Waste Management 109 (2020) 231–246

Contents lists available at ScienceDirect

Waste Management

journal homepage: www.elsevier.com/locate/wasman

Artificial intelligence applications in solid waste management: A systematic research review

Mohamed Abdallah [a,*], Manar Abu Talib [b], Sainab Feroz [a], Qassim Nasir [c], Hadeer Abdalla [a], Bayan Mahfood [b]

[a] Department of Civil and Environmental Engineering, University of Sharjah, Sharjah, United Arab Emirates
[b] Department of Computer Science, University of Sharjah, Sharjah, United Arab Emirates
[c] Department of Electrical Engineering, University of Sharjah, Sharjah, United Arab Emirates

ARTICLE INFO

Article history:
Received 31 December 2019
Revised 20 April 2020
Accepted 30 April 2020

Keywords:
Artificial intelligence
Machine learning
Modeling
Optimization
Deep learning
Neural networks

ABSTRACT

The waste management processes typically involve numerous technical, climatic, environmental, demographic, socio-economic, and legislative parameters. Such complex nonlinear processes are challenging to model, predict and optimize using conventional methods. Recently, artificial intelligence (AI) techniques have gained momentum in offering alternative computational approaches to solve solid waste management (SWM) problems. AI has been efficient at tackling ill-defined problems, learning from experience, and handling uncertainty and incomplete data. Although significant research was carried out in this domain, very few review studies have assessed the potential of AI in solving the diverse SWM problems. This systematic literature review compiled 85 research studies, published between 2004 and 2019, analyzing the application of AI in various SWM fields, including forecasting of waste characteristics, waste bin level detection, process parameters prediction, vehicle routing, and SWM planning. This review provides comprehensive analysis of the different AI models and techniques applied in SWM, application domains and reported performance parameters, as well as the software platforms used to implement such models. The challenges and insights of applying AI techniques in SWM are also discussed.

Contents

* Corresponding author.
E-mail address: mabdallah@sharjah.ac.ae (M. Abdallah).

https://doi.org/10.1016/j.wasman.2020.04.057
0956-053X/

Nomenclature

AHP	Analytic Hierarchy Process	MAE	Mean Absolute Error
AI	Artificial Intelligence	MAPE	Mean Absolute Percent Error
AIS	Artificial Immune System	MARE	Mean Absolute Relative Error
ANFIS	Adaptive Neuro-Fuzzy Inference System	MLP	Multi-Layer Perception
ANN	Artificial Neural Network	MLR	Multiple Linear Regression
BP	Back Propagation	MSE	Mean Square Error
CNN	Convolutional Neural Network	MSW	Municipal Solid Waste
DT	Decision Trees	NISE	Non-inferior Set Estimation
FL	Fuzzy Logic	NSGA	Non-dominated Sorting Genetic Algorithm
FSVM	Fuzzy Logic - Support Vector Regression	PCA	Principal Component Analysis
GA	Genetic Algorithm	PCA-MLR	Principal Component Regression Analysis
GIS	Geographic Information System	RBF	Radial Basis Function
GLAM	Gray Level Aura Matrix	RF	Random Forest
GM	Gray Model	RMSE	Root Mean Square Error
GPU	Graphics Processing Unit	RSM	Response Surface Model
GRASP	Greedy Randomized Adaptive Search Procedure	SLR	Systematic Literature Review
GT	Gamma Test	SVM	Support Vector Machine
KNN	K Nearest Neighbor	SVR	Support Vector Regression
LR	Linear Regression	SWM	Solid Waste Management
LSSVM	Least Square Support Vector Machine	WT	Wavelet Transform

1. Introduction

Rapid urbanization, population growth and economic development have resulted in increased waste generation in countries across the world. Recent statistics indicate that 2.01 billion tons of municipal solid waste (MSW) were generated in 2016, which is projected to increase to 3.40 billion tons by 2050 (World Bank, 2018). 33% of the generated solid waste are unsafely handled, with the waste being disposed in illegal waste dumps or unmonitored landfills (World Bank, 2018). Those poor practices pose multiple environmental and health risks including ground water pollution, land deterioration, increased cancer incidence, childhood mortality and birth anomalies (Triassi et al., 2015). Studies have shown that insufficient planning and inadequate operation are major reasons behind poor waste management (Hannan et al., 2013; Malakahmad and Khalil, 2011). Recently, there have been serious efforts to revolutionize the waste management industry towards sustainability and profitability by means of advanced technologies and intelligent systems.

