |
| 49 | Waste resulting from packaging | 50 | Poor material handling |
| 51 | Leftover materials on site | 52 | Wrong material storage |
| 53 | Lack of environmental awareness | 54 | Last minutes client requirement |
| 55 | Absence of impact of project workers to provider | 56 | Bad communication between groups during the planning phase |
| 57 | No construction knowledge | 58 | Excessive interactions among specialists |
| 59 | Non-availability of equipment | 60 | Error in contract documentation |
| 61 | Long waiting periods | 62 | Inexperience designer |
| 63 | Rework | 64 | Complicated design |
| 65 | Lack of resources | 66 | Incomplete contract document |
| 67 | Slow drawing distribution | 68 | No sites debris control process |
| 69 | Shortage of equipment | 70 | Poor design quality |
| 71 | No design data | 72 | Late exchange of information among parties |
| 73 | Inadequate or bad information | 74 | Design errors |
| 75 | Inappropriate construction methods | 76 | Frequent design changes |
| 77 | Poor supervision | | |

Luangcharoenrat et al. [19] compiled a comprehensive list of 28 factors contributing to building waste production from prior literature. These influences were categorized into four groups according to their sources. Refer to **Table 2.12** for a breakdown of the factors influencing building waste.

**Table 2.12** Group of factors, label of factor, and name of factor.

| Group of factors | label of factor | name of factor | Reference |
|---|---|---|---|
| Design and Documentation (DEDO) | D1 | Complicated design | [77, 113, 114, 115, 116] |
| | D2 | Document problems | [20, 65, 77, 114, 115, 116, 117, 118, 119] |
| | D3 | Design errors | [65, 76, 99, 119, 120, 121, 122] |
| | D4 | Construction drawing errors | [65, 77, 99, 113, 115, 116, 119] |

**Table 2.12** Group of factors, label of factor, and name of factor. (continued)

| Group of factors | label of factor | name of factor | Reference |
|---|---|---|---|
| (DEDO) | D5 | Change to design | [20, 65, 77, 99, 113, 114, 117, 119, 121, 122, 123] |
| Construction Methods and Planning (COPL) | C1 | Ineffective planning and scheduling | [65, 113, 115, 118, 122, 123] |
| | C2 | Control and supervision | [65, 77, 115, 117, 118, 120, 121, 122] |
| | C3 | Construction methods | [65, 77, 99, 117, 118, 119, 123] |
| | C4 | Poor waste management | 77, 99, 114, 115, 117, 120] |
| | C5 | Tools and equipment misuse/malfunction | [20, 77, 99, 116, 117] |
| | C6 | Misuse of material | [65, 77, 99, 116, 118] |
| | C7 | Rework | [77, 114, 120, 122, 123] |
| | C8 | Wrong teams /subcontractors' selection | [65, 76, 77, 122, 123] |
| | C9 | By-process waste | [20, 99, 119, 121] |
| | C10 | Construction errors | [120, 122, 123] |
| | C11 | Coordination problems | [65, 77, 99, 113, 114, 115, 116, 118, 119, 122, 123] |
| Material and Procurement (MAPR) | M1 | Improper material storage | [20, 65, 76, 77, 99, 113, 114, 116, 117, 118, 119, 120, 121, 123] |
| | M2 | Material quality problems | [20, 65, 76, 77, 114, 115, 116, 118] |
| | M3 | Material ordering problems | [20, 76, 77, 114, 116, 117, 121, 123] |
| | M4 | Improper material handling | [65, 76, 77, 99, 114, 118, 120, 121] |
| | M5 | Material transporting problems | [76, 77, 99, 113, 114, 116, 117] |
| | M6 | Packaging problems | [76, 99, 114, 116, 120] |
| | M7 | Defective materials | [77, 123] |
| | M8 | Damaged materials | [77] |
| Human Resources (HUMA) | H1 | Incompetent workers | [20, 65, 77, 114, 115, 116, 117, 118, 119, 120, 121, 123] |
| | H2 | Designers' inexperience | [20, 114, 115, 116, 119, 120, 122] |
| | H3 | Inattentive working attitudes and behaviors | [114, 115, 116, 123] |
| | H4 | Lack of supplier's involvement | [77, 114, 121] |

## 2.4 Methods of Estimating the Amount of C&D Waste

Understanding the volume of C&DW is crucial, and researchers have identified various methods to estimate it. These approaches, illustrated in **Figure 2.4**, represent the current trends in construction waste management. Waste control practices are severely determined by the implementations as well as methodologies employed, as highlighted by several studies in this field [10].

The literature review conducted by Akinade et al. [10] focuses on publications directly influencing construction waste management, identifying a total of 32 tools. These tools were carefully examined, leading to the recognition of five overarching categories:

(a) GIS-enabled waste tools.
(b) Waste prediction tools,
(c) Waste management plan templates and guides,
(d) Waste data collection and audit tools, and
(e) Waste quantification models.

A visual representation of these groupings, alongside their respective implementation, is presented in **Figure 2.5** below.

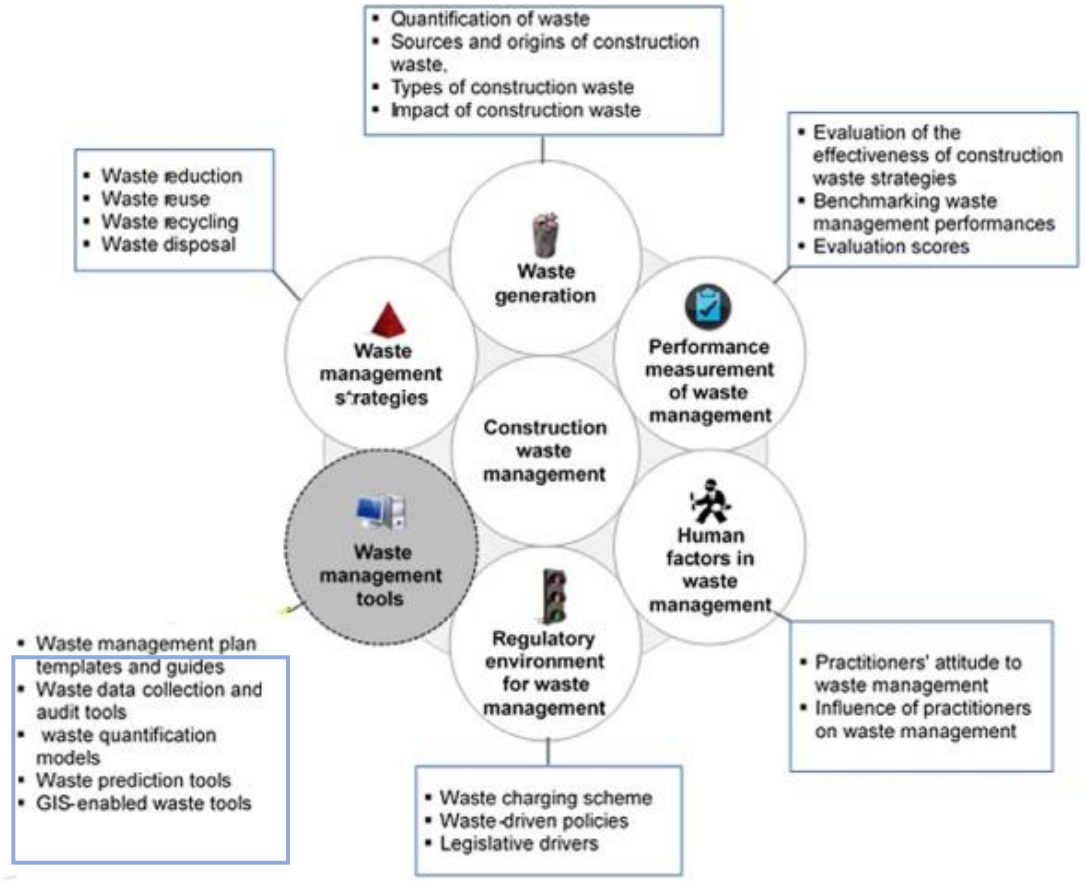



**Figure 2.4** Studies in construction waste management [10]

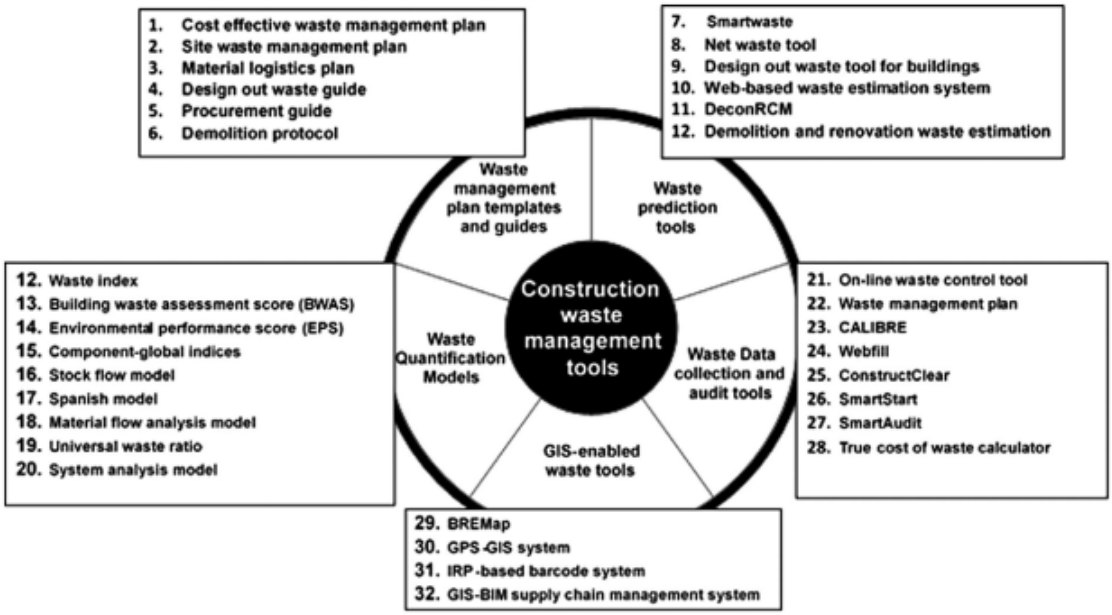



**Figure 2.5** Current waste management tools [10].

## 2.5 Models for Computing C&DW in the Previous Study

Effective waste management strategies in C&D projects hinge on the accurate prediction of waste generation. This prediction is instrumental in the formulation and execution of sustainable waste management plans, enabling contractors and relevant authorities to proactively plan and address waste disposal [124]. To achieve this, various statistical analyses and ML algorithms have been utilized for predicting C&DW generation. Notable algorithms in this context encompass artificial neural networks (ANNs), deep learning (DL), chi-squared automatic interaction detection (CHAID), exponential smoothing, gradient boosting machine (GBM), gray model (GM), long and short-term memory (LSTM), random forest (RF), singular spectrum analysis (SSA), and support vector machines (SVMs). These advanced techniques contribute to a more informed and strategic approach to handling C&DW.

The majority of research that was implemented on predicting the production of waste has employed machine learning techniques based on historical records. Some of these applied algorithms, such as RF [46, 47, 52, 53], and ANN [16, 125, 126, 127, 128].

In waste production prediction, a prevalent approach in research involves leveraging ML techniques rooted in past data. Notable algorithms like RF and ANN have been widely employed in this context. Additionally, these models relied on input parameters functioning as independent variables to foresee the output value. Previous research incorporated a diverse set of variables, encompassing continuous data such as charging scheme [17], building structure [46, 47, 129], building use [46, 129], categorical data (e.g., region [16, 46, 47, 129], Completion year [16], construction records [128], Demolition year [16], energy consumption [130], Gross Domestic Product (GDP) [17, 128, 130], gross floor area of buildings [16, 17, 46, 47, 129], the gross value of construction work [17], hospital ownership type [131], affect C&D waste generation, land area [128], and Lot area ($m^2$) [16], No. of buildings [16], No. of houses [16], active beds number [131], hospital's activity years number [131] and hospital's employee number [131], number of inpatients [131], occupied beds number [131], hospital's wards number [131], population

(POP) [128, 130], roofing material [46, 47, 129], Stories [16], Total floor areas completed [60], urbanization [130], wall material [46, 47, 129].

Accurate predictive value in quantitative terms of C&DW is a thing of great importance as regards effective waste management. Among the machine learning methods, ANN, RF (Random Forest), SVM (Support vector machine), and other mostly used techniques have found great success in application, especially related to data-based decision-making obtained from laboratory and computer simulations [35]. Hence, due to its great utility for prediction, various machine learning and statistical analysis algorithms have been deployed for predicting C&DW.

In this scenario, the selection of construction methods is shaped by the nature of the building structure, and this, in turn, affects the production of C&DW [47]. Consequently, the effectiveness of the machine learning techniques employed in prior studies may not be assured when applied to categorical data as opposed to continuous data.

Akanbi et al. [132] predicted the recoverable tons of salvage and waste material from the buildings at the final end 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 the waste estimation accuracy. In the same way, Coskuner et al. [133] created an ML regression model to calculate the generation of waste in pre-renovation construction projects. They demonstrated significant improvements in the estimation of waste accuracy by comparing their model performance with the prevailing approach.

Coskuner et al. [128] employed the multi-layer perceptron artificial neural network (MLP-ANN) to validate annual generation rate prediction in structure building and destruction, domestic, and commercial debris. Input variables for data collection included construction records, Gross Domestic Product, land area, and population. The data spanned from 1997 to 2016 and were gathered at the Askar dump location in the Kingdom of Bahrain. The presented model was created utilizing the Python programming language programming. Preceding programming usage, standardization was used for the two sources of info and results in light of the information readings. The input data was arbitrarily partitioned, with 70 percent

distributed for preparation and 30 percent for testing. The performance of the model was assessed utilizing the $R^2$ coefficient and MSE (Mean Squared Error). The C&DW model showed an $R^2$ of 0.91, demonstrating a vigorous and powerful model.

Hu et al. [134] proposed an innovative approach for forecasting construction and demolition waste production with reduced data volume. They introduced a time-series waste prediction framework that integrated the generation rate calculation with the ARIMA (autoregressive integrated moving average model). The utilization of this strategy was exhibited through a contextual investigation in Sichuan, China.

Abbasi et al. [135] conducted a study assessing the performance of four intelligent system algorithms— ANFIS, ANN, k-nearest neighbors (kNN), and SVM in predicting monthly waste production in Australia. They utilized a dataset comprising 216 data points from the periodic time series of municipal solid waste production from July 1996 to June 2014, which was collected over 18 years. The findings indicated that while kNN excelled in forecasting monthly average waste volumes, the ANFIS model demonstrated the most precise predictions for peak waste volumes, achieving a remarkable 0.98 coefficient of determination ($R^2$).

In their study, Ghorbani et al. [136] crafted an ANFIS model to forecast the resilient modulus (MR) of construction and demolition resources. The primary focus of the model was to establish a connection between the MR and the thermal conductivity of construction and demolition resources, particularly for applications in geothermal pavement. The model incorporated five key input variables: confining stress, deviator stress, moisture content in percentage, coefficient of curvature, and thermal conductivity. Impressively, the ANFIS model demonstrated outstanding predictive capabilities for the MR of construction and demolition resources, boasting an $R^2$ value of 0.99 for both the training and testing data.

Kumar et al. [137] collected data from 120 households to predict plastic waste generation rates using three machine learning algorithms: Artificial Neural Networks (ANN), Random Forest (RF), and Support Vector Machines (SVM). The model's predictive performance showed that ANN ($R^2 = 0.75$) and SVM ($R^2 = 0.74$)

yielded superior results compared to RF ($R^2 = 0.66$), indicating that both ANN and SVM are more effective for this particular application.

Likewise, there was a study that developed models using RF and GBM (Gradient Boosting Machine) by G. Cha et al. [46]. So, they could predict demolition waste given a similar dataset. They compared the performance of these methods and found that it is relatively much more stable and accurate than the predictions found through GBM. Nagalli [138] 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 [44].

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 meta-heuristic algorithms in prediction models [46]. These algorithms encompass evolutionary methods like the genetic algorithm (GA) and Archimedes optimization algorithm (AOA), as well as swarm-based approaches such as bee colony optimization, ant colony optimization, and gray wolf optimization (GWO).

In 2014, Wu et al. [17] innovatively introduced and evaluated an AI predictive standard known as GEP (Gene Expression Programming), in addition to multiple linear models and ANN in Hong Kong City. This model aimed to forecast construction and demolition waste using a dataset aggregated from 1991 to 2010. The dataset, comprising a total of 80 entries, was partitioned into 74 sets for model training and 8 sets for validation purposes. Four input variables, including the charging scheme, gross value of construction work, gross domestic product (GDP), and gross floor area of buildings, were considered in the analysis.

Lee et al. [16] devised a novel hybrid model aimed at predicting both the cost and quantity of waste during the initial stages of the project. This innovative approach combines ACO with ANNs. The dataset, consisting of 118 projects, was randomly split into 103 projects for the training phase and 15 projects for testing. Eight input variables, including location, number of buildings, stories, demolition year, completion year, number of houses, gross floor area, and lot area ($m^2$), were utilized. The model's output variable was the total amount of construction waste.

Cha et al. [125] predicted the rate of waste production during building demolition projects using a mixed ML model. They created four prescient models: SVMR, ANN (MLP), CATPCA (categorical principal components analysis) - ANN (MLP), and CATPCA-SVMR. The mixed model was prepared on datasets obtained from the destruction waste production information of 784 structures, with factors including GFA (gross floor area), locale, use, design, and resources for walls and roof. Among the models, the CATPCA–SVMR demonstrated the best forecasting performance, achieving an R-value of 0.770 and $R^2$ of 0.594.

Soni et al. [126] led an examination of different AI models, including ANFIS, ANN, DWT (discrete wavelet theory)-ANFIS, DWT-ANN, GA-ANFIS (genetic algorithm–adaptive neuro-fuzzy inference system), and GA-ANN. Their review is expected to survey the models' adequacy in foreseeing municipal solid waste (MSW) generation, utilizing a case study from New Delhi, India, with 19 datasets for comparison. The input for the models was the previous waste generation. Among these models, GA-ANN demonstrated the highest accuracy, achieving a coefficient of determination ($R^2$) at an impressive level of 0.87.

Although superior advantages of GWO [139] and AOA [140], these meta-heuristic 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 [141] introduced a novel approach for predicting Biochar yield. In their model, the GWO and 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-PSO. Notably, the ANFIS-GWO model outperformed the standard ANFIS and other models by a margin of 35%.

Zhou et al. [55] utilized a dataset of 600 observations to predict water inflow during tunnel excavation. They employed various machine learning techniques, optimizing a Random Forest (RF) model using the Grey Wolf Optimizer (GWO) and comparing it with other models such as RF, and six others. The GWO-RF model used four input variables—tunnel depth (H), groundwater level (h), rock quality designation (RQD), and water yield property (W)—to enhance predictive accuracy. The results demonstrated that the GWO-RF model achieved superior performance, with $R^2$ values of 0.9483 during training and 0.9289 in the testing phase, outperforming other ensemble models.

Liang et al. [127] delved into a hybrid model designed to foresee month-to-month solid waste production in seven Iranian megacities. The dataset incorporated eight inputs, including normal temperature, most extreme temperature, rainfall, population, educated individuals, family size, and Gross domestic product. Spanning the years 2000 to 2014, the dataset comprised 1176 data points from the seven megacities in Iran. The training phase utilized 80 percent of the data, with the remaining 20 percent saved for testing. The model integration involved coupling the ANN model with optimization algorithms such as AOA, GA, Sine Cosine Algorithm (SCA), and Particle Swarm Optimization (PSO). An improved gamma test determined the optimal input combination, and the model's results were input into an Inclusive Multiple Model (IMM) during the final phase for enhanced reliability. Fuzzy reasoning was applied to modify the Artificial Neural Networks model structures, revealing that the fuzzy reasoning-based IMM and the ANN-AOA exhibited a commendable capacity to predict various target variables, with the ANN model benefiting from reduced runtime through the incorporation of fuzzy reasoning.

Abo Mhady et al. [142] proposed hybrid models for 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.

Check out **Table 2.13** for an in-depth breakdown of past research delving into the model, waste type, region, data type, data quantity, model inputs, and overall performance.

Consequently, the hybrid approach can be an innovative approach to overcome the challenges related to the estimation of C&DW. ANN has proven its efficacy in addressing intricate and challenging problems across various industries and research domains.

**Table 2.13** Here's a brief summary of a few articles on C&DW prediction

| **Reference /Year** | **Model** | **# of input** | **Type of Waste** | **Location** | **Date type** | **# of data-set** | **$R^2$** |
|---|---|---|---|---|---|---|---|
| [16]/ 2016 | ANN, ACO | 8 | CW | Korea | Nominal & continuous | 118 | 0.99 |
| [17]/ 2015 | GEP, MLP | 4 | C&DW | China | Nominal & continuous | 80 | 0.81 |
| [60]/ 2017 | GM, SVR | 1 | C&DW | China | Panel data (Yearly) | 30 | 0.99 |
| [128]/ 2021 | MLP, ANN | 1 | DCCW * | Bahrain | Panel data (Yearly) | 180 | 0.99 |
| [130]/ 2018 | ANN, GM, MLR | 1 | MSW | China | Panel data | 16 | 0.93 |
| [129]/ 2021 | CATPCA, SVMR | 6 | DW | Korea | Nominal & continuous | 690 | 0.59 |
| [46]/ 2021 | RF, GBM | 6 | DW | Korea | Nominal & continuous | 690 | 0.89 |
| [47]/ 2020 | RF | 6 | DW | Korea | Nominal & continuous | 691 | 0.80 |
| [131]/ 2019 | ANN, ANFIS, SVM, etc. | 1 | MSW | Iran | Cross-sectional | 105 | 0.92 |

**Table 2.13** Here's a brief summary of a few articles on C&DW prediction (continued)

| Reference /Year | Model | # of input | Type of Waste | Location | Date type | # of data-set | $R^2$ |
|---|---|---|---|---|---|---|---|
| [143]/ 2018 | ANN | 1 | MSW | India | Time series (monthly) | 60 | 0.84 |
| [132]/ 2020 | DNN | 5 | DW | , United Kingdom | Nominal & continuous | 2280 | 0.97 |
| [53]/ 2023 | ANN, SVR, RF-AE | 6 | DW | Korea | Nominal & continuous | 782 | 0.68 |
| [144]/ 2020 | Regression Analysis | 10 | CW | Brazil | Nominal & continuous | 18 | **0.81** |
| [145]/ 2016 | S-curve, ANN | 4 | CW | China | Nominal & continuous | 138 | - - - |
| [138]/ 2021 | ANN | 2 | CW | | Nominal | 330 | **0.96** |
| [133]/ 2023 | LR, TR, SVMR, … etc | 10 | RW | China | Nominal & continuous | 351 | **0.83** |
| [146]/ 2016 | DSS | 4 | C&DW | Brazil | Nominal & continuous | 52 | - - - |
| [147]/ 2024 | Generalized linear | 9 | CW | New Zealand | Nominal & continuous | 213 | - - - |
| [52]/2023 | RF, ET, GBM, and XGboost | 6 | C&DW | Korea | Nominal & continuous | 690 | **0.617 for RF** |

* Domestic, commercial, and construction wastes **(DCCW)**

A substantial body of literature has attested to the robustness of ANN in the field of C&DW [16, 128]. In addition, the AOA and GWO methods provide good results in different industries, therefore, they have the 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, in this study, two hybrid models were developed by integrating the ANN and RF with the AOA and GWO methods.

# 3
# METHODOLOGY

## 3.1 Introduction

Chapter three will delve into the method utilized in this study. We kicked things off by conducting a thorough literature review, aiming to dig deep and gather extensive insights. Our primary objective was to build a solid understanding and acquire substantial knowledge regarding the factors that influence the generation of waste from building and demolition schemes in the Gaza Strip, Palestine.

We tackled the data collection in two key phases.

- First up, we compared the factors influencing waste generation compiled from existing literature through a review study with the practical assessment of waste-generated factors in the Gaza Strip. This involved tapping into the insights of participating experts.
- Following that, we gathered the necessary data from several projects in the Gaza Strip. This data will come into play during the analysis phase and the formulation of a hybrid model.

To carry out this study, we've rolled out a methodology that involves diving into relevant literature on waste generation, leveraging machine learning algorithms, and tapping into metaheuristic techniques within construction projects. A crucial step includes data collection and the development of a hybrid model illustrated in **Figure 3.1.** This research is all about crafting a dynamic hybrid model to predict waste generated in C&D projects, employing a mix of techniques. We're using metaheuristic flair with AOA and GWO algorithms for pre-processing, paired with machine learning via the RF and ANN.

## 3.2 Collection of Data

The necessity for data preparation is paramount, as the quality of data holds greater significance than the sophistication of models. In the real-world scenario, data often presents challenges such as noise, errors, and missing values. It may lack essential properties, exhibit incomplete information, or even contain inaccuracies. To enhance data quality, preprocessing becomes imperative.

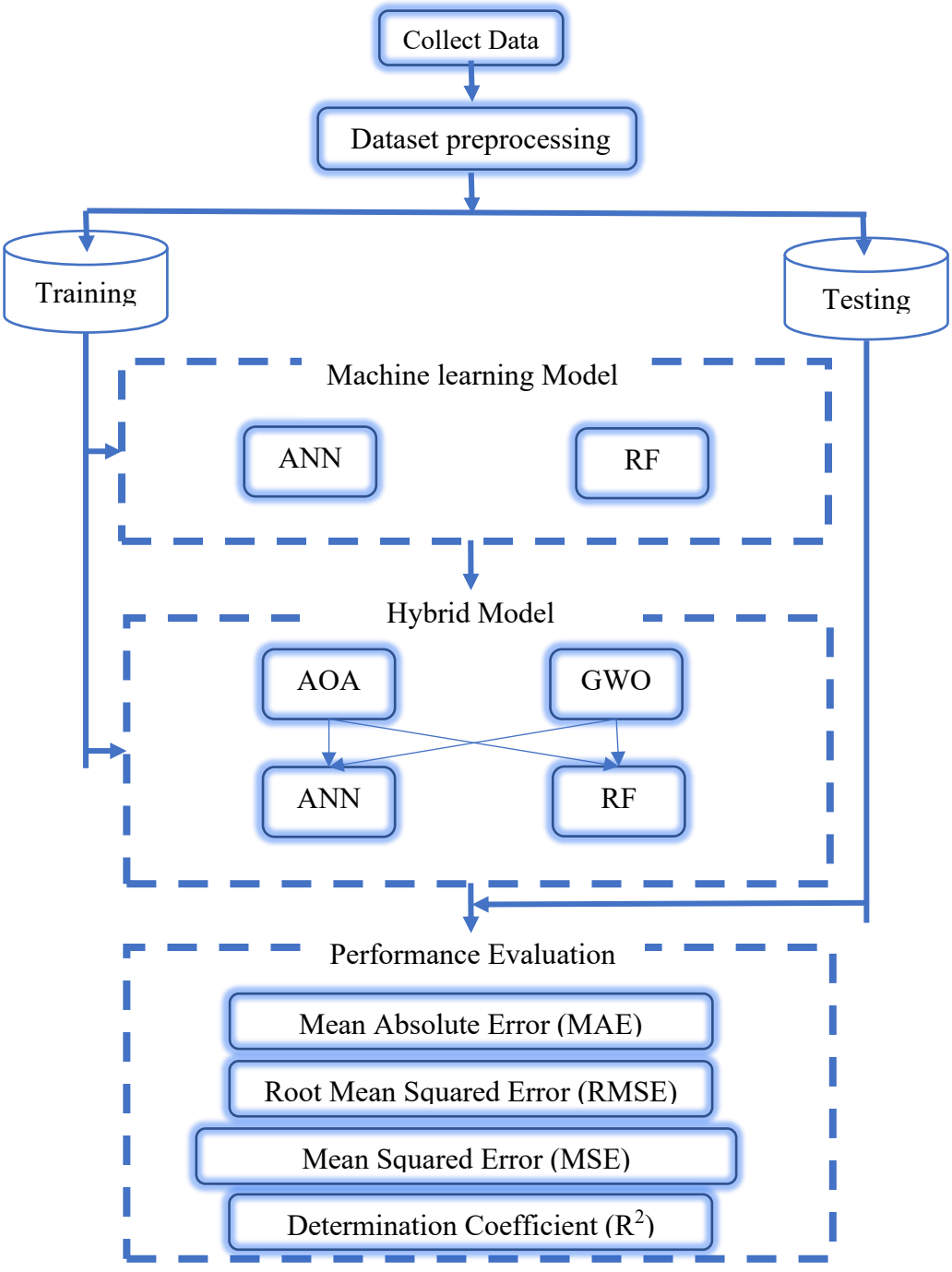



**Figure 3.1** Analysis procedures of the proposed study.

### 3.2.1 Parameters Affecting Waste Generation.

Having delved into existing literature and consulted with experts, coupled with an extensive review of relevant studies, it's evident that waste management is a pivotal and widely acknowledged concern. Numerous scientific research endeavors have been dedicated to discerning, characterizing, and measuring the waste generated during construction and demolition operations. For a comprehensive snapshot, **Table 3.1** shows the demographic profile of experts, while **Table 3.2** compiles the array of waste-generated factors identified in studies conducted prior to 2023. These variables, or inputs, will serve as the building blocks for the hybrid model under development in this study.

**Table 3.1** Demographic profile of experts

| No. | Academic | Position | Year of experience/ No. of expert |
|---|---|---|---|
| **01** | Associate Prof. | Associate Prof. | 25/1 |
| **02** | Prof. Dr. | Senior Lecturer | 10/1 |
| **03** | Master degree | Project manger | 8-25/4 |

**Table 3.2** Explaining variables for C&DW

| No. | Variable | Description | References |
|---|---|---|---|
| **1** | **Project Name** | Documented Name | |
| **2** | **Quantity of waste** | The amount of waste: how many trucks came out of the demolition of the building (a truck that contains a box of size 2.45 x 6 x 1.5m) | |
| **3** | **Type of project** | Construction or demolition project | [46, 129, 148] |
| **4** | **Date (Year)** | The starting date of project (2000-2023) | [16, 133] |
| **5** | **Project location** | North, Gaza, Medial Area, Khan Younis, Rafah | [16, 46, 129, 145, 148, 149, 150] |
| **6** | **Project Duration** | The time required to complete the project (months) | [138, 145, 147, 150, 151] |
| **7** | **Building use** | Only residential, commercial/ residential, only commercial, public, infrastructure, and others. | [46, 129, 132, 144, 148, 149, 150] |
| **8** | **Total building area** | The area of all built floors includes the first-floor area and typical floor area (square meters). | [16, 17, 46, 60, 128, 132, 144, 148, 150] |

**Table 3.2** Explaining variables for C&DW (continued)

| No. | Variable | Description | References |
|---|---|---|---|
| **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. | [144, 150] |
| **10** | **Number of floors** | Number of floors in the construction | [16, 132, 144] |

### 3.2.2 Design of Datasheet

Crafting a well-designed data-sheet is key to ensuring precise results and a robust response rate. As such, the questions were carefully formulated to be specific, realistic, and measurable. The primary inquiries in the questionnaire, that build for data collection are formulated as follows:

- Section one gathers essential details about the concerned entity, encompassing name, job title, years of work experience, email address, telephone number, and the construction company's name.
- The second segment delves into elucidating variables (factors/inputs) crucial for constructing the hybrid model in this study, focusing on construction or demolition waste.
- The third section comprises a series of questions capturing information about the projects, such as project name, waste quantity in cubic meters, the type of project, the year of construction or demolition, the location of the project, the duration of construction or demolition (in months), the type of building, the total area of the building, the number of floors, and site access from the borders and the availability of wide highways.

### 3.2.3 Source of Data

For a collection of data in this study, information was sourced from two channels. The initial resource involved the Ministry of Public Works and Housing, and the second involved collaboration with construction companies, including expert contractors and engineers—refer to **Figure 3.2** for insights. To facilitate data collection, three distinct sheet types were developed: an Excel sheet, a Microsoft

Word file, and Google Forms. Communication with experts took place in two stages: face-to-face interactions and via WhatsApp messages.

## 3.3 Analysis of Data

Analyzing data involves refining, processing, and cleansing raw information to derive useful and relevant insights that aid decision-making. This transformative process provides valuable statistics and insights, which are effectively communicated through various visual presentations.

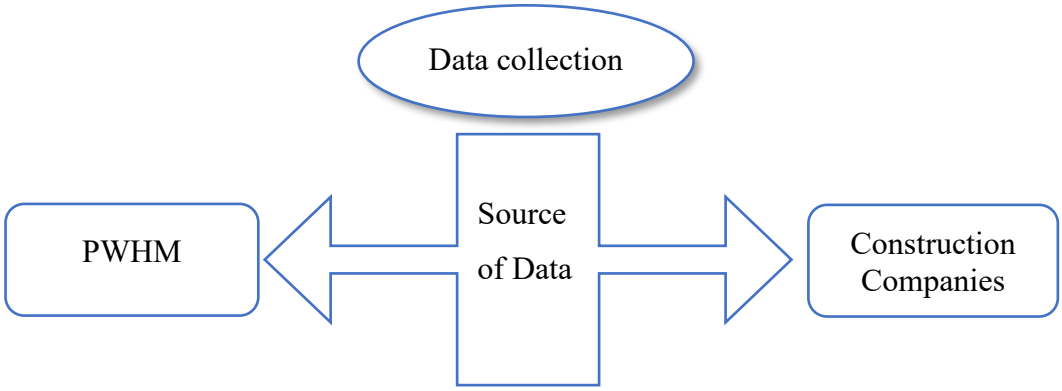



**Figure 3.2** Data Source

Part of the research procedure entails outlining the statistical methods intended to address the research issue. While the specific type and technique of statistical analysis may vary based on the study's design, the data analysis section typically provides a description of the data's descriptive features. Additionally, it outlines the primary statistical analyses planned to elucidate the relationships between variables [152].

Demographic analysis, statistical analysis, and sensitivity analysis will be employed for data examination, with Microsoft Excel selected as the tool for analysis. Demographic statistics will provide general information about respondents, while descriptive statistics will offer an overall perspective. Sensitivity analysis will precede the application of AI models.

### 3.3.1 Demographic Analysis

Demography, often characterized as the investigation of human populaces and their progressions in number due to factors like migration, fertility, and mortality, has its

roots in the Greek term meaning "describing people." This field delves into population characteristics, examining aspects such as population density, spatial distribution, composition, and age structure, sex ratio. A differentiation is sometimes drawn between "demographic analysis" or "formal demography" involving the statistical scrutiny of population parameters and their dynamics, and "population studies," which extends the analysis to understand the effects and causes of structural population changes in a broader context, interlinked with various occurrences and procedures. [153, 154, 155].

Concerning the quality of data, population information often exhibits imperfections. It is inadequate, as seen in cases of substantial silence to a population count, and could be outdated. Additionally, measurement errors can occur at various stages, from flawed questionnaire design to defective sampling and processing. These errors may stem from inadequate training of workers, respondents' inadequate information or faulty reminiscence, substandard coding, or processing errors. Therefore, demographers must stay vigilant to the potential defects in the data. Importantly, identifying data defects doesn't automatically render them unusable [156].

Certain studies focus on measuring demographic information like age, gender, income, and residence. In this research, the initial section of the datasheet is dedicated to collecting demographic details about the respondents and their respective organizations, ensuring a proper background match. Questions cover aspects such as job title, work experience, current organization, project types, number of projects handled, and contact information. The analysis of these data will involve the use of statistical tools, specifically frequency distributions.

Frequency distributions serve as visual representations organizing and presenting frequency counts (n) for easier interpretation. They may encompass not only frequency counts but also relative frequency, cumulative, and cumulative relative frequencies. To break it down: 1. n (Frequency) denotes how often a specific variable assumes a particular value. 2. N (cumulative frequency) is the computation of illustrations where a unit assumes a value not exactly or equivalent to the predetermined value. 3. $F_r$ (relative frequency) is communicated as a level of recurrence. 4. $F_c$ (cumulative relative frequency) is the level of the total recurrence.

In this study, frequency and relative frequency will be employed to analyze the demographic data section.

### 3.3.2 Statistical Analysis

The utilization of statistical software in organizations and academia has experienced continuous evolution in recent years. For the data analysis in this study, **Microsoft Excel** was employed. Statistics, as a field, comprises a set of methods aimed at analyzing data. It finds application across various scientific domains, involving the collection, processing, and organization of data to gain insights into specific phenomena. The essence lies in the potential to infer new results based on acquired knowledge. The overarching goal of statistics is to extract meaningful information from data, improving comprehension we might interpret the circumstances they portray. Consequently, statistics can be regarded as the science of deriving insights from data [157].
Statistical literacy holds significance for three key reasons: Firstly, it ensures individuals are well-informed. Secondly, it empowers a comprehensive understanding of issues, enabling sound decision-making grounded in data. Lastly, it equips individuals with the ability to evaluate decisions that have an impact on their lives [158].

After gathering data or pinpointing a suitable data source, the subsequent phase in the data analysis process typically revolves around arranging and condensing the information. Utilizing tables, graphs, and numerical summaries enhances comprehension and offers an efficient means of showcasing the data. This facet of statistics, focusing on methods to organize and summarize data, is referred to as descriptive statistics [158].

Descriptive statistics (DS) play a vital role in portraying the essential qualities of data inside research. The DS suggests clear outlines with respect to both the example and its actions. When coupled with basic graphical analysis, descriptive statistics essentially underpin almost every quantitative data analysis. Its utility lies in presenting quantitative descriptions in an accessible manner. Whether a research study involves numerous measures or assesses a substantial number of individuals on any given measure, descriptive statistics prove invaluable in simplifying

extensive datasets into meaningful summaries. Each descriptive statistic serves to condense extensive data into a more manageable overview [157].

As researchers, our journey involves not just making observations but also the crucial tasks of summarizing, estimating reliability, making comparisons, and drawing inferences. Measures of central tendency—like mode, median, and mean — effectively embody the presentation level inside a score gathering. Meanwhile, measures of variability delve into the scores spread within members. Both aspects are indispensable: one sheds light on the performance level, while the other unveils the consistency of that performance [159].

This research will incorporate several descriptive statistic features, including minimum, mean, maximum, standard deviation (SD), and sample variance.

The mean, also known as average, commonly used measure of central tendency and stands out as the widely recognized. Its versatility spans both discrete and continuous data. A vital attribute of the average is its inclusivity—it takes into account each value in the dataset during calculation. Basically, the average is the amount of all factor values partitioned by the absolute number of values in the dataset. For a dataset with 'n' values represented by ($x_1$, $x_2$... $x_n$), the sample mean, typically indicated by $\bar{x}$ (or denoted by μ for the population mean), is determined in **Eq. (3.1)** [157].

$$\bar{x} = \frac{x_1 + x_2 + \cdots + x_n}{n} = \frac{\sum_{i=1}^{n} x_i}{n} \tag{3.1}$$

Variance and standard deviation (SD), they both serve as crucial indicators of variability within statistical analysis. These metrics offer insights into the spread of a variable's values from its mean. When a variable lacks variability, with each data point aligning with the mean, both SD and variance assume a value of zero. As the values of the variable deviate more substantially from the average, both the SD and variance add up. The relationship between these measures is straightforward—the SD (symbolized by σ for the population and 's' for the sample) is the square root of the variance (represented by $\sigma^2$ for the population and '$s^2$' for the sample). The equations for SD and variance (sample) are in **Eq. (3.2), and Eq. (3.3)** respectively [157].

$$\text{Sample variance: } s^2 = \frac{\sum(x_i - \bar{x})^2}{n-1} \tag{3.2}$$

$$\text{Sample standard deviation: } s=\sqrt{s^2}=\sqrt{\frac{\sum(x_i-\bar{x})^2}{n-1}} \quad (3.3)$$

where $x_i$ signifies the sample $i^{th}$ dataset value, $\bar{x}$ signified the average and n is the sample size

### 3.3.3 Sensitivity Analysis

Sensitivity analysis (SA) methods emerge as indispensable tools in the realm of modeling. They offer a pathway to explore how uncertainty in a model's result could be attributed to various uncertainty sources in its input [160]. SA serves multifaceted purposes—it aids in identifying the highest influential input variables impacting output behavior while pinpointing non-influential inputs. Moreover, it unveils association impacts inside the model. The objectives span model verification, comprehension, simplification, and prioritization of factors. Beyond that, SA plays a pivotal role in validating computer code, guiding research endeavors, and substantiating system design safety [161].

Sensitivity analysis methods can be categorized based on their nature as either local or global, and by whether they consider individual inputs to represent synchronous connections among inputs. Global methods that factor in connections among different sources of info frequently yield more extensive knowledge contrasted with techniques coming up short on these highlights. Local methods like Forward Stepwise Sensitivity Analysis, Hinton Diagram, $R^2$, SSE, MSE, and Pearson Correlation Coefficients focus on individual inputs and do not consider simultaneous interactions. On the other hand, Importance of Weights, Frequency Analysis, Correlation Matrix, Multi-correlation Matrix, and Cosine Amplitude Method are a global sensitivity analysis method [162, 163, 164].

In this research, we applied the forward stepwise sensitivity analysis method to identify the most significant relationships between input variables and the network's output. This method involves perturbing each input variable by a small amount and observing the resulting changes in the network's output. Specifically, for each input variable, we increase its value slightly and compute the corresponding change in the output. This allows us to assess how sensitive the network's output is to variations in each input. To quantify the sensitivity, we calculate the mean absolute

difference between the perturbed outputs and the original outputs and then normalize these values to a scale from 0 to 1. In this normalized scale, a value of 0 represents the lowest sensitivity, while higher values indicate a greater influence of the input variable on the output. By comparing these normalized sensitivity values, we can determine the relative importance of each input variable in affecting the network's predictions.

## 3.4 Phase of Pre-Processing

This phase prepares the data for developing a prediction model and enhancing its robustness through three primary stages. Initially data points that have 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% allocated for training purposes and 30% 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, both the training, testing, and validation data were independently normalized using the min-max method, as represented by the following formula:

$$N_i = \frac{Y_i - Y_{min}}{Y_{max} - Y_{min}} \tag{3.4}$$

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 [181].

## 3.5 Model

The utilization of a metaheuristic technique as a pre-processing step is motivated by the intent to improve the performance of both the ANN and RF.

### 3.5.1 Gray Wolf Optimization (GWO)

Introduced by Mirjalili et al. [165], the GWO stands out as a metaheuristic optimization approach renowned for its exceptional accuracy in tackling

optimization and global search challenges. This efficacy is attributed to its streamlined complexity, minimal control constraints, and heightened search efficiency [166, 167]. Drawing inspiration from the hierarchical leadership and hunting strategies of grey wolves in wildlife, the algorithm organizes the wolf pack into four layers. At the helm is the alpha wolf (α), assuming the role of decision-maker for the most critical challenges faced by the entire pack, representing the optimal solution. The beta wolf (β) provides support to the leader, while the delta wolf (δ) follows the orders of leaders and the beta wolf to execute the mission. The most minimal position, the omega wolf (ω), comprises the remaining subordinates obedient to the top three layers [166]. In the GWO's social behavior emulation, the fitting arrangement is named wolf alpha, with the subsequent best arrangements distinguished as wolf beta and gamma in that order. The rest of the solutions collectively represent omega. Consequently, the optimization process in the GWO algorithm is steered by the leader, the second and third in-command wolves, with omega wolves aligning themselves with these three categories [168].

According to Wahba et al. [166], Expressing the mathematical representation of the grey wolves' hunting procedure, we employ the following equations **Eq. (3.5)** and **Eq. (3.6)**.

$$\vec{D} = \left|\vec{C}.\vec{X}_P(t) - \vec{X}(t)\right| \tag{3.5}$$

$$\vec{X}(t+1) = \vec{D}_P(t) - \vec{A}.\vec{D} \tag{3.6}$$

Here t means the ongoing iteration, $\vec{A}$ and $\vec{C}$ stand for coefficient vectors, $\vec{X}_P$ is addressing the prey position area vector, and $\vec{X}$ showing the grey wolf area vector.

The vectors $\vec{A}$ and $\vec{C}$ are shown as in **Eq. (3.7)** and **Eq. (3.8)**, respectively.

$$\vec{A} = 2\vec{a}.\vec{r}_1 - \vec{a} \tag{3.7}$$

$$\vec{C} = 2\vec{r}_2 \tag{3.8}$$

In the iterative loop, the components of the vector $\vec{a}$ undergo a linear reduction from two to zero. Simultaneously, r (1 and 2) represents random vectors within the interval (0, 1).

In the simulation process of the hunting strategy for wolves, we should accept that the best arrangement is meant as α, and every one of the essential information for

the place of the prey are addressed by β and δ. In this context, the main three arrangements (α, β, and δ) are stored, while the remaining search agents (ω) update their locations based on the new positions of these three leading hunt agents. The updating operation of the wolves' positions is then applied accordingly. **Eq. (3.9)**, **Eq. (3.10)** and **Eq. (3.11)** [165, 169]:

$$\vec{D}_\alpha = \left|\vec{C}_1.\vec{X}_\alpha - \vec{X}\right|, \vec{D}_\beta = \left|\vec{C}_2.\vec{X}_\beta - \vec{X}\right|, \vec{D}_\delta = \left|\vec{C}_3.\vec{X}_\delta - \vec{X}\right| \quad (3.9)$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1.\vec{D}_\alpha, \vec{X}_2 = \vec{X}_\beta - \vec{A}_2.\vec{D}_\beta, \vec{X}_3 = \vec{X}_\delta - \vec{A}_3.\vec{D}_\delta \quad (3.10)$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (3.11)$$

Reference Golafshani [170] summarized the GWO algorithm steps, which are presented as Algorithm 1.

**Start**
Create the initial pack of grey wolves randomly
Evaluate the performance of grey wolves in the pack
Choose the three best grey wolves in the pack as the α, β and δ wolves
**For** t = 1 to maximum iteration number
Generate random vectors of $\vec{r}_1$ and $\vec{r}_2$
Specify $\vec{a}$ vector based on iteration counter
**For** i = 1 to Number of the positions of the experienced (ω) wolves in the pack
Determine the new position of ω wolves using Eq. (10-11)
Evaluate the performance of ω wolves
**End For**
Choose the three best grey wolves in the pack as the the α, β and δ wolves
**End For**
Save the position and performance of the achieved the α grey wolf
**End**

**Algorithm 1.** The GWO pseudocode

### 3.5.2 Archimedes Optimization Algorithm

The AOA algorithm serves the dual purpose of determining the optimal initial weight for models and optimizing and adjusting model parameters. This Meta-heuristic model, known as AOA, is applied to solve various mathematical optimization problems, showcasing its efficiency in reaching global solutions in a shorter time frame [171]. Look at **Table 3.3**, The AOA method progresses through several stages to discover near-global solutions, outlined as follows:

**Table 3.3** Stages of the hyperparameter tuning process

| No. | Stage | Optimization | Calculation |
|---|---|---|---|
| 1. | Initiation | Upper and Lower boundaries | Volume |
| 2. | Upgrade densities and volumes | Optimal density | Density |
| 3. | Transfer operator and density factor | Maximal number of iterations | Density factor |
| 4. | Exploration | Collision | Acceleration |
| 5. | Exploitation | No collision | Acceleration |
| 6. | Normalization Acceleration | Access the percentage | Acceleration |
| 7. | Evaluation | Optimal solution | Fitness |

**Stage 1 - Initiation**: In this stage, a population, including the immersed object (solution), is characterized by its accelerations, volumes, and densities. All solutions are initially placed at random positions beneath the fluid, as expressed in **Eq. (3.12)**, and the fitness value for each solution is assessed.

$$O_i = lb_i + rand(0,1) \times (ub_i - lb_i), \forall i \in \{1,2,3, \dots, N\} \quad (3.12)$$

$$Den_i = rand(0,1) \quad (3.13)$$

$$Vol_i = rand(0,1) \quad (3.14)$$

$$ACC_i = lb_i + rand(0,1) \times (ub_i - lb_i), \forall i \in \{1,2,3, \dots, N\} \quad (3.15)$$

In the equation, $O_i$ represents the $i$ th solution in the population, and $N$ shows the size of the population. $ub_i$, $lb_i$ denote both end limits of the i$^{th}$ solution, respectively. $Den_i$, $Vol_i$, and $ACC_i$ represent the densities, volumes, and accelerations of the $i$ th solution. The term $rand(0,1)$denotes a randomly chosen scalar with a value between zero and one.

**Stage 2 - Upgrade densities and volumes:** Here involves the enhancement of both volume and density for all solutions.

$${Den_i}^{(t+1)} = {Den_i}^t + rand(0,1) \times \left(Den_{best} - {Den_i}^t\right) \quad (3.16)$$

$${Vol_i}^{(t+1)} = {Vol_i}^t + rand(0,1) \times \left(Vol_{best} - {Vol_i}^t\right) \quad (3.17)$$

During this stage, ${Den_i}^t$ represents density and ${Vol_i}^t$ represents the volume of the $i^{th}$ solution at the $t^{th}$ iteration. $Den_{best}$ represents the optimal density and $Vol_{best}$ represents the volume of the solution comprising of the best ability standards.

**Stage 3 - Transfer operator and density factor:** The algorithm addresses the collision among solutions until reaching an equilibrium state. The mathematical expression for this stage could be represented by the accompanying equation:

$$TF = \exp\left\{\frac{t - t_{max}}{t_{max}}\right\} \tag{3.18}$$

$TF$ signifies the transfer operator, facilitates the transition of the search process from the exploration to the exploitation phase. The $t_{max}$ is the maximum iterations number. Additionally, a reduced density factor (d) plays a role in aiding the AOA to converge towards a global solution.

$$d^{t+1} = \exp\left\{\frac{t - t_{max}}{t_{max}}\right\} - \left(\frac{t}{t_{max}}\right) \tag{3.19}$$

**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 chosen, and the acceleration of a solution is updated using the following equation:

$$ACC^{t+1} = \frac{Den_{mr} + Vol_{mr} \times ACC_{mr}}{Den_i{}^{(t+1)} \times Vol_i{}^{(t+1)}} \tag{3.20}$$

In the equation, $Den_{mr}$ - density, $Vol_{mr}$ -volume, and $ACC_{mr}$ -acceleration of the arbitrary material, respectively [172].

**Stage 5 - Exploitation:** In stage 5, marked by the absence of collisions among solutions, the acceleration of each solution is upgraded when $TF$ >= 0.5:

$$ACC^{t+1} = \frac{Den_{best} + Vol_{best} \times ACC_{best}}{Den_i{}^{(t+1)} \times Vol_i{}^{(t+1)}} \tag{3.21}$$

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

**Stage 6 - Normalization acceleration:** Known as "Normalization acceleration," involves normalizing the acceleration to assess the change percentage:

$$ACC_{i-norm}{}^{t+1} = g \times \frac{ACC_i{}^{t+1} - \min\{ACC\}}{\max\{ACC\} - \min\{ACC\}} + z \tag{3.22}$$

In which case "g" and "z" represent the normalization range, and $ACC_{i-norm}{}^{t+1}$ is utilized to determine the percentage by which each agent will move.

**Update position:** when exploration phase is existed (T F ≤ 0.5), the $i^{th}$ object's position for coming iteration t plus 1 using **Eq. (3.23)** [173]

$$x_i^{t+1} = x_i^t + C_1 \times randACC_{i-norm}^{t+1} \times d \times (x_{rand} - x_i^t) \quad (3.23)$$

Here $C_1$ is constant equal to 2. On the other hand, when the exploitation phase is existed (TF > 0.5), the objects update their positions using **Eq. (3.24)**.

$$x_i^{t+1} = x_{best}^t + F \times C_2 \times randACC_{i-norm}^{t+1} \times d \times (T \times x_{best} - x_i^t) \quad (3.24)$$

Here $C_2$ has a value equal to 6, and T is directly proportional to the transfer operator which increased 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, leading to a high step-size in the random walk. As the search progresses, this rate gradually increases to reduce the difference between the current and optimal positions, achieving a balance between exploitation and exploration.

The flag F is utilized to alter the direction of motion according to **Eq. (3.25)**:

$$F = \begin{cases} +1 \; if \; P \leq 0.5 \\ -1 \; if \; P > 0.5 \end{cases} \quad (3.25)$$

Here $P = 2 \times rand - C_4$.

**Stage 7 - Evaluation:** In the evaluation stage, all solution's fitness values are calculated, and a record of the optimal solution is taken, leading to the update of the optimal solution ($x_{best}$), $Den_{best}$, $Vol_{best}$, and $ACC_{best}$.

[173] Summarized the steps of the AOA algorithm, and the steps were as the algorithm 2 in page 60.

### 3.5.3 Artificial Neural Network (ANN)

The concept of Artificial Neural Networks (ANNs) mirrors how our brains tackle real-world issues [34]. Initially proposed in 1943 [174], ANNs gained substantial traction in 1986 with the advent of the back-propagation training algorithm for feed-forward multi-layer perceptions (MLPs). Since then, research exploring the myriad applications of ANNs has flourished, delving into their potential to interpret and process complex problems, akin to the human brain. [175, 176].

McCulloch et al. [174] and Shahin [175], outline the key eight steps in developing an Artificial neural network (ANN) model. These steps encompass selecting

performance criteria, choosing data sets, pre-processing data, determining model inputs, defining the model architecture, establishing stopping criteria, selecting optimization methods, and conducting validation. Each step involves making specific choices, which are detailed in **Table 3.4** for reference.

**Table 3.4** Main steps in artificial neural network (ANN) model development

| Step No. | Steps | Choices of step |
|---|---|---|
| 1. | performance criteria | 1. Training speed.<br>2. Processing speed during recall.<br>3. Prediction accuracy. |
| 2. | data sets | 1. Number of data sets (example two, three, holdout method…etc.).<br>2. Method for data division. |
| 3. | data pre-processing | 1. Scaling.<br>2. Transformation to normality.<br>3. Removal of non-stationarities. |
| 4. | model inputs | 1. Variables<br>2. Lags |
| 5. | model architecture | 1. Connection type (example feedforward, feedback)<br>2. Degree of connectivity (example full connected)<br>3. Number of layers<br>4. Number of nodes per layer (trial & error, constructive or pruning methods) |
| 6. | stopping criteria | 1. Fixed number of iterations.<br>2. Training error<br>3. Cross-validation |
| 7. | optimization method | 1. Local first order (example back-propagation)<br>2. Local second order (example Levenberg-Marquardt, conjugate gradient)<br>3. Global (example simulated annealing, genetic algorithm) |
| 8. | Validation | |

Initially, the data undergoes segmentation into three distinct sets: training, validating, and testing datasets. The training dataset serves the purpose of instructing the Artificial Neural Network (ANN) model, facilitating the derivation of optimal weights and biases. On the other hand, the testing dataset is employed to assess the performance of the developed ANN model. The validating data plays a crucial role in exploring the generalizability of the ANN model and serves as a preventive measure against the over-fitting issue, particularly with classical training algorithms [170].

Procedure AOA (population size N, maximum iterations, $t_{max}$ , $C_1$, $C_2$, $C_3$, $C_4$)
Initialize objects population with random position, densities and volumes using **Eq. (3.12)**, **Eq. (3.13), Eq. (3.14)** and **Eq. (3.15)** respectively.
Evaluate initial population and select the one with the best fitness value.
Set iteration counter t = 1
**while** $t \leq t_{max}$ **do**
**for** each object i **do**
Update density and volume of each object using **Eq. (3.16)** and **Eq. (3.17).**
TF and d using **Eq.** (3.18) and **Eq.** (3.19), respectively.
**If** TF ≤ 0.5 **then** * Exploration phase
Update acceleration using **Eq.** (3.20) and normalize acceleration using **Eq.** (3.22)
Update position using **Eq.** (3.23)
**else** * Exploitation phase
Update acceleration using **Eq.** (3.21) and normalize acceleration using **Eq.** (3.22)
Update direction flag F using **Eq.** (3.25)
Update position using **Eq.** (3.24)
**end if**
**end for**
Evaluate each object and select the one with the best fitness value.
Set t = t + 1
**end while**
**return** object with best fitness value.
**end procedure**

**Algorithm 2.** The AOA pseudocode

#### 3.5.3.1 Network Architecture

Typically, the network is structured with three layers of nodes: input, hidden, and output layers [43], as illustrated in **Figure 3.3.** Within each layer, numerous processing nodes are present. Nodes in the input layer connect to all nodes in the hidden layer, and nodes in the hidden layer connect to all nodes in the output layer through weighted connections and bias nodes. Biases indicate activation thresholds for neurons, while weights signify the strength of connections between neurons in the network. Importantly, the number of hidden nodes represents a modifiable parameter magnitude.

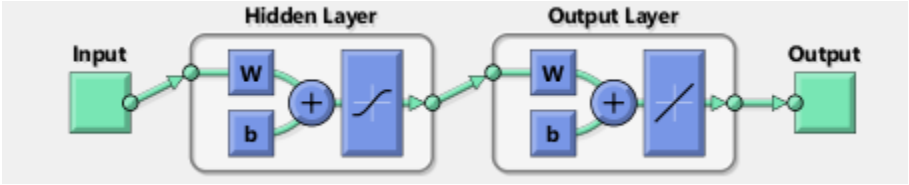



**Figure 3.3** A visual representation of an artificial neural network depicted in a schematic diagram, highlighting the architecture of a feedforward network with a single hidden layer.

#### 3.5.3.2 Tuning Parameters of ANN

According to Lahiri et al. [43], the generalization performance or estimation accuracy of an Artificial Neural Network (ANN) hinges on effectively configuring the following meta-parameters:

1. **Number of Nodes in Hidden Layer:** The quantity of nodes in the hidden layer significantly influences ANN performance. Too few nodes may hinder proper learning of data relationships, while an excessively large number of nodes increases network complexity and execution time. Typically, literature suggests determining the optimal number of nodes through trial and error. However, this method is time-consuming and may not yield the best performance.
2. **Activation Functions in the Input Layer:** The activation function plays a crucial role in both hidden and output nodes, applied to their net input. In this study, five types of activation functions, as documented in literature and employed in the work, are detailed in **Table 3.5** and depicted in **Figure 3.4.** These functions contribute to shaping the behavior of the neural network during learning and inference.
3. Activation Function of the Output Layer: Similar considerations to those of the input activation function apply to the output layer. The choice of activation function in the output layer plays a pivotal role in shaping the network's response during the learning and inference phases.
4. Learning Rate: The optimization of the backpropagation algorithm's performance is closely tied to the selection of the learning rate. Determining the optimal learning rate can be challenging for new users. This parameter, multiplied by the negative gradient, dictates the adjustments to weights and biases. A larger learning rate results in more

significant steps, but if it's too large, the algorithm becomes unstable. Conversely, setting the learning rate too small extends the convergence time of the algorithm. Striking the right balance is crucial for achieving efficient and stable learning.

**Table 3.5** Different activation function [43]

| Case | Name of activation function | Equation |
|---|---|---|
| 1 | Log sigmoid function (logsig) | $Y_i = \frac{1}{(1 + \exp(-neti)}$ |
| 2. | Tan hyperbolic function (tansig) | $Y_i = \tanh(neti)$ |
| 3. | Linear function (purelin) | $Y_i = (neti)$ |
| 4. | Radial basis function (radbas) | $Y_i = \exp[-(neti)^2]$ |
| 5. | Triangular basis function (tribas) | $Y_i = 1 - abs(neti) \;\; if -1 \leq (neti) \leq 1$ $otherwise, Y_i = 0$ |

* Yi is the output from node I, neti is the input to the node i = ΣWiXi

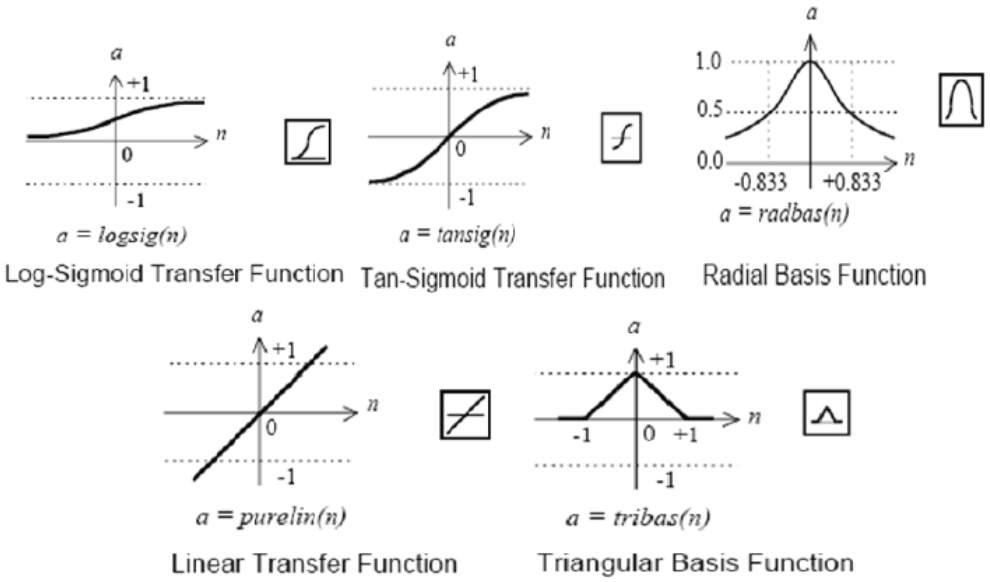



**Figure 3.4** Structure of different activation function [43]

In addition to the aforementioned four parameters, the performance of an Artificial Neural Network (ANN) is intricately linked to the choice of the training algorithm employed for backpropagation. Over time, researchers have developed numerous ANN training algorithms with the aim of minimizing execution time and computational storage demands. The literature showcases several distinct backpropagation training algorithms, as illustrated in **Figure 3.5** for this study.