Waste management processes comprise complex operations and non-linear parameters due to the multiple interconnected processes involved and the highly variable demographic and socio-economic factors affecting the overall systems. Moreover, achieving satisfactory performance in SWM systems without compromising other health and environmental factors is a rather difficult task. The emerging artificial intelligence (AI) techniques are sought to be well-suited for application in the SWM field (Vitorino et al., 2017). The AI technology deals with the design of computer systems and programs that are capable of mimicking human traits such as problem solving, learning, perception, understanding, reasoning, and awareness of surroundings. AI models such as artificial neural network (ANN), expert system, genetic algorithm (GA), and fuzzy logic (FL) have the capability to solve ill-defined problems, configure complex mapping, and predict results (Yetilmezsoy et al., 2011). Each AI model or branch of AI serves a specific function; for example, ANN models can train data for classification and prediction. Additionally, ANNs can be used to handle big data in urban geography and perform geographical analysis. Expert systems, such as FL, can acquire human cognitive and reasoning skills in addition to possessing knowledgebase. These systems have a simple linguistic syntax that is proficient at managing complex operations and qualitative attributes (Yetilmezsoy et al., 2011). On the other hand, evolutionary algorithms, such as GA adopt the concept of natural selection to obtain optimum results by selecting the best fit data to handle unforeseen conditions (Kalogirou, 2003a).

Due to the advancement of AI technologies and limitations of conventional computational techniques, AI-based models are now incorporated in almost all fields of study including medicine, linguistics, and engineering among others (Kalogirou, 2003a). The capabilities of AI modelling techniques in handling multidimensional and noisy data substantiate the increase of AI application fields. In the field of environmental engineering, AI has been widely implemented to solve problems related to air pollution, water and wastewater treatment modelling, simulation of soil remediation and ground water contamination as well as planning of SWM strategies (Yetilmezsoy et al., 2011). AI-based risk management tools such as ANN, multi-layer perception (MLP), and

Adaptive Neuro-Fuzzy Inference System (ANFIS) models were implemented to predict concentrations of pollutant and particulate matter (Roy, 2012; Shu et al., 2006). Moreover, MLP was proven to be an efficient modelling algorithm for forecasting levels of carbon monoxide, ozone and nitrogen dioxide in the atmosphere (Agirre-basurko et al., 2006). On the other hand, ANFIS was useful to predict and optimize water and wastewater treatment plant processes (Cakmakci, 2007; Chun et al., 1999). In addition to optimizing the coagulant dosage for turbidity removal in a water treatment plant, ANFIS efficiently forecasted the generation of methane and effluent volatile solids of an anaerobic digester in a wastewater treatment plant (Niska and Serkkola, 2018). Currently in the field of SWM, AI is extensively used to forecast waste generation patters, optimize waste collection truck routes, locate waste management facilities, and simulates waste conversion processes, among others.

There have been few reviews of AI research covering specific waste-related application fields such as simulation and optimization of petroleum waste management, waste combustion processes, and biogas generation (Enitan et al., 2016; Kalogirou, 2003b; Qin et al., 2009). Table 1 provides a summary of these studies based on their application fields, investigated model types, period of study, and number of articles reviewed. Yetilmezsoy et al. (2011) discussed the various AI techniques useful to model the weight, composition and rate of waste generation. Other review studies focused solely on identifying the AI models used to predict MSW generation rate based on economic and socio-demographic parameters (Goel et al., 2017; Kolekar et al., 2016). Finally, Melaré et al. (2017) discussed the use of AI-based optimization techniques in SWM to predict waste generation, manage waste collection systems, monitor waste containers, and locate disposal sites (Vitorino et al., 2017). It is clear that there is a lack of a review article that combines all research work conducted on AI applications in the different fields of SWM. To date, there has not been a comprehensive critical study assessing the application of AI-based techniques in various SWM processes.

In order to explore the potential application of AI models to solve the wide variety of issues affecting the SWM fields, a complete and rigorous discussion about the current work and reported results is critical to promote further developments in this field. This paper presents an extensive SLR and detailed discussion of AI models that have been utilized to improve existing SWM schemes throughout its different stages, from collection till final disposal. Hybrid AI-based models and comparative studies with AI/non-AI models are thoroughly discussed to impart a deeper understanding of the approach. Additionally, the AI software packages/libraries are reviewed to facilitate the selection of the most suitable platform for implementation in future studies. The potential challenges, limitations, and research opportunities are presented.