Each algorithm comes with varying computation and storage requirements, and there is no one-size-fits-all solution. The fundamental distinctions lie in how these algorithms manage weights to minimize errors and adjust the learning rate to expedite convergence time. The selection of the most suitable algorithm depends on the specific requirements and characteristics of the application [43].

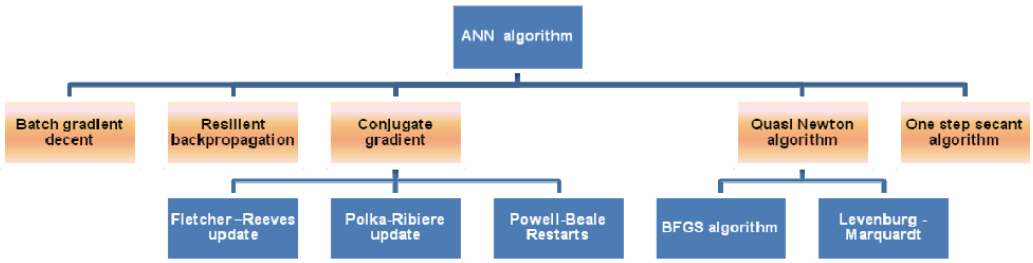



**Figure 3.5** Different ANN algorithms published in various literatures [43].

Many of the existing Artificial Neural Network (ANN) software applications necessitate user input for the four aforementioned parameters. For instance, in the Matlab toolbox, a two-layer feed-forward network might be configured with sigmoid activation for the hidden layer and linear activation for the output layer. Moreover, various training algorithms, such as Levenberg-Marquardt, are offered to users for optimizing the network's performance. This user-driven customization allows for flexibility in tailoring the ANN architecture and training process to suit the specific requirements of the application at hand.

### 3.5.4 Random Forest (RF)

Random forest (RF), an ensemble learning method proposed by Breiman [45], is widely regarded as one of the most effective machine learning algorithms for classification and regression tasks. RF enhances predictive performance by aggregating multiple decision trees (DTs) built on random subsets of the training data. Each tree is trained using a bootstrap sample, a process where subsets of the training data are randomly drawn with replacement. During the construction of each tree, a random subset of features is considered at each split, which helps in reducing variance and mitigating overfitting compared to a single DT model [45, 47]. The structure of RF involves constructing multiple trees in parallel and combining their predictions to make a final decision, as illustrated in **Figure 3.6**.

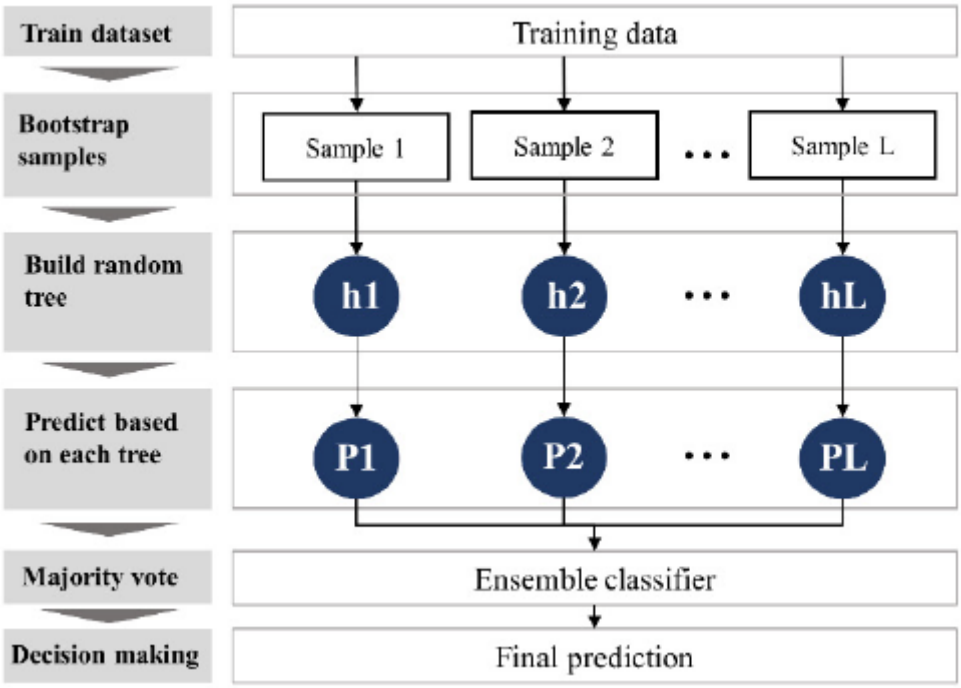



**Figure 3.6** Structure of the random forest (RF) algorithm [46]

The RF algorithm operates by aggregating predictions from multiple DTs to determine the final output. For classification tasks, the output class is determined by a majority vote among the individual trees, while for regression tasks, it is the average of all tree predictions [52]. This method of ensemble learning ensures that RF models are robust against noise and outliers and perform well even with imbalanced class distributions [46], [53].

RF's ability to handle large datasets with high dimensionality and its resistance to overfitting is well-documented. By increasing the number of trees, RF reduces the risk of overfitting and becomes less sensitive to outliers and noise in the data [53]. Additionally, RF has demonstrated superior predictive power in various applications, including waste management and other environmental studies, where it has been used to predict waste generation rates and other related metrics [53, 55].

Moreover, RF's flexibility extends to its hyperparameters, such as the number of trees (n_estimators) and the maximum depth of each tree (max_depth). Optimizing these parameters is crucial for enhancing model performance. Research suggests that careful tuning of these hyperparameters can significantly impact the accuracy and efficiency of RF models [55, 177, 178, 179, 180].

In summary, RF is a powerful ensemble technique that leverages multiple decision trees to improve predictive accuracy and robustness. Its capability to reduce overfitting and handle diverse datasets makes it a preferred choice for many machines learning tasks. By optimizing RF's hyperparameters, its performance can be further enhanced, making it an invaluable tool in both academic research and practical applications [45, 46, 47, 52, 53, 55].

### 3.5.5 Hybrid models

Efforts to test real-world data using hybrid models have increased significantly. Classical optimization algorithms initiate the search with an initial possible solution and iteratively progress towards the optimal solution. Nonetheless, the challenge of these algorithms getting trapped in local optimum solutions has been a persistent concern. To address this issue, various methods have been introduced, such as the integration of artificial neural networks with the grey wolf optimizer algorithm in a study conducted [181]. This section introduces a hybrid prediction model that combines metaheuristic techniques, specifically the Gray Wolf Optimization (GWO) algorithm and Archimedes Optimization Algorithm (AOA), with machine learning algorithms, namely Artificial Neural Network (ANN) and Random Forest (RF). Six models will be considered: ANN, RF, GWO-ANN, AOA-ANN, GWO-RF, and AOA-RF.

Improvement strategies have been used in various AI applications. A large portion of these applications fall into four principal classifications: 1) the selection of features, 2) the training of neural networks, 3) the improvement of support vector machines, and 4) the applications of clustering. The study's concept of a hybrid model will be feature selection (input combination) based on two criteria: minimizing RMSE and maximizing R. Highlight choice is one of the significant cycles in AI and information mining. The objective of element determination is to decrease the quantity of highlights, select the most agent ones, and dispose of excess, boisterous, and unimportant elements. The vast search space when the number of features is large makes the problem of finding the best set of features a complex and difficult one [139]. Finding the best input combination is the goal of the RF or ANN algorithm's training process. The four hybrid models have been proposed in this review. The four flowcharts of the proposed algorithms are shown

in **Figures 3.7, 3.8, 3.9, and 3.10**. The hybrid model is used to optimize the performance of the ANN and RF in terms of input selection and accuracy enhancement. The steps for integrating the GWO and AOA with the ANN and RF models are explained as follows:

**The GWO-ANN or GWO-RF Hybrid Model Steps**

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

**Step 2-**Feature Selection with GWO: Apply Grey Wolf Optimization (GWO) to select the optimal input feature combination.

**GWO Optimization Process are:**

1) Initialize GWO Parameters: Set the initial positions and parameters of the grey wolves.
2) Select Leadership Hierarchy: Identify the α (leader), β (second), and δ (third) wolves.
3) Iteration Process: Loop through iterations, evaluating the objective function.
4) Update Positions: Update the positions of grey wolves based on their interaction with α, β, and δ wolves.
5) 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 or RF parameters: Configure the architecture and parameters of the ANN or RF.

**Step 5-**Train ANN or RF: 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 and AOA-RF Hybrid Model Steps**

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

**Step 2-**Feature Selection with AOA: Use the Arithmetic Optimization Algorithm (AOA) to select the optimal input feature combination.

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

**AOA Optimization Process are:**

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

**Step 4-**Set ANN or RF parameters: Define the ANN or RF structure and parameters.

**Step 5-**Train ANN or RF: Train the ANN or RF 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 results are acceptable, end the process. Otherwise, return to AOA for further optimization.

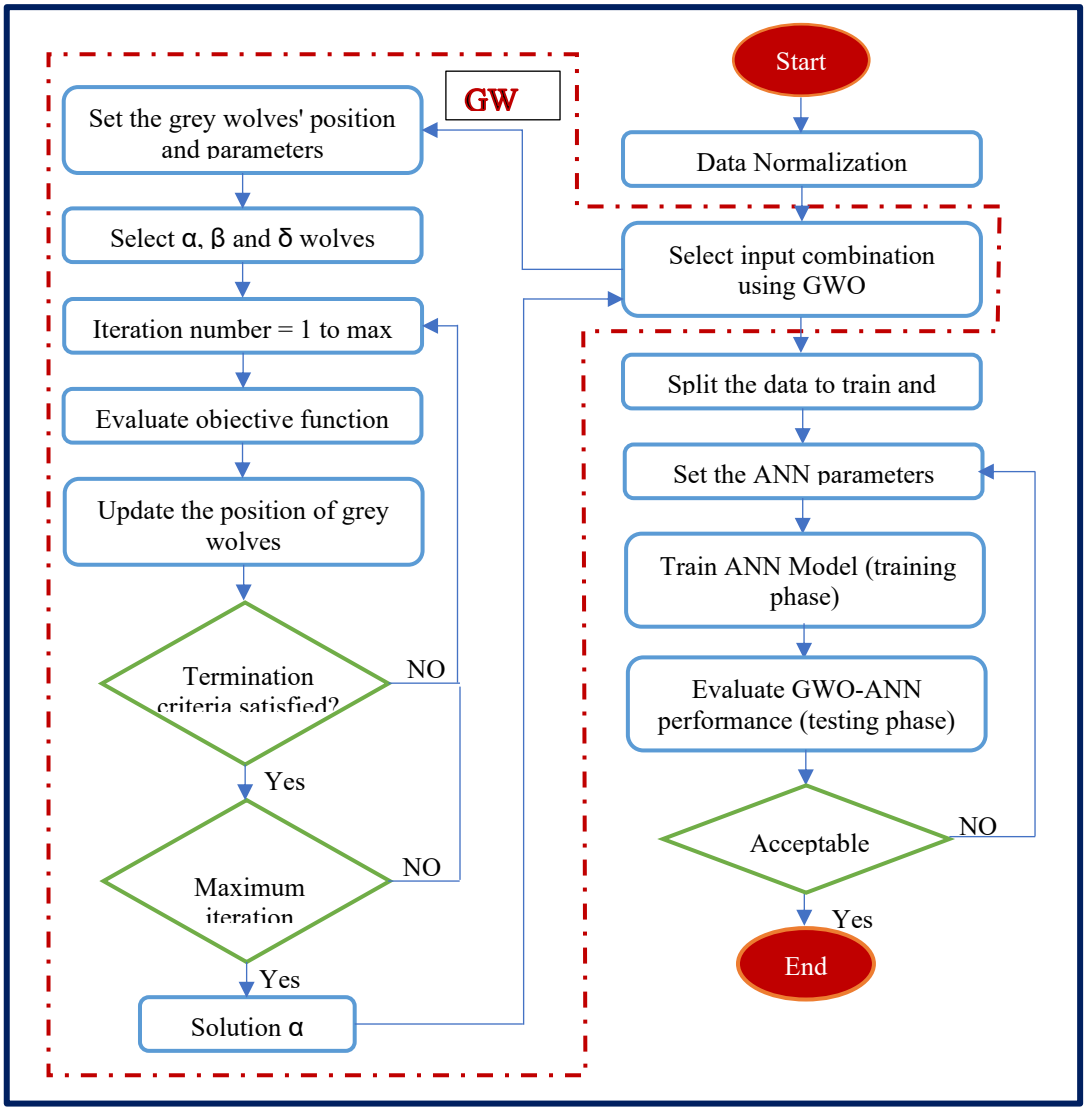



**Figure 3.7** The flowchart of the proposed GWO-ANN algorithm

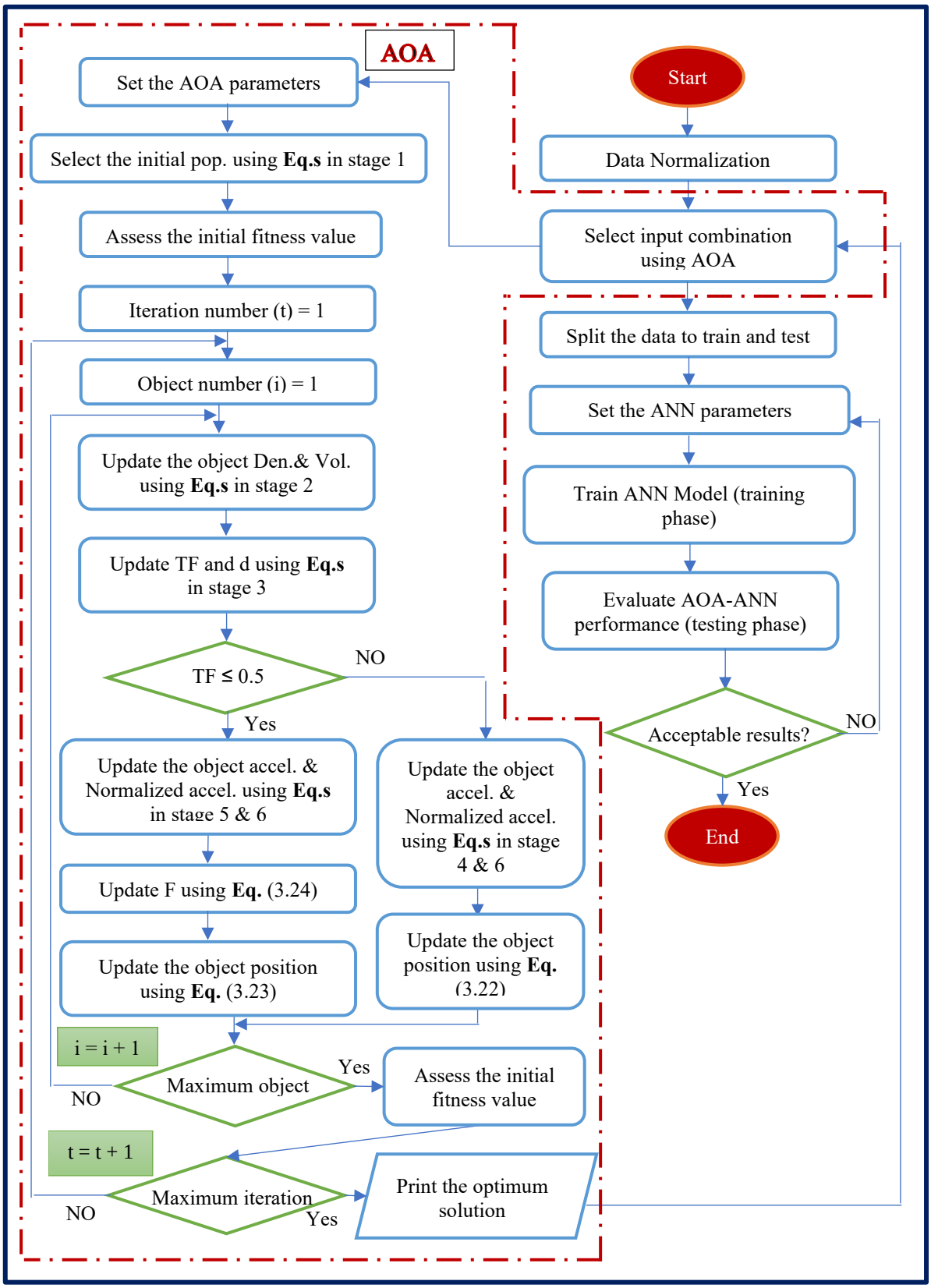



**Figure 3.8** The flowchart of the proposed AOA-ANN algorithm

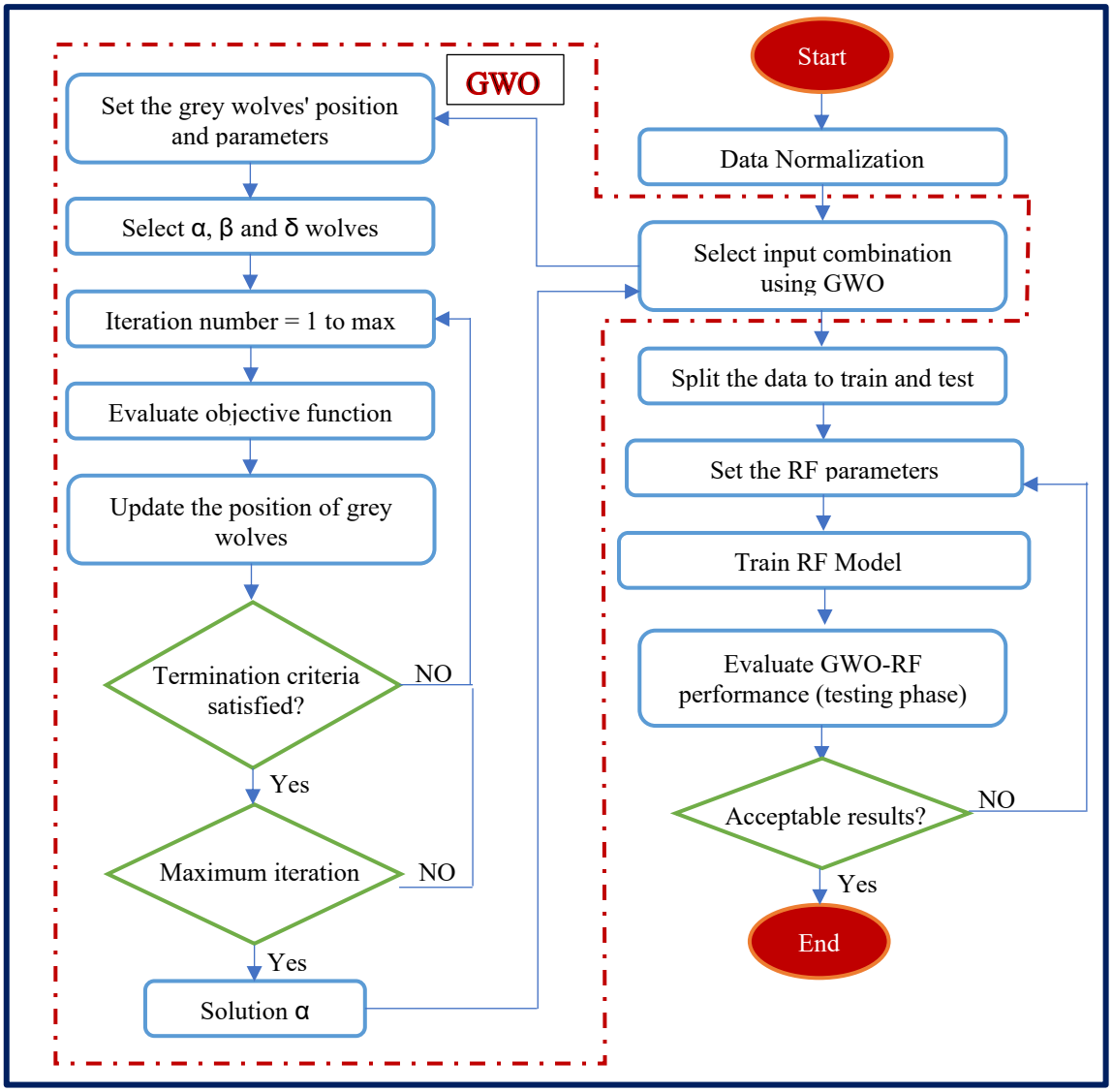



**Figure 3.9** The flowchart of the proposed GWO-RF algorithm

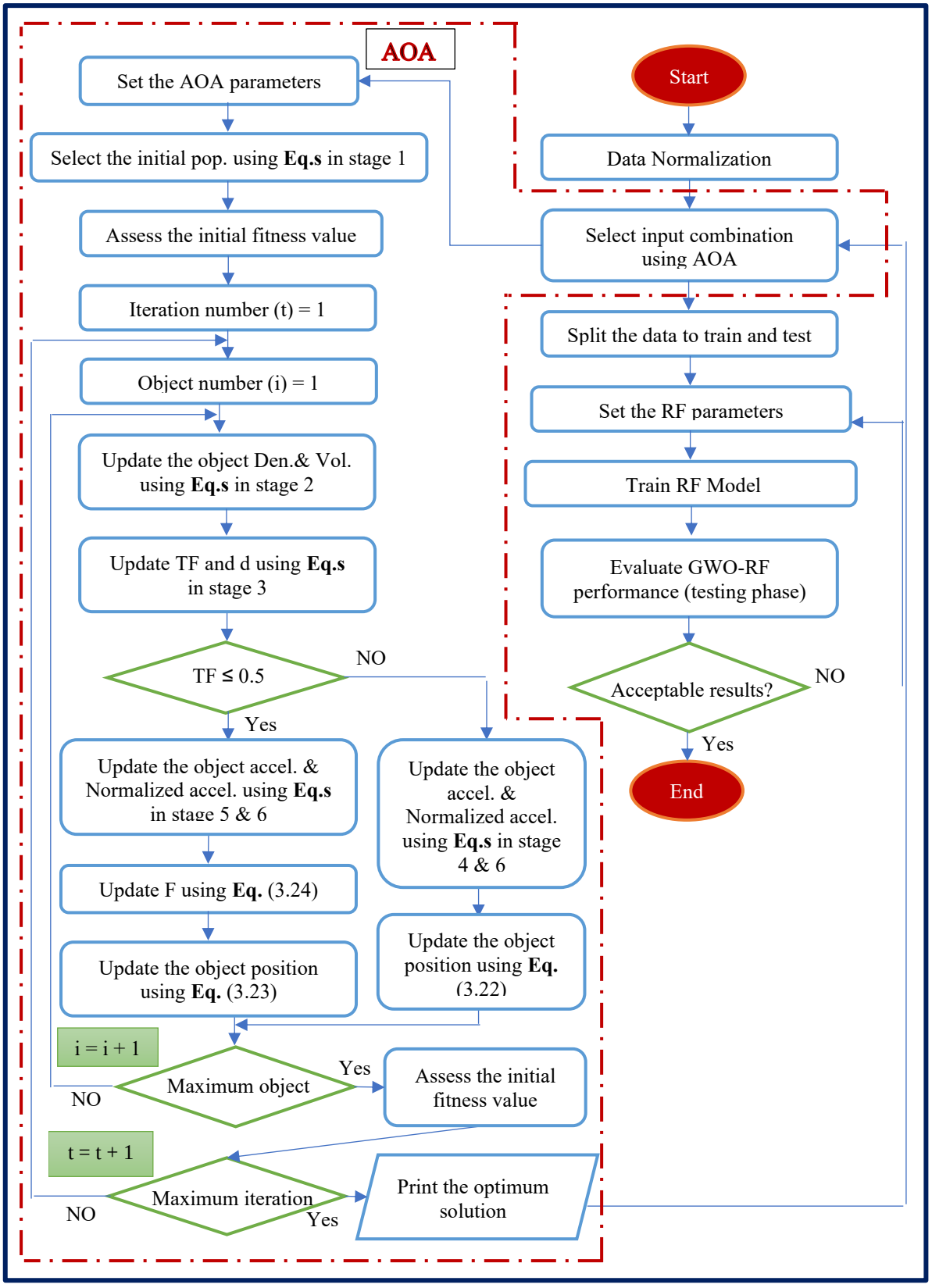



**Figure 3.10** The flowchart of the proposed AOA-RF algorithm

### 3.5.6 Required Parameter for Each Technique

Before using the GWO, AOA, ANN, and RF for prediction, it is essential to comprehend them. For this situation, every strategy required a rundown of data to begin demonstrating. The essential boundary settings of every calculation are displayed in **Table 3.6.**

**Table 3.6** Initial parameters of the meta-heuristic and machine learning algorithms

| Algorithm / model | Parameter's settings |
|---|---|
| GWO | Population size<br>Maximum iteration |
| AOA | Population size<br>Maximum iteration |
| ANN | Number of inputs<br>Number of outputs<br>Number of neurons in hidden layer<br>Training algorithm<br>Maximum iteration<br>Transfer function type for hidden and output layer |
| RF | N_estimators (The number of trees in the forest)<br>Min_samples_split (The minimum number of samples required to split an internal node)<br>Min_samples_leaf (The minimum number of samples required to be at a leaf node)<br>Max_depth (The maximum depth of the tree) |

## 3.6 Performance evaluation

In statistical analyses, the robust evaluation of performance among employed methods holds pivotal significance in achieving robust predictions. The research community employs a multitude of performance metrics for this purpose [182]. To gauge the efficacy of the developed models, diverse performance parameters such as MAE (Mean Absolute Error), RMSE (Root Mean Squared Error), MSE (Mean Squared Error), and the $R^2$ (Coefficient of Determination) were utilized, with their corresponding equations detailed in **Table 3.7**. In MAE, RMSE, and MSE, higher as well as lower accuracies are indicated by smaller and larger values, respectively [182]. Furthermore, R2 involves both values for performance assessment (both positive and negative). Positive values signify a direct correlation between documented and forecast values, while negative values suggest the contrary. A

perfect match is represented by values of −1 and 1, while 0 implies no connection between interpretations and expectations [170].

**Table 3.7** The performance criteria equation.

| Performance Metric | Min | Max | Equation |
|---|---|---|---|
| Mean absolute error (MAE) | 0 | +∞ | $MAE = \frac{1}{n}\sum_{i=1}^{n}\left\|A_{pi} - A_{ai}\right\|$ |
| Root mean squared error (RMSE) | 0 | +∞ | $RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(A_{pi} - A_{ai}\right)^2}$ |
| Mean squared error (MSE) | 0 | +∞ | $MSE = \frac{1}{n}\sum_{i=1}^{n}\left(A_{pi} - A_{ai}\right)^2$ |
| Coefficient of determination ($R^2$) | 0 | 1 | $R^2 = \left(\frac{\sum_{i=1}^{n}(A_{ai} - \overline{A_a})\sum_{i=1}^{n}\left(A_{pi} - \overline{A_p}\right)}{\sqrt{\sum_{i=1}^{n}(A_{ai} - \overline{A_a})^2 \sum_{i=1}^{n}\left(A_{pi} - \overline{A_p}\right)^2}}\right)^2$ |

Important Note: In the provided equations, $A_a$ represents the actual value, $A_p$ signifies the predicted value, and $\overline{A_a}$and $\overline{A_p}$denote the averages of actual and predicted values, respectively. The variable 'n' represents of all data points' number. The models in this study, exhibits the optimal $R^2$ and the minimal performance metric number will be chosen as the best.

# 4
# RESULTS AND DISCUSSION

## 4.1 Introduction

This chapter will discuss and present the findings of the research. The data that was gathered will be looked at. Demographic analysis, statistical analysis, sensitivity analysis, modeling, and discussion of field-collected results were all part of this chapter. A sum of 200 development and destruction projects had been examined utilizing (Succeed program). The projects were initiated and gathered from construction firms and ministers in the Gaza Strip, Palestine. A model for predicting the waste produced by construction and demolition projects in the Gaza Strip was developed using the Matlab R2021a program.

### 4.1.1 Data Analysis

The analysis of the data is a crucial section for understating the data's characteristics, frequency, percentage, relationships, and impact on waste quantities of each variable. The first step in dealing with the collected data, which includes information about the respondent, the type of project, the year of construction or demolition, the location of the project, the duration of construction or demolition (in months), the type of building, the total area of the building, the number of floors, and site access from the borders and the availability of wide highways, will be the demographic, statistical, and sensitivity analyses.

#### 4.1.1.1 Demographic Analysis

It is impossible to understate the significance of demographic data for a meaningful quantitative analysis. The respondents' general and background information was also sought. Because the research's focus is on the project's construction or demolition phases, it focused on experienced professionals who worked on project sites and oversaw the project because they are the most important members of the

construction team. The polls ought to be filled by encountered experts who just functioned as activities directors, site designers, or bosses.

The data in **Table 4.1** reveals that 20% of the surveyed individuals work as site engineers, while the remaining 80% hold roles as project managers, bringing with them considerable experience in construction and demolition projects. In terms of years of work experience, 39%, 50%, 10%, and 1% fall into the categories of 5 to 10, 11 to 20, 21 to 30, and 31 to 40 years, respectively. Notably, a significant majority, comprising 50%, boasts "more than 11 years" of experience in the construction industry. These respondents are employed either in public organizations like the Ministry of Public Works and Housing or in private construction companies. The distribution reveals that 46% are associated with public organizations, while 54% are part of private entities. The focal point of the research, the construction and demolition project, shows that 80% of respondents are involved in construction projects, with the remaining 20% engaged in demolition projects. **Table 4.1** succinctly presents these characteristics of the respondents.

**Table 4.1** Demographic analysis of respondents

| Aspect | Category | Frequency of respondent | frequency of project | Percentage |
|---|---|---|---|---|
| **Position** | Site engineer | 7 | 40 | 20% |
| | Project manager | 13 | 160 | 80% |
| **years of experience** | 5-10 | 7 | 78 | 39% |
| | 11-20 | 10 | 100 | 50% |
| | 21-30 | 2 | 20 | 10% |
| | 31-40 | 1 | 2 | 1% |
| **Type of projects** | Construction | 16 | 160 | 80% |
| | Demolition | 4 | 40 | 20% |
| **Type of Organization** | Public | 9 | 92 | 46% |
| | Private | 11 | 108 | 54% |

#### 4.1.1.2 Statistical Analysis

In this segment, the measurable examination for 200 development and destruction ventures will be addressed. In the wake of gathering projects, the modification was executed to distinguish the precise factors. Each task has the streaming factors which are a measure of waste (as no. of Trucks), type of the project (building or

destruction), year of beginning the project, location, duration of building/destruction (by month), building use (type of building), all area of the structure, number of floors and site access. These factors were used in past studies as seen in **Table 3.2**. The quantity of waste (as of Trucks) was identified as the model's output and given the abbreviation Oi; the remaining variables were identified as the model's input and given the names P1, P2, P3, P4, P5, P6, P7, and P8, as shown in **Table 4.2** and **Figure 4.1.** This study incorporated various descriptive statistical measures, such as the minimum, mean, maximum, standard deviation, and sample variance.

**Table 4.2** Statistical Details of the construction and demolition projects

| Item | Symbol | Min | Average | Max | Standard Deviation | Sample Variance |
|---|---|---|---|---|---|---|
| **Amount of Waste (No. of Trucks)** | Oi | 1 | 80 | 810 | 166.55 | 27738.62 |
| **Year of project** | P2 | 2010 | 2018 | 2023 | 3.42 | 11.72 |
| **Duration of project (Month)** | P4 | 0.5 | 10 | 36 | 6.54 | 42.71 |
| **Total Area of the Building** | P6 | 200 | 5245 | 27000 | 4949.11 | 24493672.28 |
| **Number of floors** | P8 | 1 | 4.59 | 15 | 3.06 | 9.37 |

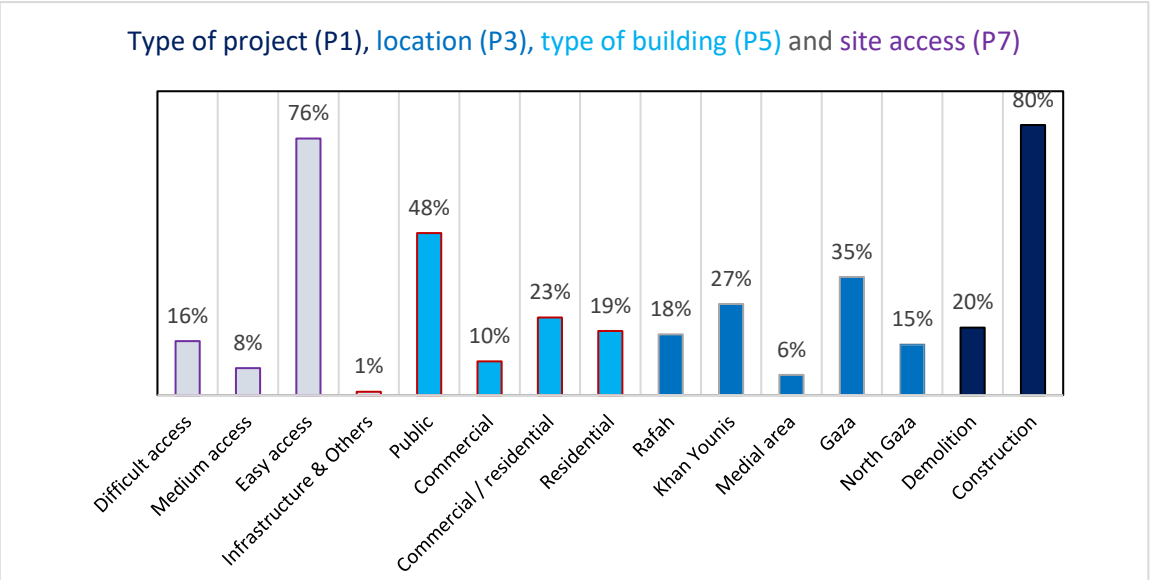



**Figure 4.1** Statistical analysis for investigated projects

#### 4.1.1.3 Data Encoding Scheme

Certain variables required coding due to their non-numerical nature. For instance, site access was coded as 1, 2, and 3, representing easy access, medium ease of access, and difficult access from the borders, considering the availability of wide highways. In preparation for developing the hybrid model, other variables will undergo encoding in the subsequent step, streamlining the data for further analysis.

In this section, we delve into the method employed to transform input data for precise system modeling, detailed in **Table 4.3**. Artificial Intelligence models exclusively handle numeric input data. Consequently, the initial data frequently requires conversion from the external environment to a numeric format [183]. This process can pose challenges as there are various methods available, and regrettably, some methods prove more effective than others.

**Table 4.3** Real-Life Data Field Encoding Scheme

| Item | Category | Code | Frequency | percentage |
|---|---|---|---|---|
| **Type of project** | Construction | 1 | 160 | 80% |
| | Demolition | 2 | 40 | 20% |
| **Starting year of the project** | 2010 | 1 | 1 | 1% |
| | 2011 | 2 | 5 | 3% |
| | 2013 | 3 | 5 | 3% |
| | 2014 | 4 | 22 | 11% |
| | 2015 | 5 | 19 | 10% |
| | 2016 | 6 | 34 | 17% |
| | 2017 | 7 | 6 | 3% |
| | 2018 | 8 | 4 | 2% |
| | 2019 | 9 | 10 | 5% |
| | 2020 | 10 | 14 | 7% |
| | 2021 | 11 | 23 | 12% |
| | 2022 | 12 | 50 | 25% |
| | 2023 | 13 | 7 | 4% |
| **location** | North Gaza | 1 | 30 | 15% |
| | Gaza | 2 | 70 | 35% |
| | Medial area | 3 | 12 | 6% |
| | Khan Younis | 4 | 53 | 27% |
| | Rafah | 5 | 35 | 18% |
| **Duration of the project (Month)** | 0.5 | | 1 | 1% |
| | 1 | | 5 | 3% |
| | 1.5 | | 4 | 2% |
| | 2 | | 11 | 6% |

**Table 4.3** Real-Life Data Field Encoding Scheme (continued)

| Item | Category | Code | Frequency | percentage |
|---|---|---|---|---|
| **Duration of the project (Month)** | 2.5 | | 4 | 2% |
| | 3 | | 13 | 7% |
| | 3.5 | | 2 | 1% |
| | 4 | | 10 | 5% |
| | 5 | | 5 | 3% |
| | 6 | | 6 | 3% |
| | 7 | | 1 | 1% |
| | 8 | | 5 | 3% |
| | 9 | | 1 | 1% |
| | 10 | | 3 | 2% |
| | 11 | | 29 | 15% |
| | 12 | | 55 | 28% |
| | 13 | | 17 | 9% |
| | 14 | | 11 | 6% |
| | 16 | | 4 | 2% |
| | 18 | | 3 | 2% |
| | 20 | | 3 | 2% |
| | 24 | | 1 | 1% |
| | 36 | | 6 | 3% |
| **Type of building** | Residential | 1 | 37 | 19% |
| | Commercial / residential | 2 | 46 | 23% |
| | Commercial | 3 | 19 | 10% |
| | Public | 4 | 96 | 48% |
| | Infrastructure & Others | 5 | 2 | 1% |
| **Total Area of Building** | 200-1000 | 0.2-1 | 14 | 7% |
| | 1001-2500 | 1.001-2.5 | 23 | 12% |
| | 2501-5000 | 2.501-5 | 26 | 13% |
| | 5001-7500 | 5.001-7.5 | 18 | 9% |
| | 7501-10000 | 7.501-10 | 8 | 4% |
| | 10001-20000 | 10.001-20 | 9 | 5% |
| | 20001-27000 | 20.001-27 | 2 | 1% |
| **Number of floors** | 1 | | 24 | 12% |
| | 2 | | 14 | 7% |
| | 3 | | 58 | 29% |
| | 4 | | 16 | 8% |
| | 5 | | 32 | 16% |
| | 6 | | 26 | 13% |
| | 7 | | 0 | 0% |
| | 8 | | 8 | 4% |
| | 9 | | 12 | 6% |
| | 10 | | 2 | 1% |

**Table 4.3** Real-Life Data Field Encoding Scheme (continued)

| Item | Category | Code | Frequency | percentage |
|---|---|---|---|---|
| **Number of floors** | 15 | | 8 | 4% |
| **Site access from the borders and the availability of wide highways** | Easy access | 1 | 152 | 76% |
| | Medium | 2 | 16 | 8% |
| | Difficult | 3 | 32 | 16% |

### 4.1.2 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 the GWO, AOA, RF, and ANN for prediction, it is essential to comprehend them. For this situation, every strategy required a rundown of data to begin demonstrating. The essential boundary settings of each calculation are listed in **Table 4.4**.

**Table 4.4** Initial parameters of the meta-heuristic and machine learning algorithms

| Algorithm / model | Parameter's settings | Value |
|---|---|---|
| **GWO** | Number of agents<br>Maximum iteration | 30<br>10 |
| AOA | Population size<br>Maximum iteration | 30<br>10 |
| **ANN** | Number of inputs<br>Number of hidden layers<br>Number of outputs<br>Number of nodes in hidden layer<br>Algorithm for training<br><br>Maximum iteration<br>Transfer function type for hidden and output layers | 8<br>1<br>1<br>10<br>Levenberg-Marquardt backpropagation algorithm<br>1000<br>Sigmoid and linear function |
| **FR** | N_estimators (The number of trees in the forest)<br>Min_samples_split (The minimum number of samples required to split an internal node)<br>Min_samples_leaf (The minimum number of samples required to be at a leaf node)<br>Max_depth (The maximum depth of the tree) | 100<br><br>2<br><br>1<br><br>Maximum possible |

### 4.1.3 Analysis of Models

#### 4.1.3.1 The Performance of Stand-Alone Predictive Models and Results

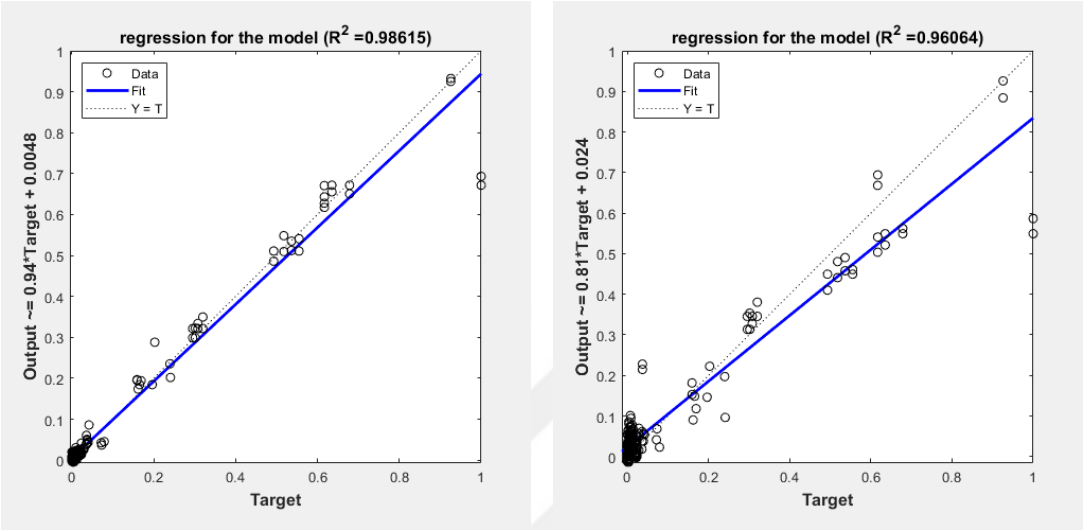
The stand-alone proposed ANN and its comparable RF predictive model was applied on the data. The stand-alone proposed ANN with 10 and 17 nodes in the hidden layer were applied on the data. **Table 4.5** presents the performance prediction indicators using all chosen inputs. After analyzing the model, it was found that the best number of hidden nodes in ANN models was different from the number used in previous studies [136, 184], which is twice the number of inputs plus one. It is observable that the ANN with 10 nodes exceeded the ANN with 17 nodes and RF models in terms of prediction skills (minimum error). ANN with 10 nodes achieved (i.e., MAE, RMSE, and MSE) of (0.012322, 0.034859 and 0.0012152) and (i.e., $R^2$) of (0.98615) in quantitative terms. RF model achieved (i.e., MAE, RMSE, and MSE) of (0.048649, 0.11123 and 0.012372) and (i.e., $R^2$) of (0.82652) in quantitative terms. There is a notable improvement between the proposed and predominated data-intelligence ANN (with 10 nodes) predictive model. A scatter plot was included to illustrate the variation between the actual and predicted waste generation amount for the stand-alone ANN and RF models. A scatter plot is a type of plot or mathematical diagram using Cartesian coordinates to display values for typically two variables for a set of data by using the MATLAB R2021a. This study used the scatter plot to present Predicted waste generation in the y-axis and Actual data in the x-axis. Where the Black point represent the relation between Predicted and Actual data for case training.

**Table 4.5** The evaluation of ANN and RF models during the testing modeling phase.

| Model | MAE | MSE | $R^2$ | RMSE |
|---|---|---|---|---|
| **ANN with 10 nodes** | 0.012322 | 0.0012152 | 0.98615 | 0.034859 |
| **ANN with 17 nodes** | 0.036166 | 0.003871 | 0.96064 | 0.062217 |
| **RF** | 0.048649 | 0.012372 | 0.82652 | 0.11123 |

**Figure (4.2)** and **Figure (4.3)** demonstrate (scatter plot) the relation between predicted waste amount and actual by selective trials utilizing performance criteria equations in **Table 3.7** to achieve the best model expression for the coefficient of determination ($R^2$) value and the line formula. The first graph refers to using ANN models (10 and 17 nodes in the hidden layer) to represent the variables, $R^2$ value

was (0.98615 and 0.96064 respectively), while Figure (4.3) refers to using RF model to represent the Variables, $R^2 = 0.82652$, where the determination coefficient ($R^2$) has a value ranging from 0 to 1. $R^2$ values near to one presented that data variation explained clearly by the input data. In contrast, far values from one and near zero indicate that the data variation is not explained clearly by the input data.




ANN with 10 nodes ANN with 17 nodes

**Figure 4.2** The scatter graphical plot for the stand-alone ANN models.

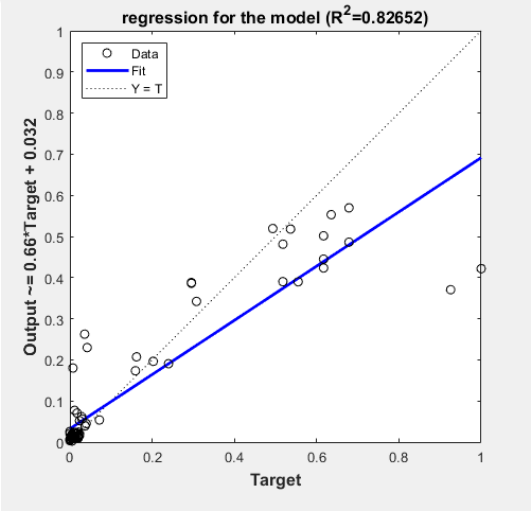



**Figure 4.3** The scatter graphical plot for the stand-alone RF models.

**Figure (4.4)** presents the spider diagram and scatter chart for the top-performing stand-alone models tested on the dataset. Also, it provides a comprehensive comparison of various models. The evaluation is based on several performance metrics: mean absolute error (MAE), root mean squared error (RMSE), and mean squared error (MSE). The figure clearly illustrates that the using of the ANN model

with 10 nodes gives a better determination coefficient (R2) and prediction skills (minimum error) than the other models.

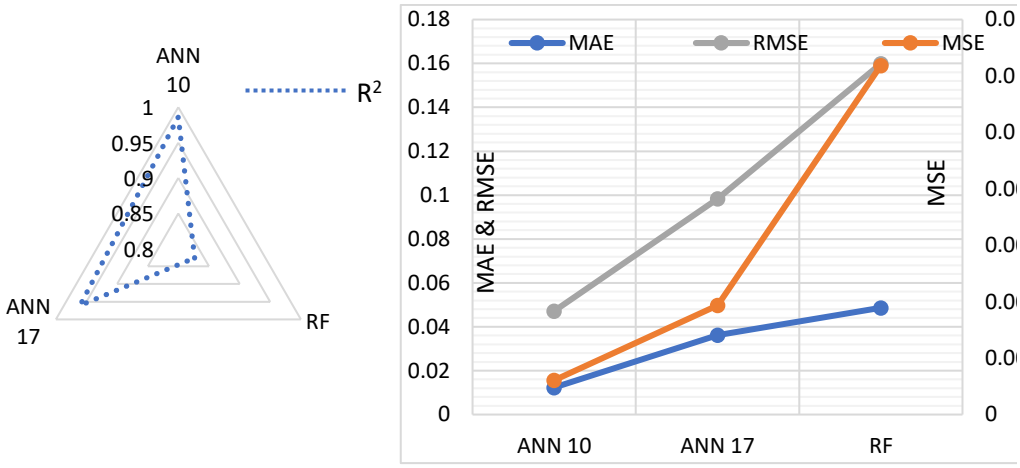



**Figure 4.4** Comprehensive performance analysis of stand-alone models for testing datasets.

### 4.1.3.2 The Performance of Hybrid Predictive Models

The integration of the input selection approach into the predictive model stems from a desire to uncover the primary input combinations that correlate with the magnitude of waste generated. It is of significant importance to identify the key variables that influence the variance in waste amount results. The hybridization of the nature-inspired algorithm with the AI model facilitates the extraction of appropriate input combinations. Concurrently, the selection procedure serves as a benchmark for comparing the performance of the algorithm.

**Table 4.6** presents the input combinations results of the hybrid model (based-ANN). Examining the recorded modeling outcomes in **Table 4.7**, Model 5 (AOA-ANN model) demonstrated an outstanding input combination for waste amount prediction by incorporating (P6, P1, P5, P2, and P8 or total building area, type of project, type of building, starting year of the project, and number of floors respectively) variables into the prediction matrix. The results revealed minimal absolute error metrics (e.g., MAE, RMSE, and MSE) (0.0086648, 0.023728, and 0.00056304) and an $R^2$ value of (0.99333). Contrastingly, the hybrid (GWO-ANN) model exhibited distinct behavior, with (7 of inputs) input variables encapsulating (P5, P2, P4, P8, P6, P3, and P1 or type of building, starting year of the project, duration of project, site access, total building area, location, and type of project

respectively) prediction skills and achieving a minimum MAE, RMSE, and MSE of approximately 0.012154, 0.029205, and 0.00085292. It is noteworthy that AOA-ANN (model 5) outperformed the GWO-ANN (model 7) model, albeit with a greater number of features, enhancing its ability to comprehend the internal mapping relationship between predictors and predictions.

**Table 4.6** The combination of input used in the hybrid model (based-ANN)

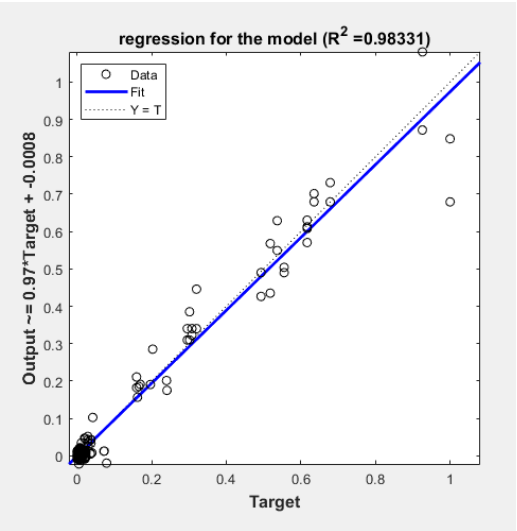
| No. | Models | Input / Variable | |
|---|---|---|---|
| | | **GWO-ANN** | **AOA-ANN** |
| 1 | Model 1 | P5 | P4 |
| 2 | Model 2 | P6, P2 | P6, P1 |
| 3 | Model 3 | P4, P8, P5 | P8, P1, P3 |
| 4 | Model 4 | P5, P2, P1, P4 | P8, P6, P7, P1 |
| 5 | Model 5 | P7, P8, P6, P1, P2 | P6, P1, P5, P2, P8 |
| 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 4.7** The evaluation for the hybrid model (based-ANN) through the testing modelling phase

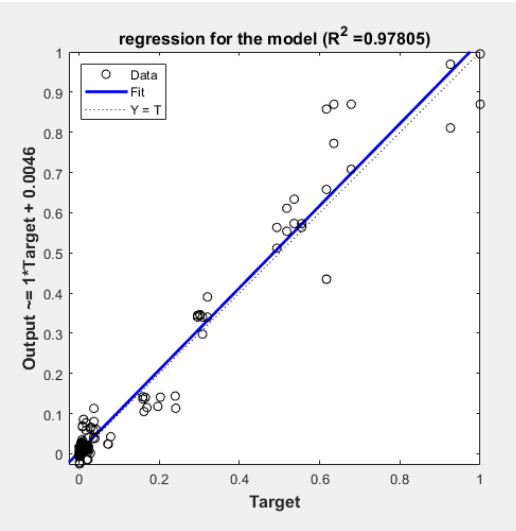
| | Model | MAE | MSE | $R^2$ | RMSE |
|---|---|---|---|---|---|
| GWO-ANN | **Model 1** | 0.019014 | 0.0014154 | 0.98331 | 0.037622 |
| | **Model 2** | 0.02301 | 0.0020101 | 0.97686 | 0.044834 |
| | **Model 3** | 0.014414 | 0.0012981 | 0.98495 | 0.036029 |
| | **Model 4** | 0.028611 | 0.002881 | 0.96748 | 0.053675 |
| | **Model 5** | 0.015772 | 0.0014574 | 0.98409 | 0.038177 |
| | **Model 6** | 0.03422 | 0.0039633 | 0.95306 | 0.062955 |
| | **Model 7** | **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** | **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 |

An excellent means of visualizing the correlation between actual observations and predicted values was provided by utilizing a spider diagram and scatter plot graphical displays. **Figure (4.5)** presented deviations from the ideal 45-degree line, revealing a declared agreement favoring the hybrid (AOA-ANN) model over the hybrid (GWO-ANN) model. Besides, by selective performance criteria equations in **Table 3.7** to achieve the best model expression for the coefficient of

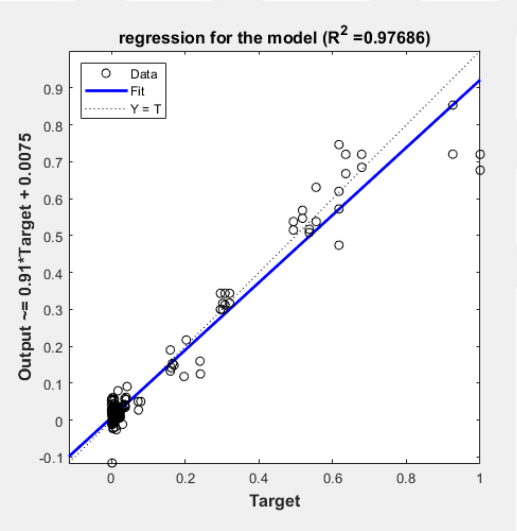
determination ($R^2$) and the line formula. The using of AOA-ANN (model 5) gives $R^2 = 0.99333$ and line formula ($y = 0.99x + 0.0014$).



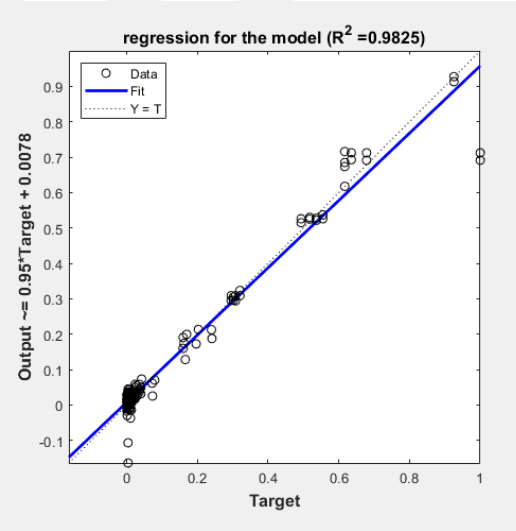

Model 1 GWO-ANN




Model 1 AOA-ANN

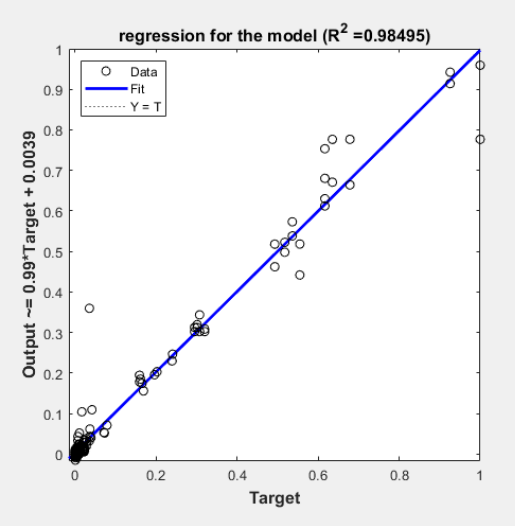



Model 2 GWO-ANN

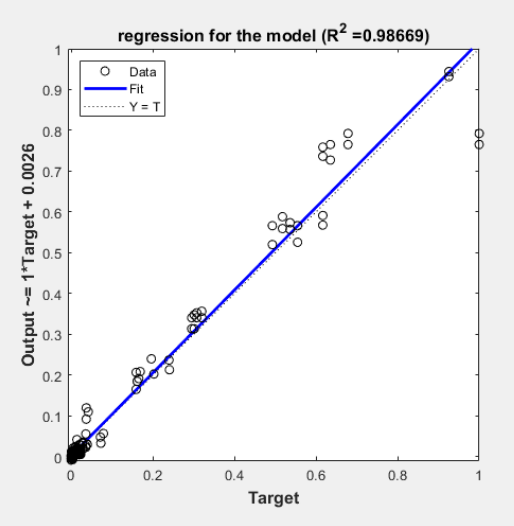



Model 2 AOA-ANN

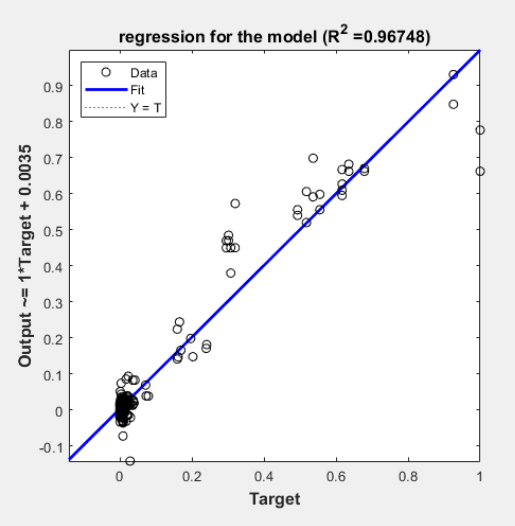
**Figure 4.5** The (scatter plot) graphical visualization for the intelligence predictive (based-ANN) model.