As more researchers are interested in AI applications in SWM, this paper presents a systematic literature review (SLR) and in-depth discussion of AI models that have the potential to provide modern, economical, and ecologically benign systems for sustainable SWM strategies. The paper is intended to guide SWM researchers interested in the application of AI in their respective field of study through key research aspects including the AI models, their advantages and disadvantages, efficiency and software platforms. The review paper is organized as follows: methodology covers the systematic framework used including the scope of work, research questions, search and selection criteria, paper quality assurance, and data extraction strategy. The major AI techniques identified in the survey are analyzed and discussed in the subsequent section; these include individual and hybrid AI systems. This section also discusses studies that compared AI techniques among each other as well as with other non-AI techniques, and provides a summary of the simulation platforms identified in the survey. The following section includes an in-depth discussion of the various SWM fields in which AI was actively used. The paper concludes with challenges and limitations facing the implementation of AI techniques in SWM, as well as future recommendations for the research and development of the AI-based SWM.

2. Methodology

2.1. Systematic review protocol

SLRs are conducted to identify, evaluate and interpret studies in a particular area of interest (Kitchenham, 2007). SLRs have been widely used in the literature in the fields of civil engineering but none in SWM research. The main aim of the SLR is to ensure unbiased review strategy, leading to credibility and comprehension of results. Fig. 1 illustrates the flowchart describing the proposed methodology. The guidelines used in this SLR followed a standard protocol that divides the process into planning, execution, and discussion phase (Kitchenham, 2007; Staples and Niazi, 2008).

2.2. Research questions

The principal goal of the SLR is to identify and evaluate published studies that tackle the application of AI techniques in SWM. To accomplish this, four specific research questions have been formulated: (1) what are the various applications of AI models in waste management? (2) what are the AI models and algorithms used in waste management applications? (3) how is the performance of various AI models compared to other methods? and (4) what are the strengths and limitations of AI applications in waste management?

2.3. Search and selection criteria

The adopted search strategy involved retrieving studies from international digital libraries such as Scopus, Google Scholar, IEEE,

Table 1
Previous review work related to the application of AI models in waste management.

Ref.	Year	Application fields	Model types	No. of studies reviewed	Period of study
(Yetilmezsoy et al., 2011)	2011	Environmental engineering, water/wastewater, air pollution, SWM processes	ANN, FL, ANFIS, Quasi-newton, MLR	111	N/A
(Kolekar et al., 2016)	2016	MSW generation models	SVM, WT, ANN, MLR, FL, GIS, System dynamics, Single regression analysis, AHP, GM, Time series analysis, GA	20	2006–2014
(Goel et al., 2017)	2017	MSW generation models	Database mining/collection, Sample survey method, LR, Econometric models, System dynamics, Time series analysis, Factor analysis, GIS, ANN, FL, ANFIS, GM, SVM	106	1972–2016
(Vitorino et al., 2017)	2017	SWM processes	SVM, ANN, GA, FL, data mining, Ant colony algorithm	87	2010–2013

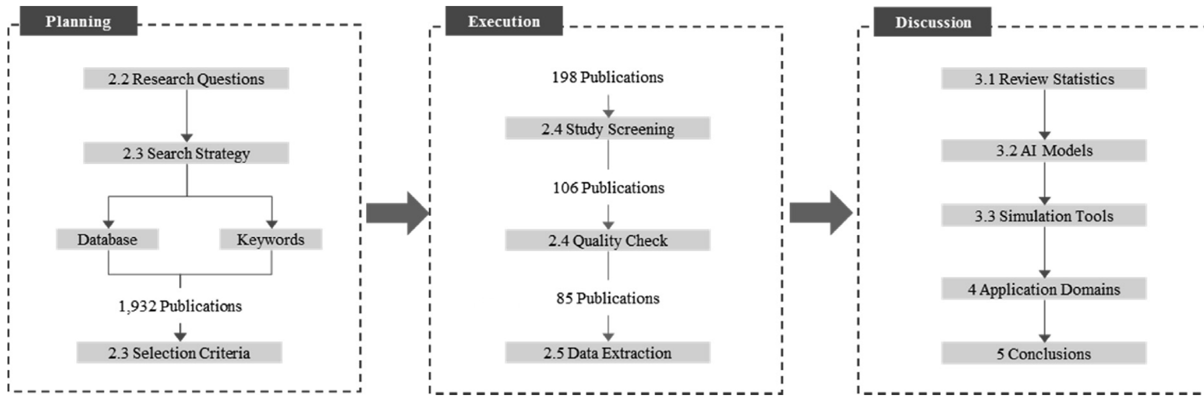

Fig. 1. Flowchart representing the systematic review methodology.