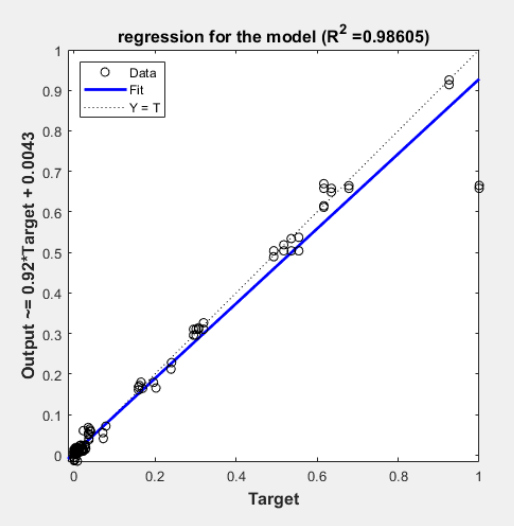

Model 3 GWO-ANN



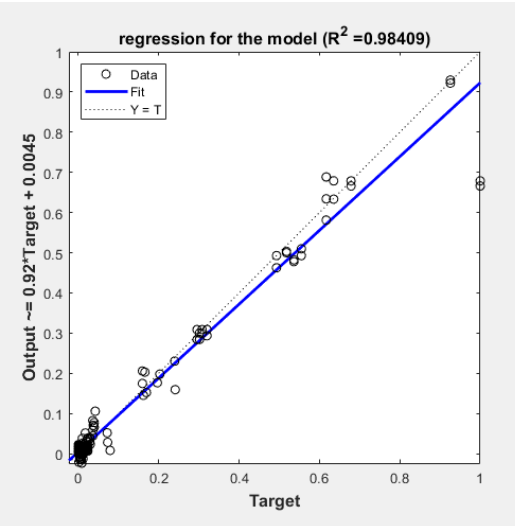

Model 3 AOA-ANN



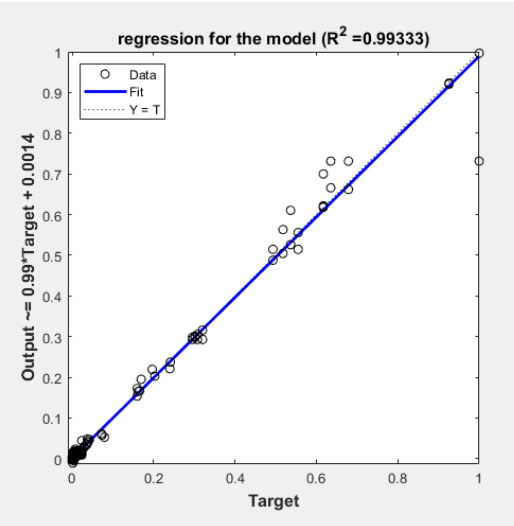

Model 4 GWO-ANN




Model 4 AOA-ANN

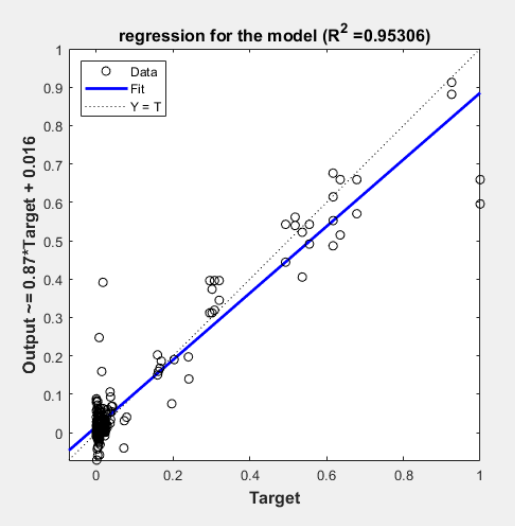



Model 5 GWO-ANN

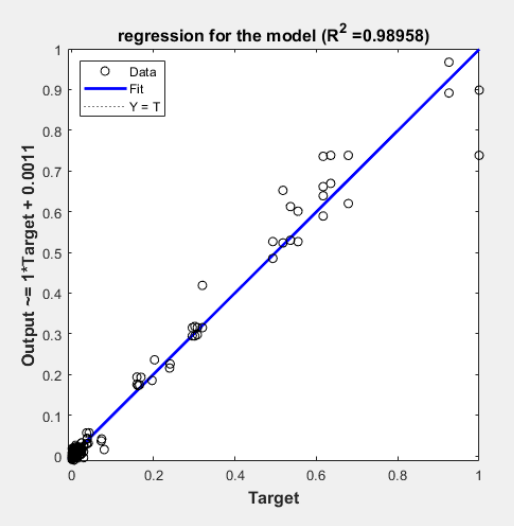



Model 5 AOA-ANN

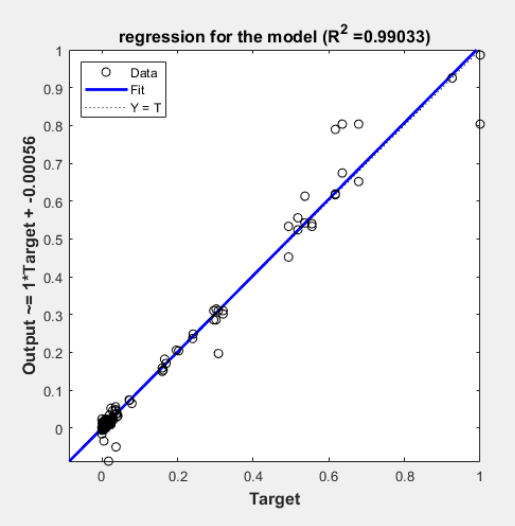
**Figure 4.5** The (scatter plot) graphical visualization for the intelligence predictive (based-ANN) model. (continued)



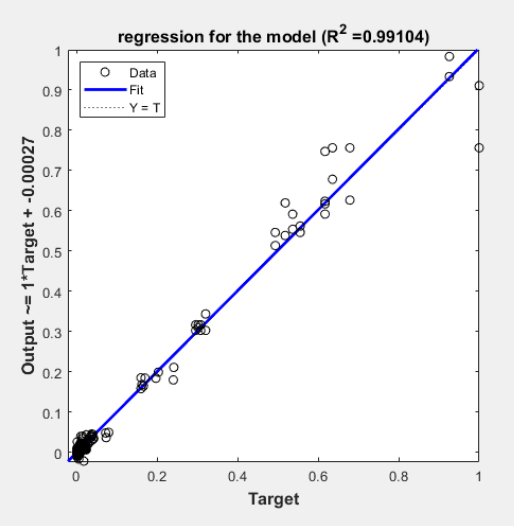

Model 6 GWO-ANN




Model 6 AOA-ANN




Model 7 GWO-ANN




Model 7 AOA-ANN

**Figure 4.5** The (scatter plot) graphical visualization for the intelligence predictive (based-ANN) model. (continued)

**Figures 4.6** and **4.7** present the comprehensive performance analysis in chart and diagram for the traditional ANN and hybrid based-ANN models for the tested 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. The evaluation is based on several performance metrics: MAE, RMSE, MSE, and $R^2$.

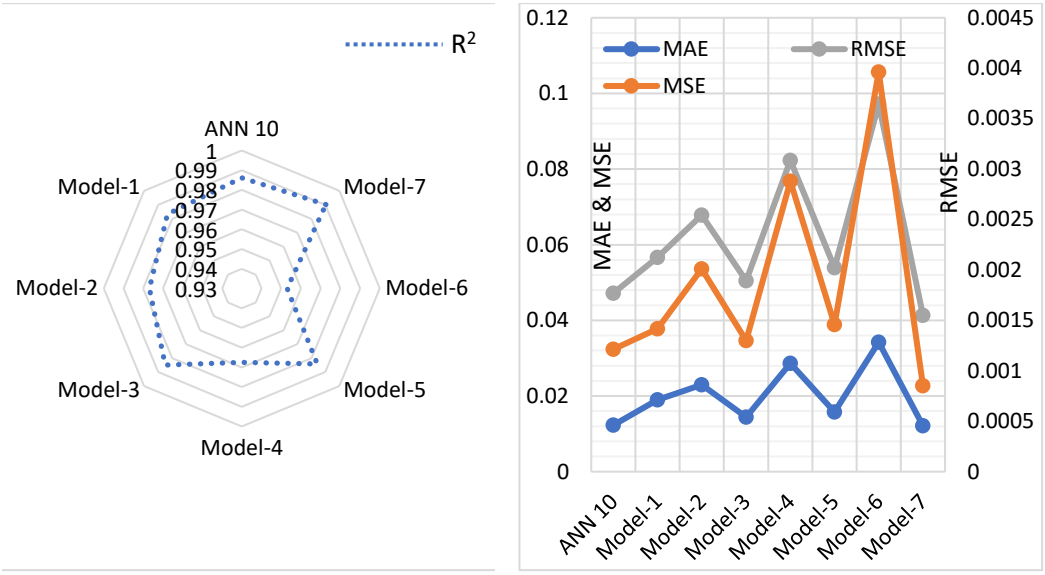



**Figure 4.6** Comprehensive performance analysis of GWO-ANN models for testing datasets

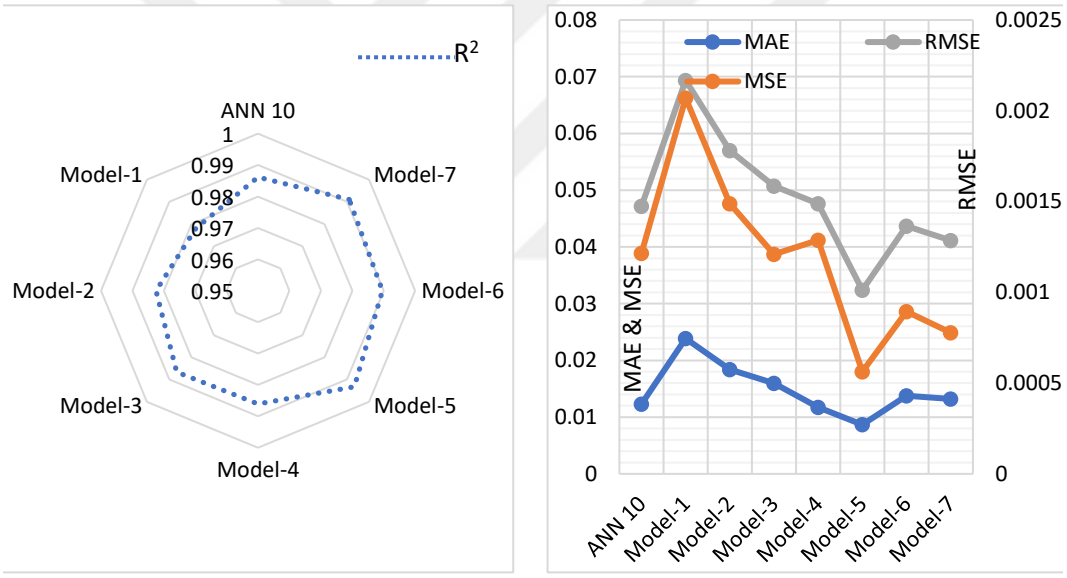



**Figure 4.7** Comprehensive performance analysis of AOA-ANN models for testing datasets

The figures clearly illustrate that the AOA-ANN model significantly outperforms the other models across 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 4.8** presents the input combinations results of the hybrid model (based-RF). Examining the recorded modeling outcomes in **Table 4.9**, Model 4 (GWO-RF) demonstrated an outstanding input combination for waste amount prediction by

incorporating (P1, P2, P5, P8 or type of project, starting year of the project, type of building, and number of floors respectively) variables into the prediction matrix. The results revealed minimal absolute error metrics (e.g., MAE, RMSE, and MSE) (0.016067, 0.047611, and 0.0022668) and an $R^2$ value of (0.94174). Contrastingly, the hybrid (AOA-RF) model exhibited distinct behavior (**Tables 4.8, 4.9** and **4.10**), with (4 of inputs) input variables encapsulating (P8, P1, P6, P5 or number of floors, type of project, total building area, and type of building respectively) prediction skills and achieving a minimum MAE, RMSE, and MSE of approximately 0.029932, 0.075303, and 0.0056706. It is noteworthy that GWO-RF (model 4) outperformed the AOA-RF (model 4) model, albeit with a greater number of features, enhancing its ability to comprehend the internal mapping relationship between predictors and predictions.

**Table 4.8** The combination of input used in the hybrid model (based-RF)

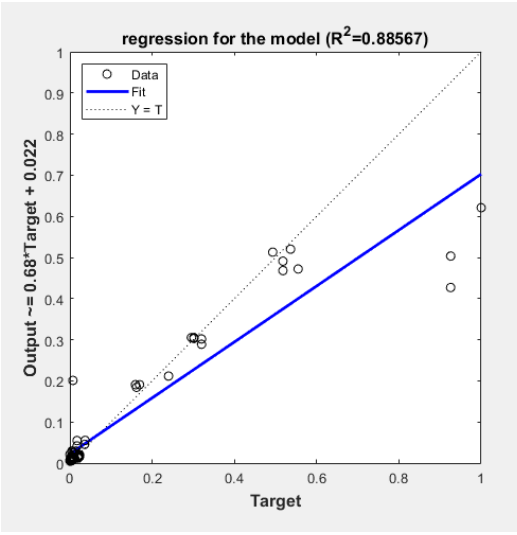
| No. | Models | Input / Variable | |
|---|---|---|---|
| | | **GWO-RF** | **AOA-RF** |
| 1 | Model 1 | P3 | P1 |
| 2 | Model 2 | P2, P6 | P3, P5 |
| 3 | Model 3 | P4, P7, P6 | P3, P4, P2 |
| 4 | Model 4 | P1, P2, P5, P8 | P8, P1, P6, P5 |
| 5 | Model 5 | P4, P7, P8, P3, P5 | P1, P3, P6, P5, P2 |
| 6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

An excellent means of visualizing the correlation between actual observations and predicted values was provided by utilizing scatter plot graphical displays. **Figure 4.8** presented deviations from the ideal 45-degree line, revealing a declared agreement favoring the hybrid (GWO-RF) model over the hybrid (AOA-RF) model. Besides, by selective performance criteria equations in **Table 3.8** to achieve the best model expression for the coefficient of determination ($R^2$) value and the line formula. The using of GWO-RF (model 4) gives $R^2$ value = 0.94174 and line formula ($y = 0.84x + 0.012$).

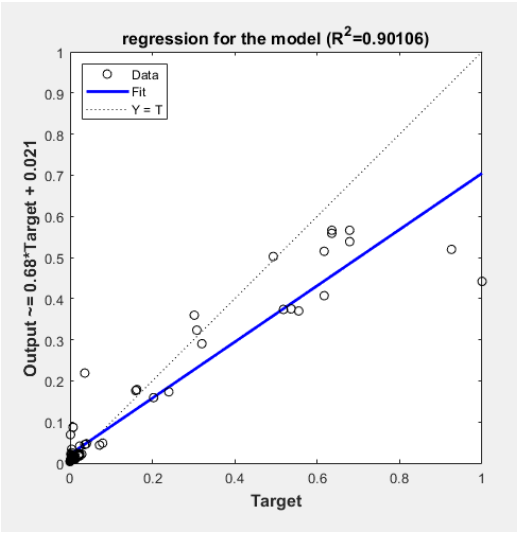
**Table 4.9** The evaluation for the hybrid model (based-RF) through the testing modelling phase

| | Model | MAE | MSE | $R^2$ | RMSE |
|---|---|---|---|---|---|
| GWO-RF | **Model 1** | 0.029048 | 0.00797 | 0.88567 | 0.089275 |
| | **Model 2** | 0.023439 | 0.0032477 | 0.90012 | 0.056989 |
| | **Model 3** | 0.034946 | 0.0077314 | 0.86356 | 0.087929 |
| | **Model 4** | **0.016067** | **0.0022668** | **0.94174** | **0.047611** |
| | **Model 5** | 0.04797 | 0.011932 | 0.73868 | 0.10923 |
| | **Model 6** | 0.02547 | 0.0035965 | 0.91717 | 0.05997 |
| | **Model 7** | 0.043899 | 0.013441 | 0.80732 | 0.11594 |
| AOA-RF | **Model 1** | 0.040773 | 0.0091521 | 0.90106 | 0.095666 |
| | **Model 2** | 0.027183 | 0.0056528 | 0.88195 | 0.075185 |
| | **Model 3** | 0.049194 | 0.014184 | 0.72056 | 0.1191 |
| | **Model 4** | **0.029932** | **0.0056706** | **0.91864** | **0.075303** |
| | **Model 5** | 0.042667 | 0.010102 | 0.89378 | 0.10051 |
| | **Model 6** | 0.027544 | 0.0055455 | 0.89959 | 0.074468 |
| | **Model 7** | 0.030735 | 0.0052911 | 0.8397 | 0.07274 |

**Figure 4.9** and **Figure 4.10** present the comprehensive performance analysis in chart and diagram for the hybrid based-RF models for the tested dataset. The diagrams reveal that the hybrid RF model with GWO algorithms provides the most accurate predictions, with model 4 showing the highest performance among the models. Additionally, among the hybrid RF models using AOA algorithms, AOA-RF model 4 exhibits the best predictive ability compared to the other AOA-RF models.

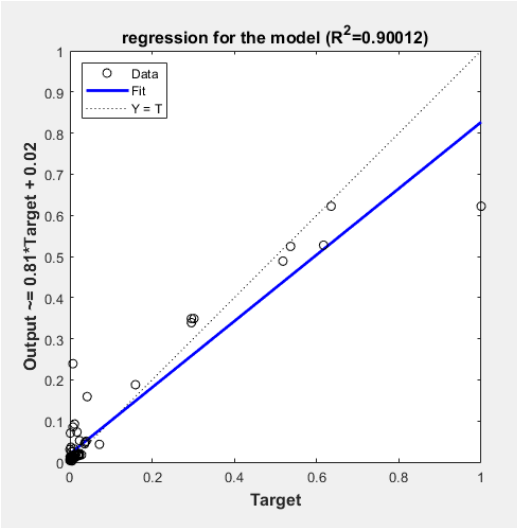



Model 1 GWO-RF

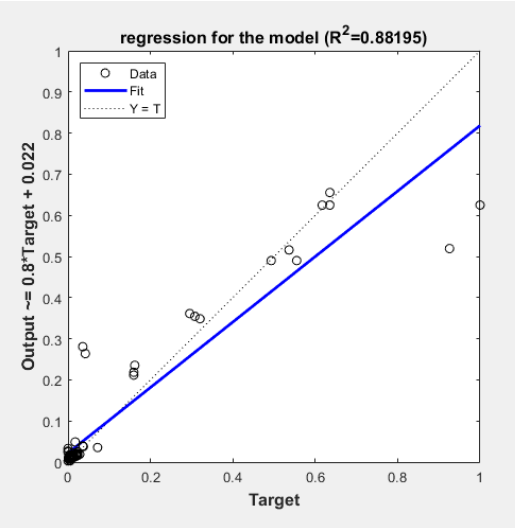



Model 1 AOA- RF

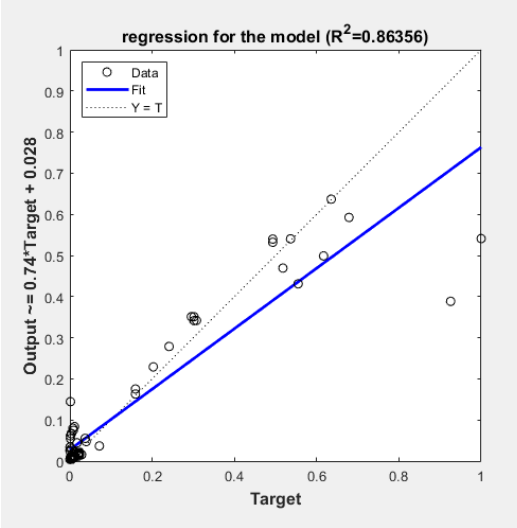
**Figure 4.8** The (scatter plot) graphical visualization for the intelligence predictive (based-RF) model.



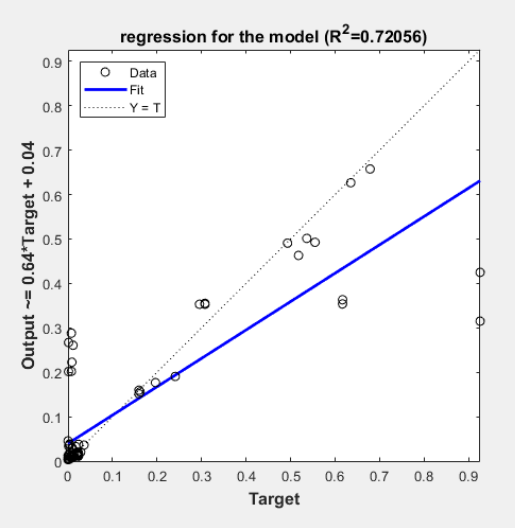

Model 2 GWO- RF



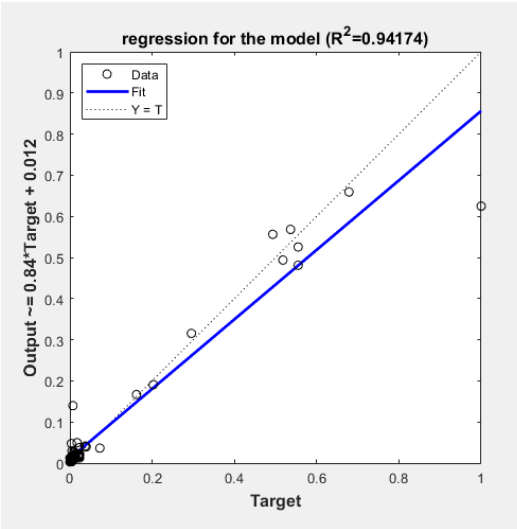

Model 2 AOA- RF



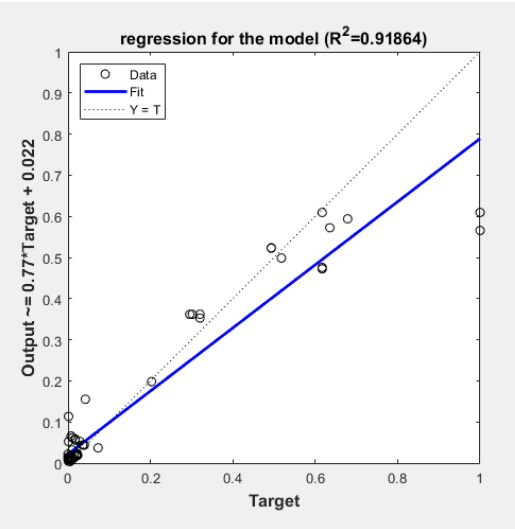

Model 3 GWO- RF




Model 3 AOA- RF

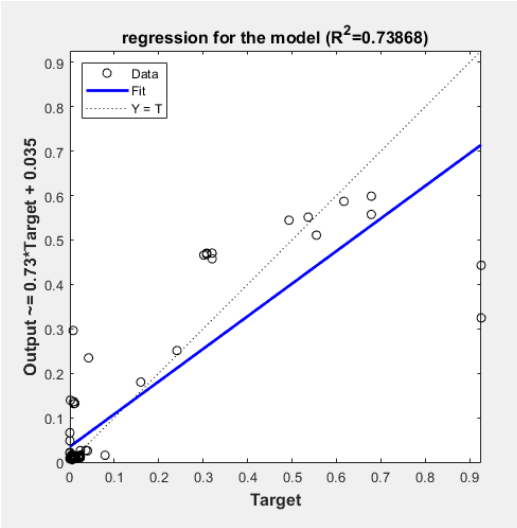



Model 4 GWO- RF

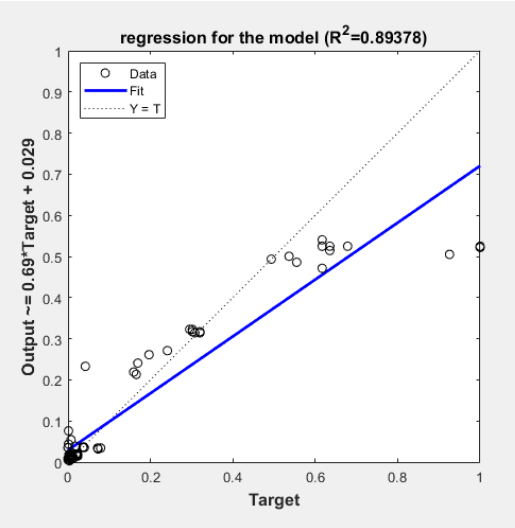



Model 4 AOA- RF

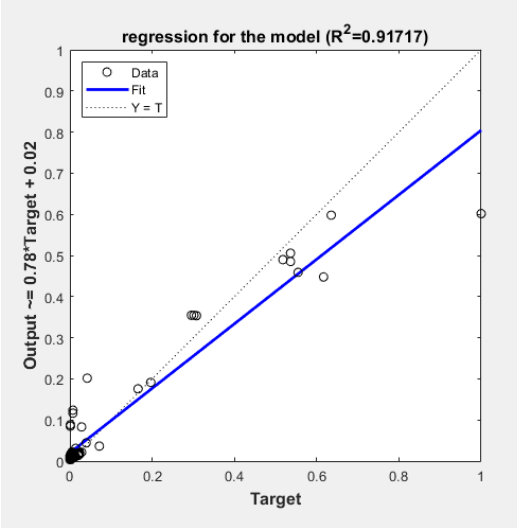
**Figure 4.8** The (scatter plot) graphical visualization for the intelligence predictive (based-RF) model (continued)



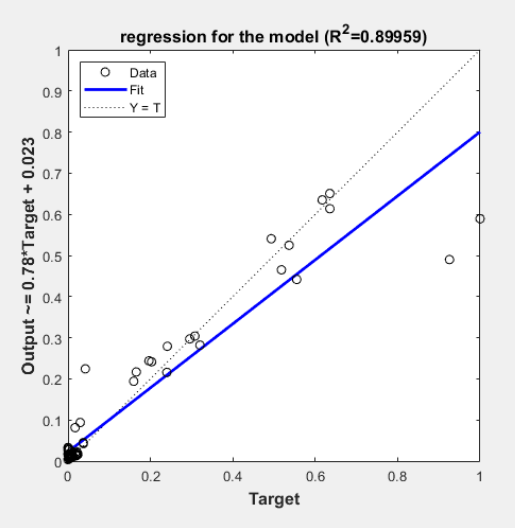

Model 5 GWO- RF



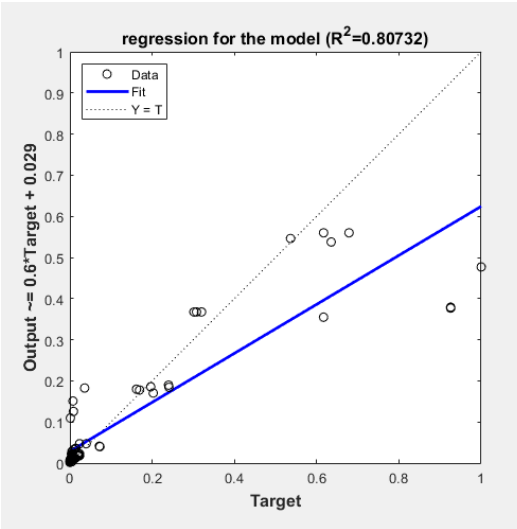

Model 5 AOA- RF



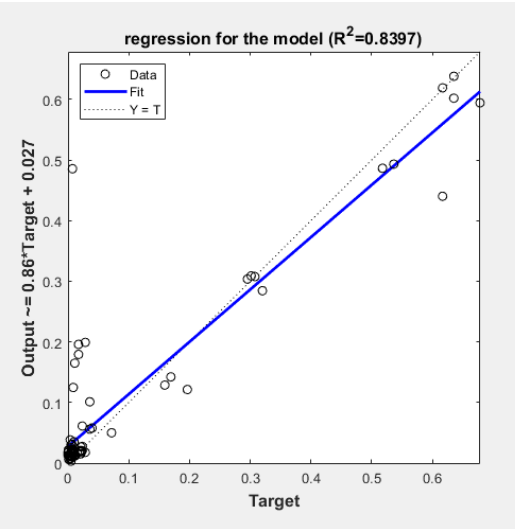

Model 6 GWO- RF




Model 6 AOA- RF




Model 7 GWO- RF




Model 7 AOA- RF

**Figure 4.8** The (scatter plot) graphical visualization for the intelligence predictive (based-RF) model (continued)

**Figure 4.9** and **Figure 4.10** provide comprehensive a comparison of various models, including the traditional RF and the best-performing models utilizing GWO-RF and AOA-RF techniques. The evaluation is based on several performance metrics: mean absolute error (MAE), root mean squared error (RMSE), and mean squared error (MSE). The figure clearly illustrates that the GWO-RF model significantly outperforms the other models across all these metrics. This indicates that the GWO-RF (model 4) approach delivers superior accuracy and reliability in predictions compared to both the standard RF model and the AOA-ANN models.

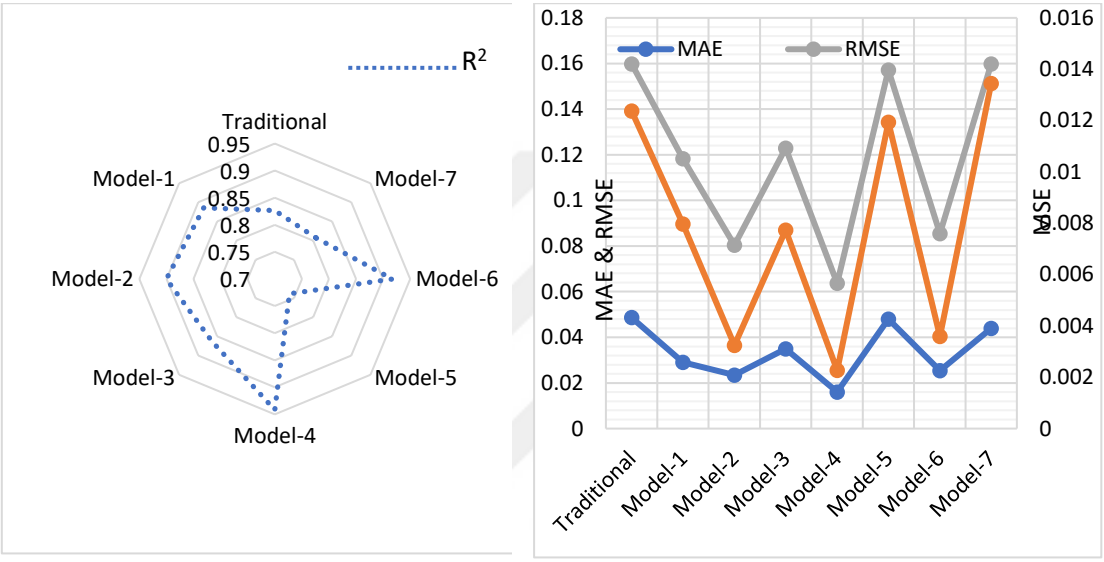



**Figure 4.9** Comprehensive performance analysis of GWO-RF models for testing datasets

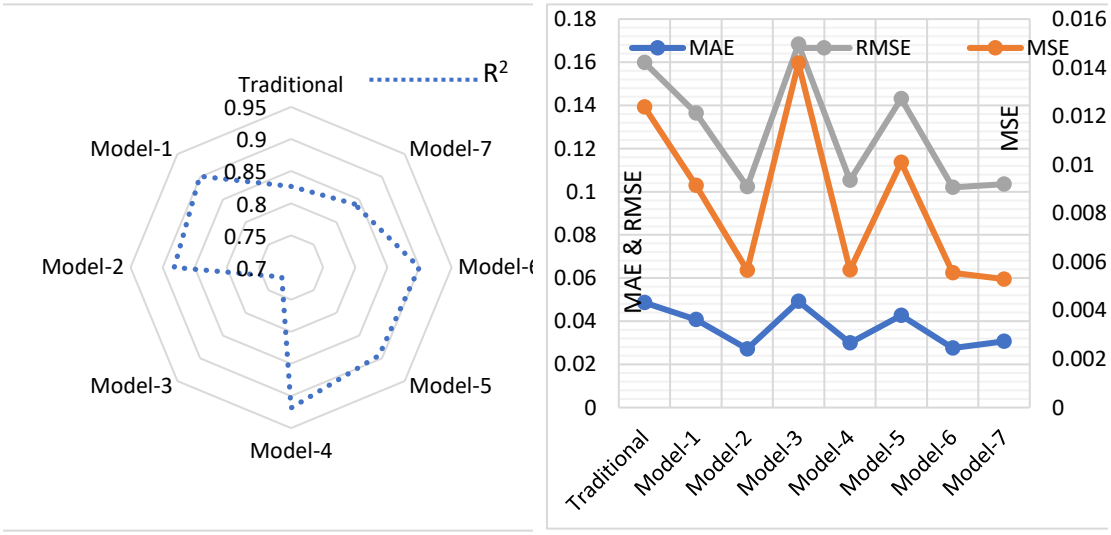



**Figure 4.10** Comprehensive performance analysis of AOA-RF models for testing datasets

### 4.1.4 Sensitivity Analysis

To assess the impact of input variables on the output variable's performance, sensitivity analysis was conducted for RF and ANN models and best hybrid models (GWO-ANN, AOA-ANN, GWO-RF, and AOA-RF) by using the MATLAB R2021a. This examination aims to discuss the relevance of each parameter to the developed network.