ScienceDirect, and Web of Science. Initial search revealed many AI-related articles outside the SWM scope such as water and wastewater treatment and industrial waste management. Numerous publications of other conventional SWM modelling techniques (such as statistical and probabilistic models) were also prevalent. This preliminary search returned a total of 1,932 records from the digital search platforms used. Inclusion and exclusion criteria were introduced to limit the number of articles retrieved. These comprised keywords or strings for the acceptance or rejection of studies (Staples and Niazi, 2008). The inclusion strings used were "waste management", "artificial intelligence", "machine learning", "K means", "deep learning" and "artificial neural networks", while the exclusion strings were "sewer systems", "wastewater treatment", and "sludge management". Articles dealing with medical waste and construction and demolition debris were considered within the scope of this study. The timeframe of the review extended along the period between 2000 and 2020.

Screening of articles using the search strings, based on the relevance of title, abstract and keywords, returned 106 publications. These publications were thoroughly inspected and 21 duplicate studies under different titles, but similar content were further excluded. The content of the remaining 85 studies were qualitatively assessed and extracted for data synthesis. Key features of the compiled studies including corresponding publisher, journal, and journal subject area are shown in the supplementary Table A1.

2.4. Quality check

Quality assessment criteria were devised to evaluate each individual study qualitatively and assist in filtering irrelevant or deficient studies (Kitchenham, 2007). Six quality aspects were identified: (1) credibility: check whether the paper includes well designed and justified practical experiments of the proposed technique with sufficient datasets, (2) scope: assure the application field and scope of work are distinctly identified, (3) clarity: examine the clearness of the research objectives, (4) methodology: assess the appropriateness of the research methods and simulation platforms, (5) analysis quality: evaluate the accuracy computations and critical discussions, and (6) significance: ensure the study contributions enrich knowledge and/or advance technology.

The score of each article was determined by the summation of the points obtained for the above mentioned ten queries. The compiled publications were assigned a score of 1 when the criterion was fulfilled, 0.75 for major fulfilment, 0.50 for partial fulfilment, 0.25 for poor fulfilment, and zero when the criterion was not fulfilled. The article was considered for review only if it attained an overall score of 5 or higher. Among the 106 selected publications, 21 articles were eliminated during the quality assessment phase. Supplementary Table A2 summarizes the compiled articles based on their year and type of publication, application domains, datasets, type of AI model, and software tools used.

2.5. Data extraction and synthesis

Relevant data including dataset details, application domains, software tools and libraries, AI techniques utilized, and performance indicators were extracted and summarized, which facilitated the data synthesis process. Several performance parameters and statistical error indicators were used throughout the present review to assess and compare the findings compiled from the literature. The definitions and equations of the used parameters are listed in Table 2.

3. Overview of survey results

3.1. Review statistics

In the present review, 84 research studies were covered worldwide, spanning from year 2004 to 2019. Asia produced the highest number of publications in this subject area (63%); majority of which were conducted in China (18), whereas the remaining studies were carried out in Iran (14), India (8), Malaysia (8), Turkey (3), Jordan (1), Iraq (1), Korea (1), and Thailand (1). 18% of the articles published in the European region were conducted in Portugal (3), Serbia (3) and the rest were carried out in Finland (2), Germany (2), Poland (2), United Kingdom (2), Bulgaria (1), Italy (1), and Spain (1). Majority of the North American publications (55%) were from the United States (5), while 33% were conducted in Canada (3) and the rest in Mexico (1). Countries like Colombia and Uruguay in South America, Tunisia and Nigeria in Africa, and Australia had a single publication each.

Analysis of the compiled studies revealed six primary AI application fields in SWM. The AI application fields include waste bin level detection, forecasting of waste characteristics, process parameters prediction, process output prediction, vehicle routing, and SWM planning. Bin level detection is associated with monitoring the fullness of waste bins, whereas the prediction of waste characteristics included the classification of waste materials, waste compression ratio, as well as waste generation, patterns or trends. Among the predicted process parameters were the waste heating value and co-melting temperature. The prediction of process output included simulation and optimization of biogas generation and leachate formation. Vehicle routing problem comprised the optimization of waste collection routes and frequency. Finally, the waste management planning included waste facility siting, location of waste accumulation and illegal disposal sites, as well

Table 2
Operational parameters and performance indicators of artificial intelligence models.