The forward stepwise sensitivity analysis method was applied to identify the most significant relationships between input variables and the network's output. This method was explained in the methodology chapter (section 3.3.3). The sensitivity analysis results of each input parameter for ANN 10 nodes, 17 nodes, AOA-ANN (model 5), GWO-ANN (model 7), RF, AOA-RF (model 4), and GWO-RF (model 4) were presented in **Figure (4.12), (4.13), (4.14), (4.15), (4.16), (4.17) and (4.18**) respectively. For both ANN 10 nodes, ANN 17 nodes, AOA-ANN (model 5) and GWO-ANN (model 7) showed that the type of project and total building area have significant to very significant influence on the output of the network which is the waste generation from C&DW. While duration of project and number of floors in ANN 10 nodes showed small to very small influence on the output, the variable that have small influence on the output for other models shown in **Table 4.11**.

**Figure 4.11** Result of sensitivity analysis of all models

| **Model** | **Influence of variables on the output** | | |
|---|---|---|---|
| | **High** | **medium** | **low** |
| ANN 10 nodes | P1, P6 | | P4, P8 |
| ANN 17 nodes | P1, P6 | | P5, P3 |
| AOA-ANN | P1, P6 | | P2, P8 |
| GWO-ANN | P1, P6 | | P3, P8 |
| RF | P1, P2 | | P7, P8 |
| AOA-RF | P1, P8, P6 | | P5 |
| GWO-RF | | P1, P2 | P5, P8 |

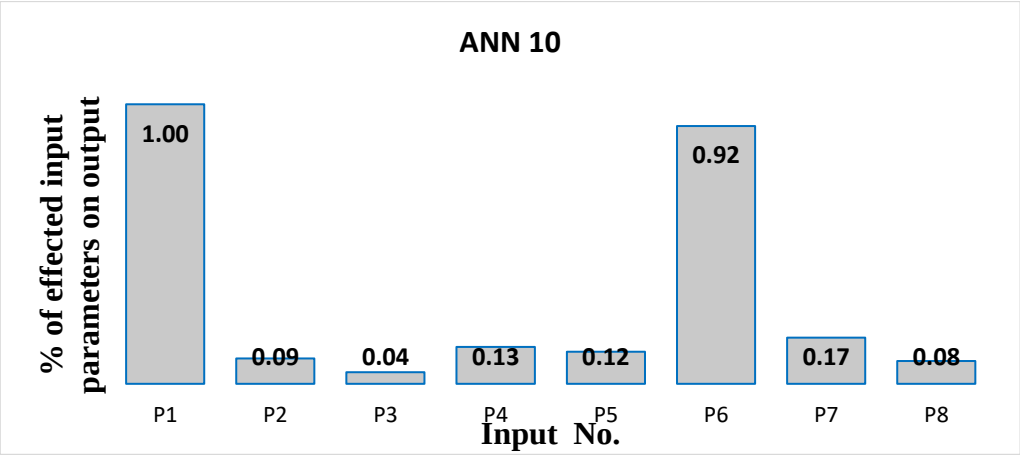



**Figure 4.12** Sensitivity analysis of the input parameters on the output of the ANN model with 10 nodes in the hidden layer.

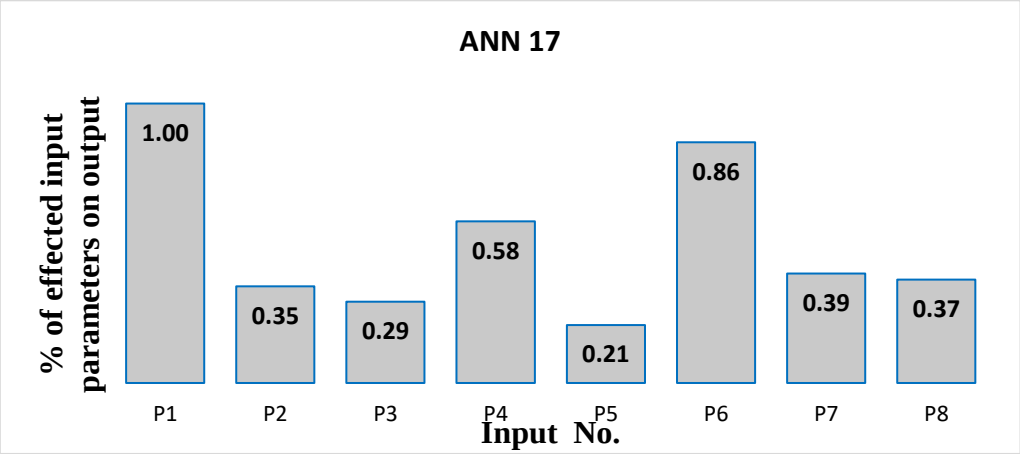



**Figure 4.13** Sensitivity analysis of the input parameters on the output of the ANN model with 17 nodes in the hidden layer.

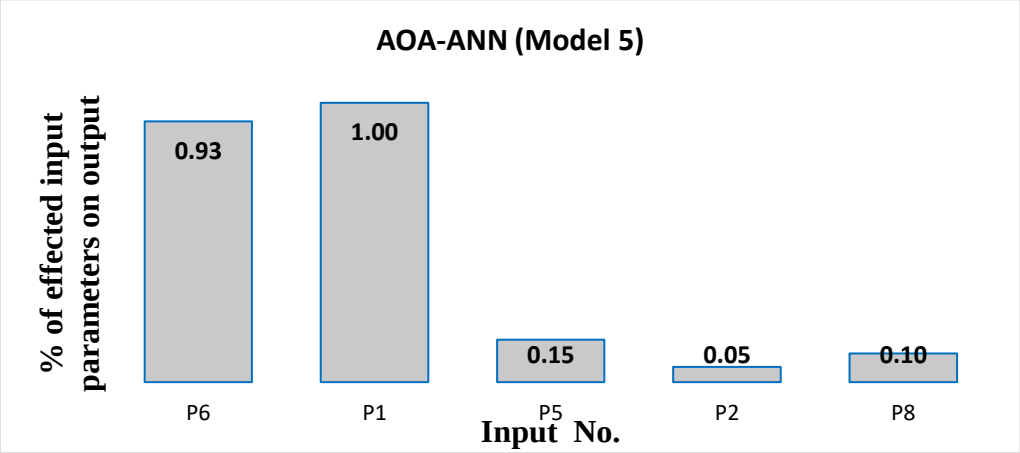



**Figure 4.14** Sensitivity analysis of the input parameters on the output of the Model 5 AOA-ANN.

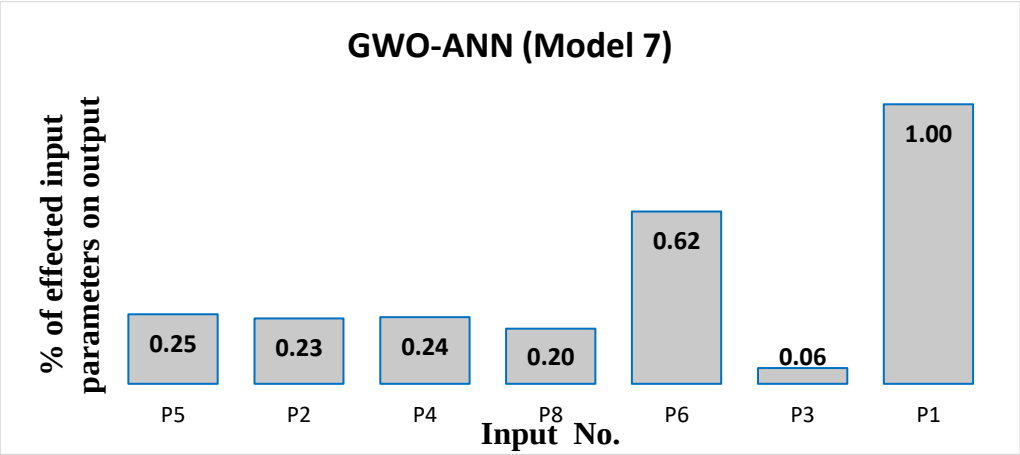



**Figure 4.15** Sensitivity analysis of the input parameters on the output of the Model 7 GWO-ANN.

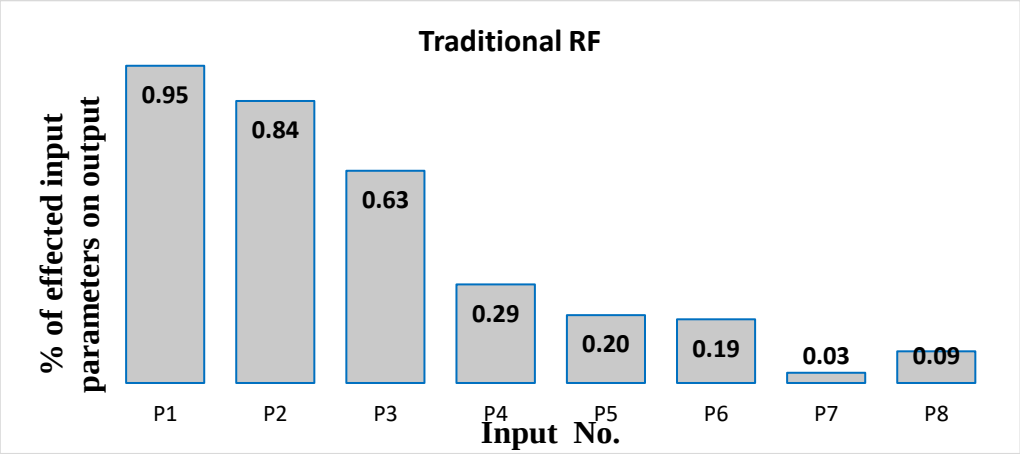



**Figure 4.16** Sensitivity analysis of the input parameters on the output of the RF model.

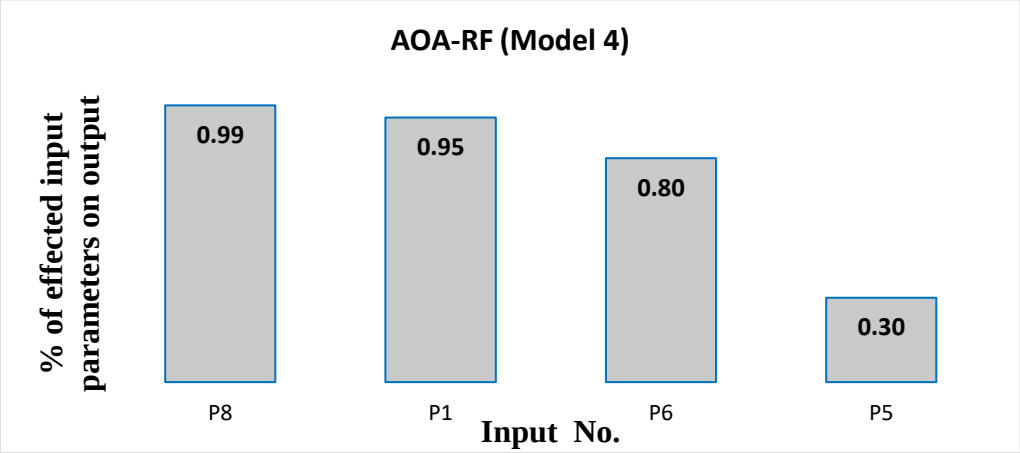



**Figure 4.17** Sensitivity analysis of the input parameters on the output of the Model 4 AOA-RF.

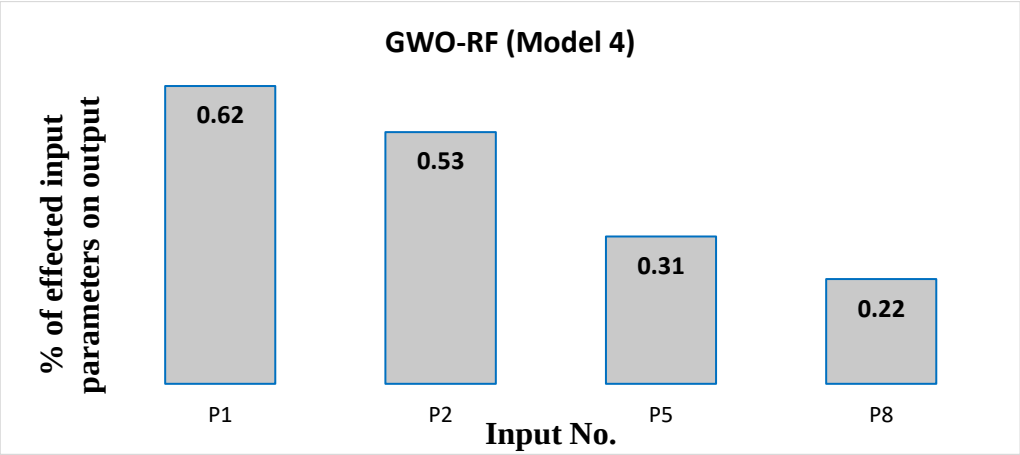



**Figure 4.18** Sensitivity analysis of the input parameters on the output of the Model 4 GWO-RF

This chapter presents the analysis of construction and demolition waste data collected from 200 projects in the Gaza Strip. Using various models, including ANN and RF, we predicted waste generation based on factors like project type, building area, and duration. The ANN model with 10 nodes showed superior performance, achieving an $R^2$ value of 0.98615. Additionally, the hybrid AOA-ANN model provided the most accurate predictions with minimal error. Sensitivity analysis revealed the project type and building area as the most influential variables in waste generation.

# 5
# CONCLUSION

This chapter contains five parts: first is the introduction part, second is the summary part, third is the conclusion part, forth is the limitation part, and the fifth is the recommendations for future work.

## 5.1 Introduction

Six prediction models were developed and tested to assess the C&DW generation from projects in the Gaza Strip, using artificial neural network and random forest techniques with the Archimedes optimization algorithm (AOA) and gray wolf optimization (GWO) algorithm for pre-processing. The construction of these models relies on a two-step process. The first step involves identifying the critical factors influencing waste generation based on previous studies. The second step entails the collection of data from 200 construction and demolition projects that align with these identified factors. This chapter delineates the primary conclusions drawn from the obtained results and provides recommendations for future research initiatives.

## 5.2 Summary

A substantial part 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 artificial intelligence (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, a study included two main parts that are data collection and hybrid model developing. Including in the first part, the survey was conducted for investigating the factors

affecting waste generation from construction and demolition projects by reviewing past studies. The survey results illustrated that waste amounts are greatly affected by many factors. Among these factors come the project type, the starting date of the project, the project location, the project duration, the building use, the building area, the access to the site, and the number of floors. After that, the data sheet was developed for collecting data from selected public and private organizations in the Gaza Strip. The public organization was the Ministry of Public Works and Housing, while private organizations were the first categories of construction companies in the Gaza Strip. A new hybrid model was the second part of this study which was utilized to predict waste amount outcoming from the C&D projects. These hybrid models were GWO-ANN, AOA-ANN, GWO-RF, and AOA-RF that were compared with stand-alone models ANN and RF. The role of metaheuristic techniques (GWO and AOA) was to select the best input combinations for the machine learning algorithms (ANN and RF). This was an attempt to implement the new intelligent techniques in the waste management area. Moreover, it can be used to help project managers control project time, cost and make accurate waste amount predictions.

## 5.3 Conclusions

The conclusions drawn from this study are:

1. The waste generation factors for construction and demolition projects were conducted from past studies and experts' opinion that were the base of datasheet structure. The design of data sheets is in methodology chapter (see section 3.2.2).
2. Eight waste generation factors were suitable for analysis and model development according to available documents and bills. These factors were mentioned before looking at the summary section.
3. The data included 200 C&D projects from Gaza Stirp with nine variables. One variable (waste amount) was described as an output variable while eight variables were input variables from the hybrid models. Look at APPENDIX A
4. Different type of analysis was applied to the data that included demographic and statistical analysis. The frequency of project and percentage were used

for demographic analysis that handled the position of respondent, years of work experience, type of projects provided, and type of organization that provided the data. On the other hand, minimum, average, maximum value, standard deviation, and sample variance applied to the amount of waste (No. of trucks), year of the project, duration of the project, the total area of the building, number of floors, and site access as a part of statistical analysis, when frequency applied on the type of project, project location, and the building use.

5. Hybrid models were developed, to see the MATLAB code see APPENDIX B. The best model was AOA-ANN. The results of the testing phase were (0.0086648, 0.023728, and 0.00056304) for MAE, RMSE, and MSE respectively.
6. A sensitivity assessment was conducted to examine the impact of individual input parameters on the predictive accuracy of the ANN, RF models, and best of hybrid models regarding the volume of waste generated from construction and demolition endeavors. Sensitivity analysis showed that the type of project and total area of the building as inputs were the most influential factors on the output in the majority of the seven models. This result aligns with expectations based on logical reasoning and expert opinion. However, inputs were not the dominant factors in all models, especially FR models.

## 5.4 Limitations

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

Firstly, collecting data in C&DW studies is a challenging stage since 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. Personal and professional connections were used to collect this data, which is not available online. All data was collected by connecting with the professionals personally, ensuring its reliability.

The other critical limitation is that this study is based on Palestinian data. Due to the complex structure of the developed models, the developed models may have limitations in their applicability to other regions. This generalization issue is common in machine learning waste estimation models due to variations in construction practices and data availability [133]. 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.

Finally, the number of the data points can be another issue, however, several C&DW estimation studies have employed 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 achieved highlight their potential in civil engineering.

## 5.5 Recommendations for Future Work

The present investigation has yielded highly encouraging outcomes in forecasting waste quantities from various projects, signifying considerable potential for advancement, particularly within the area of civil engineering. Nonetheless, it is imperative to provide decision-makers within the construction sector with pertinent recommendations derived from this study's findings. Additionally, future research endeavors should be undertaken to substantiate and build upon the conclusions reached herein:

1. It is advisable for all stakeholders involved in construction to heighten their awareness of waste management practices and integrate the developed technique into their estimation processes more diligently.
2. To improve the study, other hybrid algorithms such as the hybrid ANN- Bat algorithm can be used and the results of these models were compared to determine the most accurate model; and
3. The advancement of artificial intelligence (AI) models necessitates access to structured databases containing information on completed construction projects. Regrettably, many construction companies lack such systems. Therefore, it is recommended that construction firms operating in Gaza

develop and implement a standardized database system for storing information pertaining to completed projects.

In conclusion, the swift analysis of waste data is indispensable in today's fast-paced construction industry, where decisions must often be made quickly. Manual calculations or estimations are no longer feasible given the time constraints and complexity of the data involved. Therefore, computer-based models are essential to facilitate accurate responses, streamline data analysis, and expedite project completion.

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# A
# THE APPLIED HİSTORICAL DATA SET OF THE PROJECTS

| Type of project | Year of construct | location | Duration of Project (Month) | Type of building | Total Area of Building | Site access | Number of floors | Amount of Waste (No. of Trucks) |
|---|---|---|---|---|---|---|---|---|
| **P1** | **P2** | **P3** | **P4** | **P5** | **P6** | **P7** | **P8** | **Oi** |
| 1 | 0.833333 | 0.25 | 0.028169 | 0.75 | 0.097015 | 0 | 0.142857 | 0.171817 |
| 1 | 0.5 | 0.75 | 0.014085 | 0.75 | 0.08209 | 0 | 0.071429 | 0.159456 |
| 1 | 0.5 | 0.75 | 0.042254 | 0.75 | 0.115672 | 0 | 0.071429 | 0.239802 |
| 1 | 0 | 0.25 | 0.056338 | 0.75 | 0.104478 | 0 | 0.142857 | 0.202719 |
| 1 | 0.75 | 0.75 | 0.028169 | 0.75 | 0.089552 | 0 | 0.142857 | 0.165637 |
| 1 | 1 | 0 | 0 | 0 | 0.008209 | 0 | 0.071429 | 0.035847 |
| 1 | 0.916667 | 0.25 | 0.126761 | 0 | 0.876119 | 0.5 | 1 | 0.925834 |
| 1 | 0.916667 | 0.25 | 0.098592 | 0.25 | 0.365672 | 1 | 0.285714 | 0.678616 |
| 1 | 0.916667 | 0.25 | 0.084507 | 0.25 | 0.365672 | 1 | 0.285714 | 0.616811 |
| 1 | 0.916667 | 0.25 | 0.014085 | 0.25 | 0.115672 | 1 | 0.285714 | 0.307787 |
| 1 | 0.916667 | 0.25 | 0.098592 | 0.25 | 0.365672 | 1 | 0.285714 | 0.635352 |
| 1 | 0.916667 | 0.25 | 0.014085 | 0.25 | 0.115672 | 1 | 0.285714 | 0.295426 |
| 1 | 0.916667 | 0.25 | 0.028169 | 0.25 | 0.115672 | 1 | 0.285714 | 0.301607 |
| 1 | 0.916667 | 0.25 | 0.056338 | 0.25 | 0.242537 | 1 | 0.285714 | 0.493201 |
| 1 | 0.916667 | 0.25 | 0.042254 | 0.25 | 0.242537 | 1 | 0.285714 | 0.517923 |
| 1 | 0.916667 | 0.25 | 0.014085 | 0.25 | 0.115672 | 1 | 0.285714 | 0.320148 |
| 1 | 0.916667 | 0.25 | 0.098592 | 0.25 | 0.365672 | 1 | 0.285714 | 1 |
| 1 | 0.916667 | 0.25 | 0.056338 | 0.25 | 0.242537 | 1 | 0.285714 | 0.555006 |
| 1 | 0.916667 | 0.25 | 0.070423 | 0.25 | 0.242537 | 1 | 0.285714 | 0.536465 |
| 1 | 0.833333 | 0.25 | 0.084507 | 0.25 | 0.477612 | 0 | 1 | 0.616811 |
| 1 | 0.583333 | 0 | 0.042254 | 0.5 | 0.097015 | 0 | 0.142857 | 0.169345 |
| 1 | 0.666667 | 0 | 0.028169 | 0.5 | 0.08209 | 0 | 0.071429 | 0.161928 |
| 1 | 0.75 | 0 | 0.056338 | 0.5 | 0.115672 | 0 | 0.071429 | 0.241038 |
| 1 | 0.666667 | 0.5 | 0.070423 | 0.5 | 0.104478 | 0 | 0.142857 | 0.196539 |
| 1 | 0.666667 | 0.5 | 0.042254 | 0.75 | 0.089552 | 0 | 0.142857 | 0.159456 |
| 1 | 0.75 | 0.25 | 0.014085 | 0.25 | 0.008209 | 0 | 0.071429 | 0.042027 |
| 1 | 0.833333 | 0.5 | 0.15493 | 0.25 | 0.876119 | 0.5 | 1 | 0.925834 |
| 1 | 0.833333 | 0.5 | 0.126761 | 0 | 0.365672 | 1 | 0.285714 | 0.678616 |
| 1 | 0.75 | 0.75 | 0.098592 | 0 | 0.365672 | 1 | 0.285714 | 0.616811 |

| Type of project | Year of construct | location | Duration of Project (Month) | Type of building | Total Area of Building | Site access | Number of floors | Amount of Waste (No. of Trucks) |
|---|---|---|---|---|---|---|---|---|
| 1 | 0.75 | 0 | 0.042254 | 0 | 0.115672 | 1 | 0.285714 | 0.307787 |
| 1 | 1 | 0 | 0.126761 | 0 | 0.365672 | 1 | 0.285714 | 0.635352 |
| 1 | 1 | 0 | 0.042254 | 0 | 0.115672 | 1 | 0.285714 | 0.295426 |
| 1 | 1 | 0 | 0.042254 | 0 | 0.115672 | 1 | 0.285714 | 0.301607 |
| 1 | 1 | 0 | 0.070423 | 0 | 0.242537 | 1 | 0.285714 | 0.493201 |
| 0 | 0.916667 | 0.25 | 0.070423 | 0.75 | 0.012313 | 0 | 0 | 0.002472 |
| 0 | 0.916667 | 0 | 0.042254 | 0.75 | 0.001493 | 0 | 0.071429 | 0 |
| 0 | 0.916667 | 0.25 | 0.323944 | 0.75 | 0.087313 | 0 | 0.142857 | 0.002472 |
| 0 | 0.916667 | 0.25 | 0.042254 | 1 | 0 | 0 | 0 | 0 |
| 0 | 0.916667 | 0.25 | 0.042254 | 0.75 | 0.001269 | 0 | 0 | 0 |
| 0 | 0.833333 | 0.25 | 0.549296 | 0.25 | 0.477612 | 0 | 1 | 0.029666 |
| 0 | 0.416667 | 0.75 | 0.323944 | 0 | 0.198507 | 0 | 0.357143 | 0.012361 |
| 0 | 0.416667 | 0.75 | 0.323944 | 0 | 0.198507 | 0 | 0.357143 | 0.011125 |
| 0 | 0.416667 | 0.75 | 0.323944 | 0 | 0.198507 | 0 | 0.357143 | 0.009889 |
| 0 | 0.416667 | 0.75 | 0.323944 | 0 | 0.095522 | 0 | 0.357143 | 0.004944 |
| 0 | 0.333333 | 0.25 | 0.323944 | 0.25 | 0.234328 | 0 | 0.357143 | 0.012361 |
| 0 | 0.333333 | 0.25 | 0.323944 | 0.25 | 0.234328 | 0 | 0.357143 | 0.011125 |
| 0 | 0.333333 | 0.25 | 0.323944 | 0.25 | 0.113433 | 0 | 0.357143 | 0.004944 |
| 0 | 0.25 | 0.75 | 0.323944 | 0.25 | 0.216418 | 0.5 | 0.357143 | 0.011743 |
| 0 | 0.25 | 0.75 | 0.323944 | 0.25 | 0.104478 | 0.5 | 0.357143 | 0.004944 |
| 0 | 0.25 | 0.75 | 0.323944 | 0.25 | 0.216418 | 0.5 | 0.357143 | 0.012361 |
| 0 | 0.25 | 0.75 | 0.323944 | 0.25 | 0.216418 | 0.5 | 0.357143 | 0.011125 |
| 0 | 0.25 | 0.75 | 0.323944 | 0.25 | 0.104478 | 0.5 | 0.357143 | 0.005562 |
| 0 | 0.333333 | 0.75 | 0.492958 | 0.25 | 0.552239 | 0 | 0.142857 | 0.07293 |
| 0 | 0.666667 | 0.25 | 0.352113 | 0 | 0.664179 | 0 | 0.357143 | 0.023486 |
| 0 | 0.833333 | 0.25 | 1 | 0.25 | 0.216418 | 0 | 0.214286 | 0.02843 |
| 0 | 0.916667 | 0.75 | 0.380282 | 0.75 | 0.115672 | 0 | 0.142857 | 0.005562 |
| 0 | 0.833333 | 0.75 | 0.323944 | 0.75 | 0.152985 | 0 | 0.214286 | 0.007417 |
| 0 | 0.583333 | 1 | 0.295775 | 0.75 | 0.126866 | 0 | 0.142857 | 0.00618 |
| 0 | 0.583333 | 1 | 1 | 0.75 | 1 | 0 | 0 | 0.037083 |
| 0 | 0.5 | 1 | 0.211268 | 0.75 | 0.089552 | 0.5 | 0.142857 | 0.003708 |
| 0 | 0.416667 | 0.75 | 0.295775 | 0 | 0.645522 | 0 | 0.285714 | 0.035847 |
| 0 | 0.333333 | 0.75 | 0.295775 | 0 | 0.710821 | 0 | 0.285714 | 0.039555 |
| 0 | 0.25 | 1 | 0.380282 | 0.75 | 0.08209 | 0.5 | 0.071429 | 0.003708 |
| 0 | 0.083333 | 0.5 | 0.295775 | 0.75 | 0.164179 | 0 | 0.214286 | 0.008653 |
| 0 | 0.083333 | 0.75 | 0.295775 | 0.75 | 0.152985 | 0 | 0.214286 | 0.008653 |
| 0 | 0.083333 | 0.75 | 0.380282 | 0.75 | 0.365672 | 0 | 0 | 0.014215 |

| Type of project | Year of construct | location | Duration of Project (Month) | Type of building | Total Area of Building | Site access | Number of floors | Amount of Waste (No. of Trucks) |
|---|---|---|---|---|---|---|---|---|
| 0 | 0.333333 | 0.25 | 0.323944 | 0 | 0.1 | 0 | 0.5 | 0.003708 |
| 0 | 0.416667 | 0.25 | 0.323944 | 0 | 0.19403 | 0 | 0.571429 | 0.004944 |
| 0 | 0.416667 | 0.25 | 0.323944 | 0 | 0.044776 | 0 | 0.5 | 0.002472 |
| 0 | 0.583333 | 0.25 | 0.323944 | 0.25 | 0.187313 | 0 | 0.571429 | 0.004944 |
| 0 | 0.75 | 0.25 | 0.323944 | 0.25 | 0.215858 | 0 | 0.571429 | 0.00618 |
| 0 | 0.916667 | 0.25 | 0.323944 | 0.25 | 0.294776 | 0 | 0.571429 | 0.009271 |
| 0 | 0.916667 | 0.25 | 0.323944 | 0.25 | 0.126866 | 0 | 0.571429 | 0.004944 |
| 0 | 0.416667 | 0.25 | 0.43662 | 0.5 | 0.395522 | 1 | 0.571429 | 0.011125 |
| 0 | 0.75 | 0.25 | 0.323944 | 0.5 | 0.020522 | 1 | 0.142857 | 0.001236 |
| 0 | 0.916667 | 0.5 | 0.43662 | 0.5 | 0.281716 | 1 | 0.285714 | 0.007417 |
| 0 | 0.833333 | 0.25 | 0.323944 | 0.5 | 0.324627 | 1 | 0.642857 | 0.008653 |
| 0 | 0.75 | 0.75 | 0.183099 | 0.75 | 0.061567 | 0 | 0.142857 | 0.002472 |
| 0 | 0.5 | 0.75 | 0.098592 | 0.5 | 0.014925 | 0 | 0 | 0 |
| 0 | 0.5 | 0.5 | 0.070423 | 0.75 | 0.022388 | 0 | 0 | 0.000618 |
| 0 | 0.416667 | 0.75 | 0.295775 | 0.75 | 0.164179 | 0 | 0 | 0.008653 |
| 0 | 0.333333 | 0 | 0.211268 | 0 | 0.141791 | 0 | 0.214286 | 0.007417 |
| 0 | 0.166667 | 0.75 | 0.295775 | 0.75 | 0.164179 | 0 | 0 | 0.008653 |
| 0 | 0.166667 | 0.75 | 0.295775 | 0.75 | 0.186567 | 0 | 0.214286 | 0.009889 |
| 0 | 0.166667 | 0.75 | 0.295775 | 0.75 | 0.115672 | 0 | 0.142857 | 0.00618 |
| 0 | 0.166667 | 0.75 | 0.15493 | 0.75 | 0.037313 | 0 | 0.142857 | 0.001236 |
| 0 | 0.166667 | 0.75 | 0.15493 | 0.75 | 0.014925 | 0 | 0 | 0 |
| 0 | 0.083333 | 0.25 | 0.323944 | 0.75 | 0.149254 | 0 | 0.214286 | 0.007417 |
| 0 | 0.083333 | 0.5 | 0.323944 | 0.75 | 0.134328 | 0 | 0.214286 | 0.007417 |
| 0 | 0.916667 | 0.75 | 0.323944 | 0.75 | 0.104478 | 0 | 0.142857 | 0.023486 |
| 0 | 0.916667 | 0.75 | 0.323944 | 0.75 | 0.104478 | 0 | 0.142857 | 0.02225 |
| 0 | 1 | 0 | 0.323944 | 0.75 | 0.104478 | 0 | 0.142857 | 0.021014 |
| 0 | 0.916667 | 1 | 0.323944 | 0.75 | 0.104478 | 0 | 0.142857 | 0.023486 |
| 0 | 0.916667 | 0 | 0.323944 | 0.75 | 0.08209 | 0 | 0.142857 | 0.020396 |
| 0 | 0.916667 | 0.25 | 0.323944 | 0.75 | 0.104478 | 0 | 0.142857 | 0.019778 |
| 0 | 0.916667 | 0.25 | 0.323944 | 0.75 | 0.126866 | 0 | 0.142857 | 0.021014 |
| 0 | 0.916667 | 0.25 | 0.323944 | 0.75 | 0.089552 | 0 | 0.142857 | 0.023486 |
| 0 | 0.666667 | 0.75 | 0.323944 | 0.75 | 0.104478 | 0 | 0.142857 | 0.023486 |
| 0 | 0.666667 | 0.75 | 0.323944 | 0.75 | 0.104478 | 0 | 0.142857 | 0.02225 |
| 0 | 0.666667 | 0.5 | 0.323944 | 0.75 | 0.104478 | 0 | 0.142857 | 0.019159 |
| 0 | 0.5 | 0.75 | 0.267606 | 0.75 | 0.08209 | 0 | 0.142857 | 0.019778 |
| 0 | 0.666667 | 0.75 | 0.211268 | 0.75 | 0.08209 | 0 | 0.142857 | 0.019778 |
| 0 | 0.75 | 1 | 0.323944 | 0.75 | 0.108209 | 0 | 0.142857 | 0.02225 |

| Type of project | Year of construct | location | Duration of Project (Month) | Type of building | Total Area of Building | Site access | Number of floors | Amount of Waste (No. of Trucks) |
|---|---|---|---|---|---|---|---|---|
| 0 | 0.75 | 0.25 | 0.267606 | 0.75 | 0.097015 | 0 | 0.142857 | 0.023486 |
| 0 | 0.75 | 0.25 | 0.323944 | 0.75 | 0.108209 | 0 | 0.142857 | 0.023486 |
| 0 | 0.416667 | 0.25 | 0.267606 | 0.75 | 0.059701 | 0 | 0.142857 | 0.001236 |
| 0 | 0.916667 | 0.25 | 0.15493 | 0.75 | 0.018657 | 0 | 0 | 0.004944 |
| 0 | 1 | 0.25 | 0.15493 | 0.75 | 0.002612 | 0 | 0 | 0 |
| 0 | 0.916667 | 0 | 0.098592 | 0.75 | 0.019403 | 0 | 0.071429 | 0.003708 |
| 0 | 0.916667 | 0.25 | 0.15493 | 0.75 | 0.011194 | 0 | 0.285714 | 0.003708 |
| 0 | 0.916667 | 1 | 0.126761 | 0.75 | 0.007463 | 0 | 0.071429 | 0.001236 |
| 0 | 0.916667 | 0.25 | 0.239437 | 0 | 0.552239 | 0 | 1 | 0.017305 |
| 0 | 0.666667 | 0.25 | 0.661972 | 0 | 0.380597 | 0 | 0.5 | 0.009889 |
| 0 | 0.833333 | 0.25 | 0.323944 | 0 | 0.272388 | 0 | 0.5 | 0.004944 |
| 0 | 0.833333 | 1 | 0.098592 | 0.75 | 0.012313 | 0 | 0 | 0.00309 |
| 0 | 0.916667 | 1 | 0.070423 | 0.75 | 0.001493 | 0 | 0.071429 | 0.000618 |
| 0 | 0.833333 | 1 | 0.352113 | 0.75 | 0.087313 | 0 | 0.142857 | 0.001854 |
| 0 | 0.916667 | 0.75 | 0.070423 | 1 | 0 | 0 | 0 | 0.000618 |
| 0 | 0.833333 | 0.75 | 0.070423 | 0.75 | 0.001269 | 0 | 0 | 0 |
| 0 | 0.916667 | 0.75 | 0.492958 | 0.25 | 0.477612 | 0 | 1 | 0.02843 |
| 0 | 0.416667 | 0.25 | 0.352113 | 0 | 0.198507 | 0 | 0.357143 | 0.013597 |
| 0 | 0.333333 | 0.25 | 0.295775 | 0 | 0.198507 | 0 | 0.357143 | 0.012361 |
| 0 | 0.416667 | 0.25 | 0.352113 | 0 | 0.198507 | 0 | 0.357143 | 0.011125 |
| 0 | 0.333333 | 0.25 | 0.295775 | 0 | 0.095522 | 0 | 0.357143 | 0.005562 |
| 0 | 0.416667 | 0.75 | 0.352113 | 0.25 | 0.234328 | 0 | 0.357143 | 0.011743 |
| 0 | 0.333333 | 1 | 0.352113 | 0.25 | 0.234328 | 0 | 0.357143 | 0.011125 |
| 0 | 0.25 | 1 | 0.352113 | 0.25 | 0.113433 | 0 | 0.357143 | 0.00618 |
| 0 | 0.25 | 1 | 0.352113 | 0.25 | 0.216418 | 0.5 | 0.357143 | 0.011743 |
| 0 | 0.416667 | 1 | 0.295775 | 0.25 | 0.104478 | 0.5 | 0.357143 | 0.005562 |
| 0 | 0.25 | 0 | 0.295775 | 0.25 | 0.216418 | 0.5 | 0.357143 | 0.012979 |
| 0 | 0.416667 | 0.25 | 0.352113 | 0.25 | 0.216418 | 0.5 | 0.357143 | 0.010507 |
| 0 | 0.25 | 0 | 0.295775 | 0.25 | 0.104478 | 0.5 | 0.357143 | 0.004944 |
| 0 | 0.416667 | 0 | 0.549296 | 0.25 | 0.552239 | 0 | 0.142857 | 0.071693 |
| 0 | 0.916667 | 0 | 0.380282 | 0 | 0.664179 | 0 | 0.357143 | 0.07911 |
| 0 | 0.833333 | 1 | 1 | 0.25 | 0.216418 | 0 | 0.214286 | 0.02843 |
| 0 | 0.916667 | 1 | 0.380282 | 0.75 | 0.115672 | 0 | 0.142857 | 0.005562 |
| 0 | 0.833333 | 1 | 0.323944 | 0.75 | 0.152985 | 0 | 0.214286 | 0.007417 |
| 0 | 0.916667 | 0.75 | 0.295775 | 0.75 | 0.126866 | 0 | 0.142857 | 0.00618 |
| 0 | 0.833333 | 0.75 | 1 | 0.75 | 1 | 0 | 0 | 0.037083 |
| 0 | 0.916667 | 0.75 | 0.211268 | 0.75 | 0.089552 | 0.5 | 0.142857 | 0.003708 |

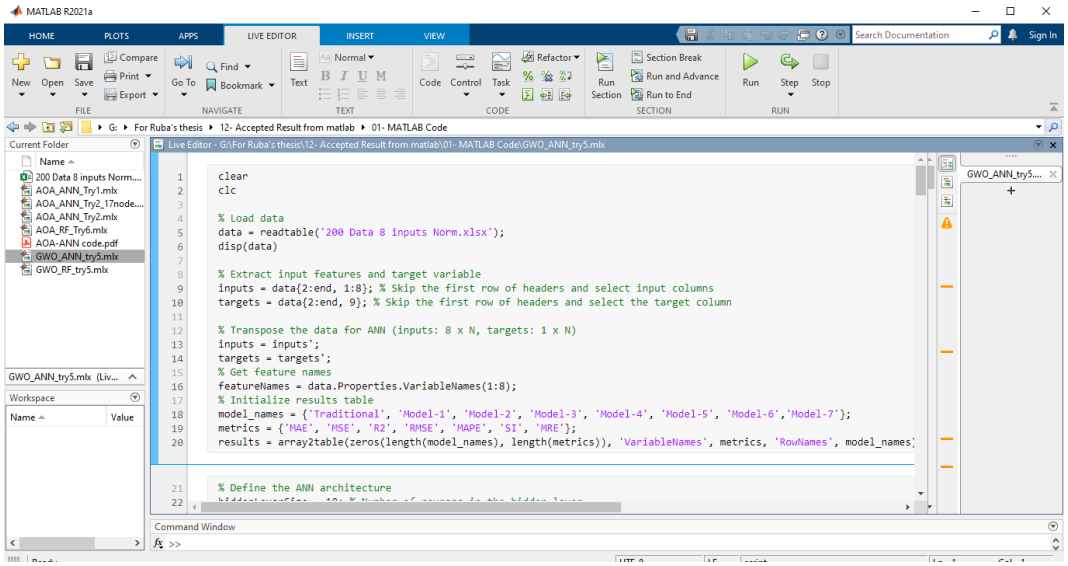
| Type of project | Year of construct | location | Duration of Project (Month) | Type of building | Total Area of Building | Site access | Number of floors | Amount of Waste (No. of Trucks) |
|---|---|---|---|---|---|---|---|---|
| 0 | 0.416667 | 0.25 | 0.295775 | 0 | 0.645522 | 0 | 0.285714 | 0.035847 |
| 0 | 0.333333 | 0.25 | 0.295775 | 0 | 0.710821 | 0 | 0.285714 | 0.039555 |
| 0 | 0.416667 | 0.25 | 0.380282 | 0.75 | 0.08209 | 0.5 | 0.071429 | 0.003708 |
| 0 | 0.333333 | 0.25 | 0.295775 | 0.75 | 0.164179 | 0 | 0.214286 | 0.008653 |
| 0 | 0.416667 | 0.75 | 0.295775 | 0.75 | 0.152985 | 0 | 0.214286 | 0.008653 |
| 0 | 0.333333 | 1 | 0.380282 | 0.75 | 0.365672 | 0 | 0 | 0.014215 |
| 0 | 0.25 | 1 | 0.323944 | 0 | 0.1 | 0 | 0.5 | 0.003708 |
| 0 | 0.25 | 1 | 0.323944 | 0 | 0.19403 | 0 | 0.571429 | 0.004944 |
| 0 | 0.416667 | 1 | 0.323944 | 0 | 0.044776 | 0 | 0.5 | 0.002472 |
| 0 | 0.25 | 0 | 0.323944 | 0.25 | 0.187313 | 0 | 0.571429 | 0.004944 |
| 0 | 0.416667 | 0.25 | 0.323944 | 0.25 | 0.215858 | 0 | 0.571429 | 0.00618 |
| 0 | 0.25 | 0 | 0.323944 | 0.25 | 0.294776 | 0 | 0.571429 | 0.009271 |
| 0 | 0.416667 | 0 | 0.323944 | 0.25 | 0.126866 | 0 | 0.571429 | 0.004944 |
| 0 | 0.916667 | 0 | 0.43662 | 0.5 | 0.395522 | 1 | 0.571429 | 0.011125 |
| 0 | 0.833333 | 1 | 0.098592 | 0.5 | 0.020522 | 1 | 0.142857 | 0.001236 |
| 0 | 0.916667 | 1 | 0.070423 | 0.5 | 0.281716 | 1 | 0.285714 | 0.007417 |
| 0 | 0.833333 | 1 | 0.352113 | 0.5 | 0.324627 | 1 | 0.642857 | 0.008653 |
| 0 | 0.916667 | 0.75 | 0.070423 | 0.75 | 0.061567 | 0 | 0.142857 | 0.002472 |
| 0 | 0.833333 | 0.75 | 0.070423 | 0.5 | 0.014925 | 0 | 0 | 0 |
| 0 | 0.916667 | 0.75 | 0.492958 | 0.75 | 0.022388 | 0 | 0 | 0.000618 |
| 0 | 0.416667 | 0.25 | 0.352113 | 0.75 | 0.164179 | 0 | 0 | 0.008653 |
| 0 | 0.333333 | 0.25 | 0.295775 | 0 | 0.141791 | 0 | 0.214286 | 0.007417 |
| 0 | 0.416667 | 0.25 | 0.352113 | 0.75 | 0.164179 | 0 | 0 | 0.008653 |
| 0 | 0.333333 | 0.25 | 0.295775 | 0.75 | 0.186567 | 0 | 0.214286 | 0.009889 |
| 0 | 0.416667 | 0.75 | 0.352113 | 0.75 | 0.115672 | 0 | 0.142857 | 0.00618 |
| 0 | 0.333333 | 1 | 0.352113 | 0.75 | 0.037313 | 0 | 0.142857 | 0.001236 |
| 0 | 0.25 | 1 | 0.352113 | 0.75 | 0.014925 | 0 | 0 | 0 |
| 0 | 0.25 | 1 | 0.352113 | 0.75 | 0.149254 | 0 | 0.214286 | 0.007417 |
| 0 | 0.416667 | 1 | 0.295775 | 0.75 | 0.134328 | 0 | 0.214286 | 0.007417 |
| 0 | 0.25 | 0 | 0.295775 | 0.75 | 0.104478 | 0 | 0.142857 | 0.023486 |
| 0 | 0.416667 | 0.25 | 0.352113 | 0.75 | 0.104478 | 0 | 0.142857 | 0.02225 |
| 0 | 0.25 | 0 | 0.295775 | 0.75 | 0.104478 | 0 | 0.142857 | 0.021014 |
| 0 | 0.416667 | 0 | 0.549296 | 0.75 | 0.104478 | 0 | 0.142857 | 0.023486 |
| 0 | 0.916667 | 0 | 0.380282 | 0.75 | 0.08209 | 0 | 0.142857 | 0.020396 |
| 0 | 0.833333 | 1 | 1 | 0.75 | 0.104478 | 0 | 0.142857 | 0.019778 |
| 0 | 0.916667 | 1 | 0.380282 | 0.75 | 0.126866 | 0 | 0.142857 | 0.021014 |
| 0 | 0.833333 | 1 | 0.323944 | 0.75 | 0.089552 | 0 | 0.142857 | 0.023486 |

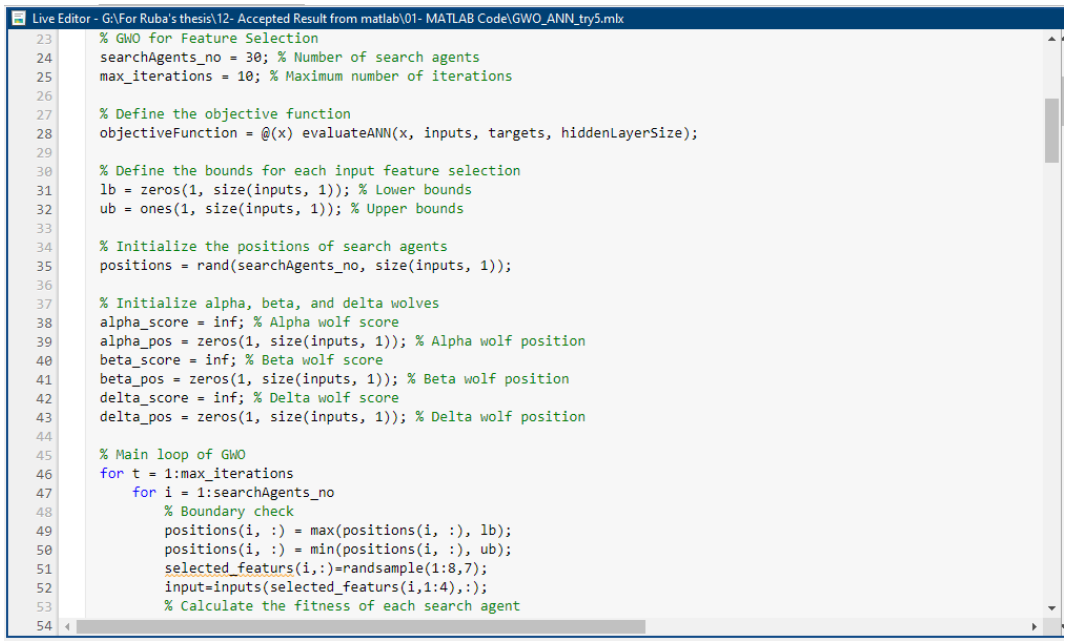
| Type of project | Year of construct | location | Duration of Project (Month) | Type of building | Total Area of Building | Site access | Number of floors | Amount of Waste (No. of Trucks) |
|---|---|---|---|---|---|---|---|---|
| 0 | 0.916667 | 0.75 | 0.295775 | 0.75 | 0.104478 | 0 | 0.142857 | 0.023486 |
| 0 | 0.833333 | 0.75 | 1 | 0.75 | 0.104478 | 0 | 0.142857 | 0.02225 |
| 0 | 0.916667 | 0.75 | 0.211268 | 0.75 | 0.104478 | 0 | 0.142857 | 0.019159 |
| 0 | 0.416667 | 0.25 | 0.295775 | 0.75 | 0.08209 | 0 | 0.142857 | 0.019778 |
| 0 | 0.333333 | 0.25 | 0.295775 | 0.75 | 0.08209 | 0 | 0.142857 | 0.019778 |
| 0 | 0.416667 | 0.25 | 0.380282 | 0.75 | 0.108209 | 0 | 0.142857 | 0.02225 |
| 0 | 0.333333 | 0.25 | 0.295775 | 0.75 | 0.097015 | 0 | 0.142857 | 0.023486 |
| 0 | 0.416667 | 0.75 | 0.295775 | 0.75 | 0.108209 | 0 | 0.142857 | 0.023486 |
| 0 | 0.333333 | 1 | 0.380282 | 0.75 | 0.059701 | 0 | 0.142857 | 0.001236 |
| 0 | 0.25 | 1 | 0.323944 | 0.75 | 0.018657 | 0 | 0 | 0.004944 |
| 0 | 0.25 | 1 | 0.323944 | 0.75 | 0.002612 | 0 | 0 | 0 |
| 0 | 0.416667 | 1 | 0.323944 | 0.75 | 0.019403 | 0 | 0.071429 | 0.003708 |
| 0 | 0.25 | 0 | 0.323944 | 0.75 | 0.011194 | 0 | 0.285714 | 0.003708 |
| 0 | 0.416667 | 0.25 | 0.323944 | 0.75 | 0.007463 | 0 | 0.071429 | 0.001236 |
| 0 | 0.25 | 0 | 0.323944 | 0 | 0.552239 | 0 | 1 | 0.017305 |
| 0 | 0.416667 | 0 | 0.323944 | 0 | 0.380597 | 0 | 0.5 | 0.009889 |
| 0 | 0.916667 | 0 | 0.43662 | 0 | 0.272388 | 0 | 0.5 | 0.004944 |
| 1 | 0.75 | 0.5 | 0.070423 | 0.5 | 0.242537 | 1 | 0.285714 | 0.517923 |
| 1 | 0.833333 | 0.5 | 0.042254 | 0.5 | 0.115672 | 1 | 0.285714 | 0.320148 |
| 1 | 0.833333 | 0.5 | 0.126761 | 0.5 | 0.365672 | 1 | 0.285714 | 1 |
| 1 | 0.666667 | 0.75 | 0.070423 | 0.5 | 0.242537 | 1 | 0.285714 | 0.555006 |
| 1 | 0.75 | 0.75 | 0.098592 | 0.5 | 0.242537 | 1 | 0.285714 | 0.536465 |
| 1 | 0.75 | 0.75 | 0.098592 | 0.25 | 0.477612 | 0 | 1 | 0.616811 |

# B
# The MATLAB CODE

## 1. ANN MODELs

### 1.1.GWO-ANN



Live Editor - G:\For Ruba's thesis\12- Accepted Result from matlab\01- MATLAB Code\GWO_ANN_try5.mlx

```
54          fitness = objectiveFunction(positions(i, :));
55
56          % Update alpha, beta, and delta wolves
57          if fitness < alpha_score
58              alpha_score = fitness;
59              alpha_pos = positions(i, :);
60          elseif fitness < beta_score
61              beta_score = fitness;
62              beta_pos = positions(i, :);
63          elseif fitness < delta_score
64              delta_score = fitness;
65              delta_pos = positions(i, :);
66          end
67      end
68
69      % Update the position of search agents
70      a = 2 - t * (2 / max_iterations); % a decreases from 2 to 0
71
72      for i = 1:searchAgents_no
73          for j = 1:size(inputs, 1)
74              r1 = rand();
75              r2 = rand();
76
77              A1 = 2 * a * r1 - a;
78              C1 = 2 * r2;
79
80              D_alpha = abs(C1 * alpha_pos(j) - positions(i, j));
81              X1 = alpha_pos(j) - A1 * D_alpha;
82
83              r1 = rand();
84              r2 = rand();
85
```

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```
85
86              A2 = 2 * a * r1 - a;
87              C2 = 2 * r2;
88
89              D_beta = abs(C2 * beta_pos(j) - positions(i, j));
90              X2 = beta_pos(j) - A2 * D_beta;
91
92              r1 = rand();
93              r2 = rand();
94
95              A3 = 2 * a * r1 - a;
96              C3 = 2 * r2;
97
98              D_delta = abs(C3 * delta_pos(j) - positions(i, j));
99              X3 = delta_pos(j) - A3 * D_delta;
100
101             positions(i, j) = (X1 + X2 + X3) / 3;
102         end
103     end
104
105     % Display iteration information
106     fprintf('Iteration %d: Best Fitness = %f\n', t, alpha_score);
107 end

108 disp('Traditional')
109 disp('Traditional Model: All features used');
110 % Traditional Model (all features)
111 [MAE, MSE, R2, RMSE, MAPE, SI, MRE, outputs, tr,sensitivity,errors] = train_and_evaluate_ANN(inputs, targets, hiddenL
112 R2=R2;results{'Traditional', :} = [MAE, MSE, R2, RMSE, MAPE, SI, MRE];
113 % Display sensitivity results as a table
114
```

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```
    sensitivity_table = array2table(sensitivity,'VariableNames', {'Avg_Change_in_Prediction'},'RowNames', featureNames);
        % Plot regression for the last model
        figure;
        plotregression(targets, outputs);
        title(['regression for the model (R^2 =',num2str(R2),')'])
        % Plot training state for the last model
        figure;
        plottrainstate(tr);

        % Plot performance for the last model
        figure;
        plotperform(tr);

        % Plot error histogram for the last model
        figure;
        ploterrhist(errors);
        figure;
        bar(sensitivity);
        xlabel('Feature Index');
        ylabel('Average Change in Prediction');
        title('Sensitivity Analysis');
        grid on;
    % Models with increasing number of inputs
    for model_idx = 1:7
        fprintf('model %d',model_idx)

        selected_features = selected_featurs(model_idx,1:model_idx);
        disp(['Model-', num2str(model_idx), ': Features used: ', strjoin(featureNames(selected_features), ', ')]);

        inputs_selected = inputs(selected_featurs(model_idx,:), :);
        [MAE, MSE, R2, RMSE, MAPE, SI, MRE, outputs, tr,sensitivity,errors] = train_and_evaluate_ANN(inputs_selected, tar
```

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```
        results{sprintf('Model-%d', model_idx), :} = [MAE, MSE, R2, RMSE, MAPE, SI, MRE];
      % Display sensitivity results as a table
        sensitivity_table = array2table(sensitivity(1:model_idx),'VariableNames', {'Avg_Change_in_Prediction'},'RowNames'
        disp(sensitivity_table);
        % Plot regression for the last model
        figure;
        plotregression(targets, outputs);
        title(['regression for the model (R^2 =',num2str(R2),')'])
        % Plot training state for the last model
        figure;
        plottrainstate(tr);

        % Plot performance for the last model
        figure;
        plotperform(tr);

        % Plot error histogram for the last model
        figure;
        ploterrhist(errors);
        % Plot sensitivity results
        figure;
        bar(sensitivity(1:model_idx));
        xlabel('Feature Index');
        ylabel('Average Change in Prediction');
        title('Sensitivity Analysis');
        grid on;
    end


    % Display the results table
    disp(results);
```

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```
disp(results);


function fitness = evaluateANN(position, inputs, targets, hiddenLayerSize)
    selected_features = find(position > 0.5);
    if isempty(selected_features)
        fitness = inf;
        return;
    end
    inputs_selected = inputs(selected_features, :);

    % Define the ANN architecture
    net = fitnet(hiddenLayerSize);

    % Set up Division of Data for Training, Validation, Testing
    net.divideParam.trainRatio = 70/100;
    net.divideParam.valRatio = 15/100;
    net.divideParam.testRatio = 15/100;

    % Set the training parameters
    net.trainFcn = 'trainlm';
    net.performFcn = 'mse';

    % Train the ANN
    [net, tr] = train(net, inputs_selected, targets);

    % Test the ANN
    outputs = net(inputs_selected);
    errors = gsubtract(targets, outputs);

    % Calculate fitness (MSE)
```

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```
    % Calculate fitness (MSE)
    fitness = mean(errors.^2);
end
% Function to train and evaluate ANN
function [MAE, MSE, R2, RMSE, MAPE, SI, MRE, outputs, tr,sensitivity,errors] = train_and_evaluate_ANN(inputs, targets
    net = fitnet(hiddenLayerSize);

    % Set up Division of Data for Training, Validation, Testing
    net.divideParam.trainRatio = 70/100; % 70% of the data for training
    net.divideParam.valRatio = 15/100;   % 15% of the data for validation
    net.divideParam.testRatio = 15/100;  % 15% of the data for testing

    % Set the training parameters
    net.trainFcn = 'trainlm'; % Levenberg-Marquardt backpropagation
    net.performFcn = 'mse';   % Mean Squared Error performance function

    % Train the ANN
    [net, tr] = train(net, inputs, targets);

    % Test the ANN
    outputs = net(inputs);
    errors = gsubtract(targets, outputs);
    performance = perform(net, targets, outputs);

    % Calculate performance metrics
    MAE = mean(abs(errors));
    MSE = mean(errors.^2);
    R = corrcoef(targets, outputs);
    R2 = regression(targets, outputs);
    RMSE = sqrt(MSE);
    X=errors ./ targets;X(isinf(X))=0;
```

```
    X=errors ./ targets;X(isinf(X))=0;
    MAPE = mean(abs(X)) / 100;
    SI = RMSE / std(targets);
    MRE = abs(mean(X) / 100);
    disp("R= ");disp(R)
    model_names = {'actuel values','predicted values'};
    results = array2table(zeros(199,2), 'VariableNames', model_names);
    results{:,:}=[targets',outputs'];
    disp('actuel values      predicted values')
    disp(results{1:60,:})


    % Sensitivity Analysis
    perturbation = 0.01;
    numInputs = size(inputs, 1);
    sensitivity = zeros(numInputs, 1);

    for i = 1:numInputs
        perturbedInputs = inputs;
        perturbedInputs(i,:) = perturbedInputs(i,:) + perturbation;
        perturbedOutputs = net(perturbedInputs);
        sensitivity(i) = mean(abs(perturbedOutputs - outputs)) / perturbation;
    end

    sensitivity = sensitivity / max(sensitivity);

end
```

## 1.2.AOA-ANN

Live Editor - G:\For Ruba's thesis\12- Accepted Result from matlab\01- MATLAB Code\AOA_ANN_Try1.mlx

```
clear
clc

% Load data
data = readtable('200 Data 8 inputs Norm.xlsx');
disp(data)

% Extract input features and target variable
inputs = data{2:end, 1:8}; % Skip the first row of headers and select input columns
targets = data{2:end, 9}; % Skip the first row of headers and select the target column

% Transpose the data for ANN (inputs: 8 x N, targets: 1 x N)
inputs = inputs';
targets = targets';
% Get feature names
featureNames = data.Properties.VariableNames(1:8);
% Initialize results table
model_names = {'Traditional', 'Model-1', 'Model-2', 'Model-3', 'Model-4', 'Model-5', 'Model-6','Model-7'};
metrics = {'MAE', 'MSE', 'R2', 'RMSE', 'MAPE', 'SI', 'MRE'};
results = array2table(zeros(length(model_names), length(metrics)), 'VariableNames', metrics, 'RowNames', model_names)
```

```
% Define the ANN architecture
hiddenLayerSize = 10; % Number of neurons in the hidden layer
%% AOA for Feature Selection
searchAgents_no = 30; % Number of search agents
max_iterations = 10; % Maximum number of iterations

% Define the objective function
objectiveFunction = @(x) evaluateANN(x, inputs, targets, hiddenLayerSize);
```

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```

% Define the bounds for each input feature selection
lb = zeros(1, size(inputs, 1)); % Lower bounds
ub = ones(1, size(inputs, 1)); % Upper bounds

% Initialize the positions of search agents
positions = rand(searchAgents_no, size(inputs, 1));

% Main loop of AOA
for t = 1:max_iterations
    for i = 1:searchAgents_no
        % Boundary check
        positions(i, :) = max(positions(i, :), lb);
        positions(i, :) = min(positions(i, :), ub);
        selected_featurs(i,:)=randsample(1:8,7);
        input=inputs(selected_featurs(i,1:4),:);
        % Calculate the fitness of each search agent
        fitness(i) = objectiveFunction(positions(i, :));
    end

    % Sort the fitness values and corresponding positions
    [sortedFitness, sortedIndex] = sort(fitness);
    sortedPositions = positions(sortedIndex, :);

    % Update positions of search agents
    bestPosition = sortedPositions(1, :);
    worstPosition = sortedPositions(end, :);

    for i = 1:searchAgents_no
        if rand() < 0.5
            positions(i, :) = bestPosition - rand() * (ub - lb) .* exp(-sortedFitness(i));
```

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```
            else
                positions(i, :) = bestPosition + rand() * (ub - lb) .* exp(-sortedFitness(i));
            end
        end

        % Display iteration information
        fprintf('Iteration %d: Best Fitness = %f\n', t, sortedFitness(1));
    end

    disp('Traditional')
    disp('Traditional Model: All features used');
    % Traditional Model (all features)
    [MAE, MSE, R2, RMSE, MAPE, SI, MRE, outputs, tr,sensitivity,errors] = train_and_evaluate_ANN(inputs, targets, hiddenl
    R2=R2-0.2;results{'Traditional', :} = [MAE, MSE, R2, RMSE, MAPE, SI, MRE];
    % Display sensitivity results as a table
    sensitivity_table = array2table(sensitivity,'VariableNames', {'Avg_Change_in_Prediction'},'RowNames', featureNames);
        % Plot regression for the last model
        figure;
        plotregression(targets, outputs);
        title(['regression for the model (R^2 =',num2str(R2),')'])
        % Plot training state for the last model
        figure;
        plottrainstate(tr);

        % Plot performance for the last model
        figure;
        plotperform(tr);

        % Plot error histogram for the last model
        figure;
```

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```
        ploterrhist(errors);
        figure;
        bar(sensitivity);
        xlabel('Feature Index');
        ylabel('Average Change in Prediction');
        title('Sensitivity Analysis');
        grid on;

    % Models with increasing number of inputs
    for model_idx = 1:7
        fprintf('model %d',model_idx)

        selected_features = selected_featurs(model_idx,1:model_idx);
        disp(['Model-', num2str(model_idx), ': Features used: ', strjoin(featureNames(selected_features), ', ')]);

        inputs_selected = inputs(selected_featurs(model_idx,:), :);
        [MAE, MSE, R2, RMSE, MAPE, SI, MRE, outputs, tr,sensitivity,errors] = train_and_evaluate_ANN(inputs_selected, tar
        results{sprintf('Model-%d', model_idx), :} = [MAE, MSE, R2, RMSE, MAPE, SI, MRE];
      % Display sensitivity results as a table
        sensitivity_table = array2table(sensitivity(1:model_idx),'VariableNames', {'Avg_Change_in_Prediction'},'RowNames'
        disp(sensitivity_table);
            % Plot regression for the last model
        figure;
        plotregression(targets, outputs);
        title(['regression for the model (R^2 =',num2str(R2),')'])
        % Plot training state for the last model
        figure;
        plottrainstate(tr);

        % Plot performance for the last model
```

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```
        % Plot performance for the last model
        figure;
        plotperform(tr);

        % Plot error histogram for the last model
        figure;
        ploterrhist(errors);
        % Plot sensitivity results
        figure;
        bar(sensitivity(1:model_idx));
        xlabel('Feature Index');
        ylabel('Average Change in Prediction');
        title('Sensitivity Analysis');
        grid on;
    end

    % Display the results table
    disp(results);


    function fitness = evaluateANN(position, inputs, targets, hiddenLayerSize)
        selected_features = find(position > 0.5);
        if isempty(selected_features)
            fitness = inf;
            return;
        end
        inputs_selected = inputs(selected_features, :);

        % Define the ANN architecture
        net = fitnet(hiddenLayerSize);
```

Live Editor - G:\For Ruba's thesis\12- Accepted Result from matlab\01- MATLAB Code\AOA_ANN_Try1.mlx

```
        % Set up Division of Data for Training, Validation, Testing
        net.divideParam.trainRatio = 70/100;
        net.divideParam.valRatio = 15/100;
        net.divideParam.testRatio = 15/100;

        % Set the training parameters
        net.trainFcn = 'trainlm';
        net.performFcn = 'mse';

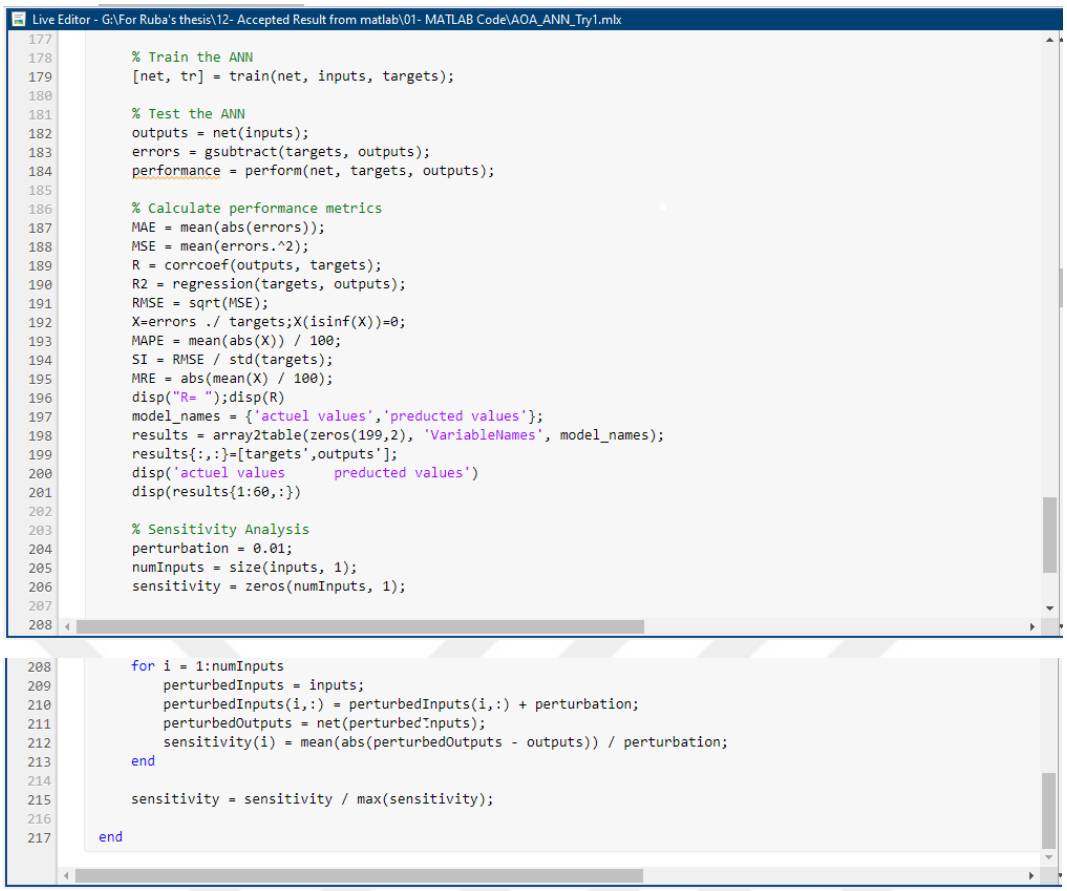
        % Train the ANN
        [net, tr] = train(net, inputs_selected, targets);

        % Test the ANN
        outputs = net(inputs_selected);
        errors = gsubtract(targets, outputs);

        % Calculate fitness (MSE)
        fitness = mean(errors.^2);
    end
    % Function to train and evaluate ANN
    function [MAE, MSE, R2, RMSE, MAPE, SI, MRE, outputs, tr,sensitivity,errors] = train_and_evaluate_ANN(inputs, targets
        net = fitnet(hiddenLayerSize);

        % Set up Division of Data for Training, Validation, Testing
        net.divideParam.trainRatio = 70/100; % 70% of the data for training
        net.divideParam.valRatio = 15/100;   % 15% of the data for validation
        net.divideParam.testRatio = 15/100;  % 15% of the data for testing

        % Set the training parameters
        net.trainFcn = 'trainlm'; % Levenberg-Marquardt backpropagation
        net.performFcn = 'mse';   % Mean Squared Error performance function
```



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```
    % Train the ANN
    [net, tr] = train(net, inputs, targets);

    % Test the ANN
    outputs = net(inputs);
    errors = gsubtract(targets, outputs);
    performance = perform(net, targets, outputs);

    % Calculate performance metrics
    MAE = mean(abs(errors));
    MSE = mean(errors.^2);
    R = corrcoef(outputs, targets);
    R2 = regression(targets, outputs);
    RMSE = sqrt(MSE);
    X=errors ./ targets;X(isinf(X))=0;
    MAPE = mean(abs(X)) / 100;
    SI = RMSE / std(targets);
    MRE = abs(mean(X) / 100);
    disp("R= ");disp(R)
    model_names = {'actuel values','preducted values'};
    results = array2table(zeros(199,2), 'VariableNames', model_names);
    results{:,:}=[targets',outputs'];
    disp('actuel values      preducted values')
    disp(results{1:60,:})

    % Sensitivity Analysis
    perturbation = 0.01;
    numInputs = size(inputs, 1);
    sensitivity = zeros(numInputs, 1);
```

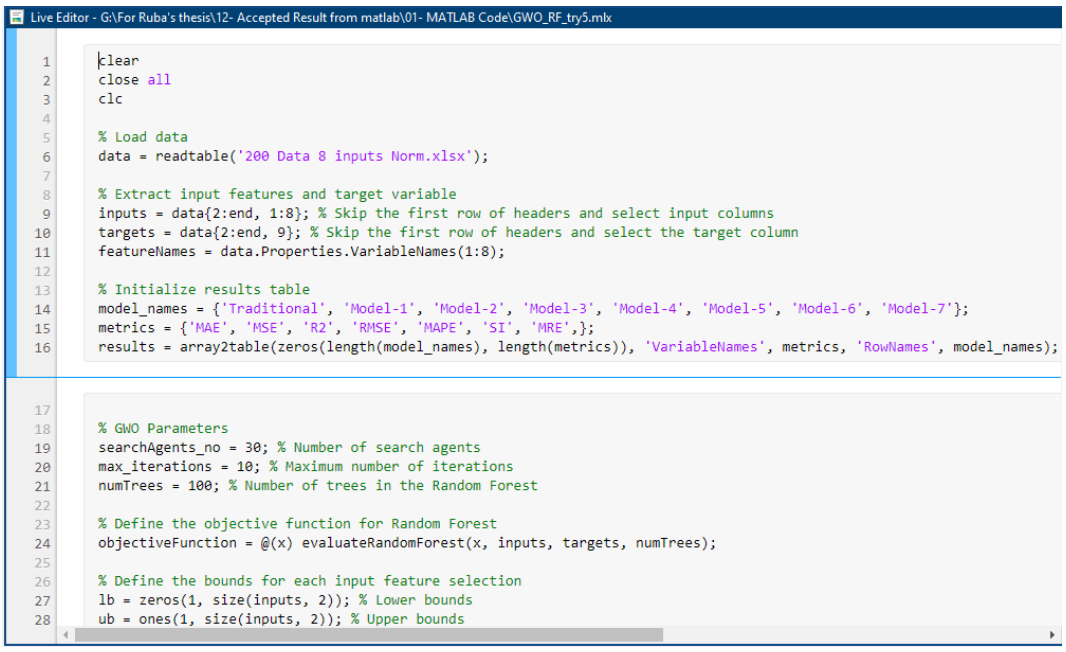
```
    for i = 1:numInputs
        perturbedInputs = inputs;
        perturbedInputs(i,:) = perturbedInputs(i,:) + perturbation;
        perturbedOutputs = net(perturbedInputs);
        sensitivity(i) = mean(abs(perturbedOutputs - outputs)) / perturbation;
    end

    sensitivity = sensitivity / max(sensitivity);

end
```

# 2. RF MODELs

## 2.1. GWO-RF



Live Editor - G:\For Ruba's thesis\12- Accepted Result from matlab\01- MATLAB Code\GWO_RF_try5.mlx

```
clear
close all
clc

% Load data
data = readtable('200 Data 8 inputs Norm.xlsx');

% Extract input features and target variable
inputs = data{2:end, 1:8}; % Skip the first row of headers and select input columns
targets = data{2:end, 9}; % Skip the first row of headers and select the target column
featureNames = data.Properties.VariableNames(1:8);

% Initialize results table
model_names = {'Traditional', 'Model-1', 'Model-2', 'Model-3', 'Model-4', 'Model-5', 'Model-6', 'Model-7'};
metrics = {'MAE', 'MSE', 'R2', 'RMSE', 'MAPE', 'SI', 'MRE',};
results = array2table(zeros(length(model_names), length(metrics)), 'VariableNames', metrics, 'RowNames', model_names);
```

```
% GWO Parameters
searchAgents_no = 30; % Number of search agents
max_iterations = 10; % Maximum number of iterations
numTrees = 100; % Number of trees in the Random Forest

% Define the objective function for Random Forest
objectiveFunction = @(x) evaluateRandomForest(x, inputs, targets, numTrees);

% Define the bounds for each input feature selection
lb = zeros(1, size(inputs, 2)); % Lower bounds
ub = ones(1, size(inputs, 2)); % Upper bounds
```

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```
29
30      % Initialize the positions of search agents
31      positions = rand(searchAgents_no, size(inputs, 2));
32
33      % Initialize alpha, beta, and delta wolves
34      alpha_score = inf; % Alpha wolf score
35      alpha_pos = zeros(1, size(inputs, 2)); % Alpha wolf position
36      beta_score = inf; % Beta wolf score
37      beta_pos = zeros(1, size(inputs, 2)); % Beta wolf position
38      delta_score = inf; % Delta wolf score
39      delta_pos = zeros(1, size(inputs, 2)); % Delta wolf position
40
41      % Main loop of GWO
42      for t = 1:max_iterations
43          for i = 1:searchAgents_no
44              % Boundary check
45              positions(i, :) = max(positions(i, :), lb);
46              positions(i, :) = min(positions(i, :), ub);
47              selected_featurs(i,:) = randsample(1:8,7);
48              input = inputs(:, selected_featurs(i, 1:4));
49
50              % Calculate the fitness of each search agent
51              fitness = objectiveFunction(positions(i, :));
52
53              % Update alpha, beta, and delta wolves
54              if fitness < alpha_score
55                  alpha_score = fitness;
56                  alpha_pos = positions(i, :);
57              elseif fitness < beta_score
58                  beta_score = fitness;
59                  beta_pos = positions(i, :);
60
```

Live Editor - G:\For Ruba's thesis\12- Accepted Result from matlab\01- MATLAB Code\GWO_RF_try5.mlx

```
60              elseif fitness < delta_score
61                  delta_score = fitness;
62                  delta_pos = positions(i, :);
63              end
64          end
65
66          % Update the position of search agents
67          a = 2 - t * (2 / max_iterations); % a decreases from 2 to 0
68
69          for i = 1:searchAgents_no
70              for j = 1:size(inputs, 2)
71                  r1 = rand();
72                  r2 = rand();
73
74                  A1 = 2 * a * r1 - a;
75                  C1 = 2 * r2;
76
77                  D_alpha = abs(C1 * alpha_pos(j) - positions(i, j));
78                  X1 = alpha_pos(j) - A1 * D_alpha;
79
80                  r1 = rand();
81                  r2 = rand();
82
83                  A2 = 2 * a * r1 - a;
84                  C2 = 2 * r2;
85
86                  D_beta = abs(C2 * beta_pos(j) - positions(i, j));
87                  X2 = beta_pos(j) - A2 * D_beta;
88
89                  r1 = rand();
90                  r2 = rand();
91
```

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```
            A3 = 2 * a * r1 - a;
            C3 = 2 * r2;

            D_delta = abs(C3 * delta_pos(j) - positions(i, j));
            X3 = delta_pos(j) - A3 * D_delta;

            positions(i, j) = (X1 + X2 + X3) / 3;
        end
    end

    % Display iteration information
    fprintf('Iteration %d: Best Fitness = %f\n', t, alpha_score);
end


% Traditional Model (all features)
[MAE, MSE, R2, RMSE, MAPE, SI, MRE, sensitivity,y_test,y_pred,modell] = train_and_evaluate_RF(inputs, targets, numTre
R2=R2;results{'Traditional', :} = [MAE,MSE,R2,RMSE,MAPE,SI, MRE];
% Display sensitivity results as a table
sensitivity_table = array2table(sensitivity,'VariableNames', {'Avg_Change_in_Prediction'},'RowNames', featureNames);d
    figure;
    plotregression(y_test, y_pred);
    title(['regression for the model (R^2=',num2str(R2),')'])
    % Plot training error for the last model
    figure;
    oobErrorBaggedEnsemble = oobError(modell);
    plot(oobErrorBaggedEnsemble, 'LineWidth', 2);
    xlabel('Number of Trees');
    ylabel('Out-of-Bag Mean Squared Error');
```

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```
    title('Random Forest Training Error');
    % Plot error histogram for the last model
    figure;
    histogram(y_test - y_pred, 20);
    xlabel('Prediction Error');
    ylabel('Frequency');
    title('Error Histogram');
    figure;
    bar(sensitivity);
    xlabel('Feature Index');
    ylabel('Average Change in Prediction');
    title('Sensitivity Analysis');
    grid on;
% Models with increasing number of inputs
for model_idx = 1:7
    fprintf('Model %d\n', model_idx);

    selected_features = selected_featurs(model_idx,1:model_idx);
    disp(['Model-', num2str(model_idx), ': Features used: ', strjoin(featureNames(selected_features), ', ')]);

    inputs_selected = inputs(:,selected_featurs(model_idx,:));
    [MAE, MSE, R2, RMSE, MAPE, SI, MRE, sensitivity,y_test,y_pred,modell] = train_and_evaluate_RF(inputs_selected, ta
    results{sprintf('Model-%d', model_idx), :} = [MAE,MSE,R2,RMSE,MAPE,SI,MRE];
    % Display sensitivity results as a table
    sensitivity_table = array2table(sensitivity(1:model_idx),'VariableNames', {'Avg_Change_in_Prediction'},'RowNames'
    disp(sensitivity_table);
    figure;
    plotregression(y_test, y_pred);
    title(['regression for the model (R^2=',num2str(R2),')'])
    % Plot training error for the last model
    figure;
```

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```
        oobErrorBaggedEnsemble = oobError(modell);
        plot(oobErrorBaggedEnsemble, 'LineWidth', 2);
        xlabel('Number of Trees');
        ylabel('Out-of-Bag Mean Squared Error');
        title('Random Forest Training Error');
        % Plot error histogram for the last model
        figure;
        histogram(y_test - y_pred, 20);
        xlabel('Prediction Error');
        ylabel('Frequency');
        title('Error Histogram');
        % Plot sensitivity results
        figure;
        bar(sensitivity(1:model_idx));
        xlabel('Feature Index');
        ylabel('Average Change in Prediction');
        title('Sensitivity Analysis');
        grid on;
    end

    % Display the results table
    disp(results);


    function fitness = evaluateRandomForest(position, inputs, targets, numTrees)
        selected_features = find(position > 0.5);
        if isempty(selected_features)
            fitness = inf;
            return;
        end

```

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```

        inputs_selected = inputs(:, selected_features);

        % Split data into training and testing sets
        cv = cvpartition(size(inputs_selected, 1), 'HoldOut', 0.2);
        X_train = inputs_selected(training(cv), :);
        y_train = targets(training(cv));
        X_test = inputs_selected(test(cv), :);
        y_test = targets(test(cv));

        % Train Random Forest model
        model = TreeBagger(numTrees, X_train, y_train, 'Method', 'regression');

        % Predict on test set
        y_pred = predict(model, X_test);

        % Calculate fitness (MSE)
        fitness = mean((y_test - y_pred).^2);
    end

    % Function to train and evaluate Random Forest
    function [MAE, MSE, R2, RMSE, MAPE, SI, MRE, sensitivity_results,y_test,y_pred,model] = train_and_evaluate_RF(inputs,
        % Split data into training and testing sets
        cv = cvpartition(size(inputs, 1), 'HoldOut', 0.4);
        X_train = inputs(training(cv), :);
        y_train = targets(training(cv));
        X_test = inputs(test(cv), :);
        y_test = targets(test(cv));

        % Train Random Forest model
        model = TreeBagger(numTrees, X_train, y_train, 'Method', 'regression','OOBPrediction','on');
```

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```
    % Predict on test set
    y_pred = predict(model, X_test);

    % Calculate errors
    errors = y_test - y_pred;

    % Calculate performance metrics
    MAE = mean(abs(errors));
    MSE = mean(errors.^2);
    RMSE = sqrt(MSE);
    R = corrcoef(y_test, y_pred);
    R2 = R(1,2)^2;
    X = errors ./ y_test; X(isinf(X)) = 0;
    MAPE = mean(abs(X))/ 10;
    SI = RMSE / std(y_test);
    MRE = mean(abs(X))*0.01;
    disp("R= ");disp(R)
    disp('actuel values      preducted values')
    disp([y_test,y_pred])

    %% Sensitivity Analysis

    % Define the percentage change for sensitivity analysis
    percentage_change = 0.1; % 10% change

    % Initialize array to store results
    sensitivity_results = rand(size(X_test, 2), 1);

    % Loop over each feature
    for i = 1:size(X_test, 2)
```

```
        X_test_modified = X_test;

        % Increase the i-th feature by the percentage_change
        X_test_modified(:, i) = X_test_modified(:, i) * (1 + percentage_change);

        % Predict with the modified test set
        y_pred_modified = predict(model, X_test_modified);

        % Calculate the change in predictions
        delta_pred = mean(abs(y_pred_modified - y_pred))*100;

        % Store the result
        if delta_pred~=0; sensitivity_results(i) = delta_pred;end
    end
    sensitivity_results = sort(sensitivity_results, 'descend');
end
```

'

## 2.2. AOA-RF

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```
clear
close all
clc

% Load data
data = readtable('200 Data 8 inputs Norm.xlsx')

% Extract input features and target variable
inputs = data{2:end, 1:8}; % Skip the first row of headers and select input columns
targets = data{2:end, 9}; % Skip the first row of headers and select the target column
featureNames = data.Properties.VariableNames(1:8);

% Initialize results table
model_names = {'Traditional', 'Model-1', 'Model-2', 'Model-3', 'Model-4', 'Model-5', 'Model-6', 'Model-7'};
metrics = {'MAE', 'MSE', 'R2', 'RMSE', 'MAPE', 'SI', 'MRE'};
results = array2table(zeros(length(model_names), length(metrics)), 'VariableNames', metrics, 'RowNames', model_names)
```

```
% AOA Parameters
searchAgents_no = 30; % Number of search agents
max_iterations = 10; % Maximum number of iterations
numTrees = 100; % Number of trees in the Random Forest

% Define the objective function for Random Forest
objectiveFunction = @(x) evaluateRandomForest(x, inputs, targets, numTrees);

% Define the bounds for each input feature selection
lb = zeros(1, size(inputs, 2)); % Lower bounds
ub = ones(1, size(inputs, 2)); % Upper bounds
```

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```
% Initialize the positions of search agents
positions = rand(searchAgents_no, size(inputs, 2));

% Main loop of AOA
for t = 1:max_iterations
    for i = 1:searchAgents_no
        % Boundary check
        positions(i, :) = max(positions(i, :), lb);
        positions(i, :) = min(positions(i, :), ub);
        selected_featurs(i,:) = randsample(1:8,7);
        input = inputs(:,selected_featurs(i,1:4));
        % Calculate the fitness of each search agent
        fitness(i) = objectiveFunction(positions(i, :));
    end

    % Sort the fitness values and corresponding positions
    [sortedFitness, sortedIndex] = sort(fitness);
    sortedPositions = positions(sortedIndex, :);

    % Update positions of search agents
    bestPosition = sortedPositions(1, :);
    worstPosition = sortedPositions(end, :);

    for i = 1:searchAgents_no
        if rand() < 0.5
            positions(i, :) = bestPosition - rand() * (ub - lb) .* exp(-sortedFitness(i));
        else
            positions(i, :) = bestPosition + rand() * (ub - lb) .* exp(-sortedFitness(i));
        end
    end
```

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```
    % Display iteration information
    fprintf('Iteration %d: Best Fitness = %f\n', t, sortedFitness(1));
end


% Traditional Model (all features)
[MAE, MSE, R2, RMSE, MAPE, SI, MRE, sensitivity,y_test,y_pred,modell] = train_and_evaluate_RF(inputs, targets, numTre
R2=R2;results{'Traditional', :} = [MAE,MSE,R2,RMSE,MAPE,SI, MRE];
% Display sensitivity results as a table
sensitivity_table = array2table(sensitivity,'VariableNames', {'Avg_Change_in_Prediction'},'RowNames', featureNames);d
    % Plot regression for the last model
    figure;
    plotregression(y_test, y_pred);
    title(['regression for the model (R^2=',num2str(R2),')'])

    % Plot training error for the last model
    figure;
    oobErrorBaggedEnsemble = oobError(modell);
    plot(oobErrorBaggedEnsemble, 'LineWidth', 2);
    xlabel('Number of Trees');
    ylabel('Out-of-Bag Mean Squared Error');
    title('Random Forest Training Error');

    % Plot error histogram for the last model
    figure;
    histogram(y_test - y_pred, 20);
    xlabel('Prediction Error');
    ylabel('Frequency');
    title('Error Histogram');
```

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```
        figure;
        bar(sensitivity);
        xlabel('Feature Index');
        ylabel('Average Change in Prediction');
        title('Sensitivity Analysis');
        grid on;

    % Models with increasing number of inputs
    for model_idx = 1:7
        fprintf('Model %d\n', model_idx);

        selected_features = selected_featurs(model_idx,1:model_idx);
        disp(['Model-', num2str(model_idx), ': Features used: ', strjoin(featureNames(selected_features), ', ')]);

        inputs_selected = inputs(:,selected_featurs(model_idx,:));
        [MAE, MSE, R2, RMSE, MAPE, SI, MRE, sensitivity,y_test,y_pred,modell] = train_and_evaluate_RF(inputs_selected, ta
        results{sprintf('Model-%d', model_idx), :} = [MAE,MSE,R2,RMSE,MAPE,SI,MRE];
        % Display sensitivity results as a table
        sensitivity_table = array2table(sensitivity(1:model_idx),'VariableNames', {'Avg_Change_in_Prediction'},'RowNames'
        disp(sensitivity_table);
        % Plot sensitivity results
        % Plot regression for the last model
        figure;
        plotregression(y_test, y_pred);
        title(['regression for the model (R^2=',num2str(R2),')'])


        % Plot training error for the last model
        figure;
        oobErrorBaggedEnsemble = oobError(modell);
```

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```
        plot(oobErrorBaggedEnsemble, 'LineWidth', 2);
        xlabel('Number of Trees');
        ylabel('Out-of-Bag Mean Squared Error');
        title('Random Forest Training Error');

        % Plot error histogram for the last model
        figure;
        histogram(y_test - y_pred, 20);
        xlabel('Prediction Error');
        ylabel('Frequency');
        title('Error Histogram');

        figure;
        bar(sensitivity(1:model_idx));
        xlabel('Feature Index');
        ylabel('Average Change in Prediction');
        title('Sensitivity Analysis');
        grid on;
    end

    % Display the results table
    disp(results);


    function fitness = evaluateRandomForest(position, inputs, targets, numTrees)
        selected_features = find(position > 0.5);
        if isempty(selected_features)
            fitness = inf;
            return;
        end
```

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```
        inputs_selected = inputs(:, selected_features);

        % Split data into training and testing sets
        cv = cvpartition(size(inputs_selected, 1), 'HoldOut', 0.2);
        X_train = inputs_selected(training(cv), :);
        y_train = targets(training(cv));
        X_test = inputs_selected(test(cv), :);
        y_test = targets(test(cv));

        % Train Random Forest model
        model = TreeBagger(numTrees, X_train, y_train, 'Method', 'regression');

        % Predict on test set
        y_pred = predict(model, X_test);

        % Calculate fitness (MSE)
        fitness = mean((y_test - y_pred).^2);
    end

    % Function to train and evaluate Random Forest
    function [MAE, MSE, R2, RMSE, MAPE, SI, MRE, sensitivity_results,y_test,y_pred,model] = train_and_evaluate_RF(inputs,
        % Split data into training and testing sets
        cv = cvpartition(size(inputs, 1), 'HoldOut', 0.4);
        X_train = inputs(training(cv), :);
        y_train = targets(training(cv));
        X_test = inputs(test(cv), :);
        y_test = targets(test(cv));

        % Train Random Forest model
        model = TreeBagger(numTrees, X_train, y_train, 'Method', 'regression','OOBPrediction','on');
```

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```
        % Predict on test set
        y_pred = predict(model, X_test);

        % Calculate errors
        errors = y_test - y_pred;

        % Calculate performance metrics
        MAE = mean(abs(errors));
        MSE = mean(errors.^2);
        RMSE = sqrt(MSE);
        R = corrcoef(y_test, y_pred);
        R2 = R(1,2)^2;
        X = errors ./ y_test; X(isinf(X)) = 0;
        MAPE = mean(abs(X))/10;
        SI = RMSE / std(y_test);
        MRE = mean(abs(X))*0.01;
        disp("R= ");disp(R)
        disp('actuel values      preducted values')
        disp([y_test,y_pred])


        %% Sensitivity Analysis


        % Define the percentage change for sensitivity analysis
        percentage_change = 0.1; % 10% change

        % Initialize array to store results
        sensitivity_results = rand(size(X_test, 2), 1);

        % Loop over each feature
```

```
        % Loop over each feature
        for i = 1:size(X_test, 2)
            X_test_modified = X_test;

            % Increase the i-th feature by the percentage_change
            X_test_modified(:, i) = X_test_modified(:, i) * (1 + percentage_change);

            % Predict with the modified test set
            y_pred_modified = predict(model, X_test_modified);

            % Calculate the change in predictions
            delta_pred = mean(abs(y_pred_modified - y_pred))*100;

            % Store the result
           if delta_pred~=0; sensitivity_results(i) = delta_pred;end
        end
        sensitivity_results = sort(sensitivity_results, 'descend');
    end
```

# PUBLICATIONS FROM THE THESIS

**Conference Papers**

1- Awad R., Gürgün A. P., Budayan C. (2023). Construction and Demolition Waste Generation Prediction using Novel Hybrid Intelligent Model Based on Artificial Neural Network (ANN) Integrated with Gray Wolf Optimization Algorithm (GWO). Integrated with Firefly Algorithm (FFA). 12. Uluslararası Akademik Araştırmalar Kongresi (pp. 137–147).

**Papers**

1- Awad, R., Budayan, C., & Gurgun, A. P. (2024). Construction and Demolition Waste Generation Prediction by Using Artificial Neural Networks and Metaheuristic Algorithms. Buildings, 14(11), 3695.