Term	Equation	Definition*
Performance parameters		
Computational cost	–	The execution time required per time step during simulation
Fault tolerance	–	Property that enables normal operation in the event of failure of (or one or more faults within) some of its components
Noise	–	Unwanted data points that corrupt the quality of the dataset
Overfitting	–	An issue that occurs when a model closely explains a training dataset, but fail to generalize when applied to other datasets
Statistical Metrics		
Correlation coefficient (R)	$R = \frac{\sum XY}{n\sigma_x\sigma_y}, X = x - \bar{x}, Y = y - \bar{y}$	Numerical measure that estimates the statistical relationship between two variables
Coefficient of determination (R^2)	$R^2 = \left(\frac{\sum XY}{n\sigma_x\sigma_y}\right)^2$	Proportion of variance in the dependent variable that is predictable from the independent variable(s)
Mean absolute error (MAE)	$MAE = \frac{1}{n}\sum \lvert Av - Pv \rvert$	Average magnitude of errors in a set of prediction ignoring their direction
Mean absolute percent error (MAPE)	$MAPE = \frac{1}{n}\sum \frac{\lvert Av - Pv \rvert}{Av} \times 100$	Measures the prediction accuracy of a forecast system
Mean squared error (MSE)	$MSE = \frac{1}{n}\sum (Av - Pv)^2$	Indicates how close a regression line is to a set of points
Root mean square error (RMSE)	$RMSE = \sqrt{\frac{\sum (Pv - Av)^2}{n}}$	Standard deviation of residual points which measure the error of data points from the regression line

* Obtained from (Butterfield et al., 2016; Upton and Cook, 2014). Where n is the number of data points, x and y are the datasets, $\bar{x}$ is the mean of dataset x, $\bar{y}$ is the mean of dataset y, σ_x is the standard deviation of dataset x, σ_y is the standard deviation of dataset y, Av is the actual value of data point, and Pv is the predicted value of data point.

as optimization of cost and environmental impacts of collection, transportation, treatment, and disposal. Fig. 2 illustrates the number of publications conducted in each application field during the assessment period (2004–2019). Evidently, interest in AI research in SWM has been recently increasing; 72 out of the 85 reviewed articles were published in the last decade.

3.2. Artificial intelligence models

The literature review indicated that the frequently used AI systems for the modelling and optimization of SWM processes included ANN, support vector machine (SVM), linear regression (LR), decision trees (DT) and GA (as illustrated in Fig. 3). ANN was the most recurrent AI model; different ANN algorithms including radial basis function (RBF), MLP, back propagation (BP), feed forward, autoregressive and recurrent ANNs were used in literature. GA was another commonly used algorithm followed by LR which comprises multiple and multivariate LR, as well as gradient boosting regression. Other models were used less frequently in individual studies, such as ANFIS, random forest (RF), wavelet transform (WT), K-means, data mining, Naïve Bayes, rough sets, logistic model tree, Q-type clustering, ant colony optimization, non-inferior set estimation (NISE), goal programming, and artificial

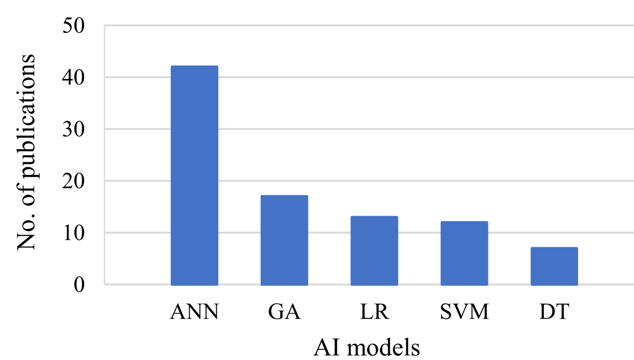

Fig. 3. Distribution of publications by AI model type.

immune system (AIS). It should be noted that this review covers only the trainable version of FL models, namely ANFIS; a review of FL applications in waste management can be found elsewhere (refer to Table 1). The following sections discuss those AI techniques, as well as their advantages and limitations. In order to facilitate the discussion, the reviewed papers are classified under different AI models and SWM application domains in Table 3.

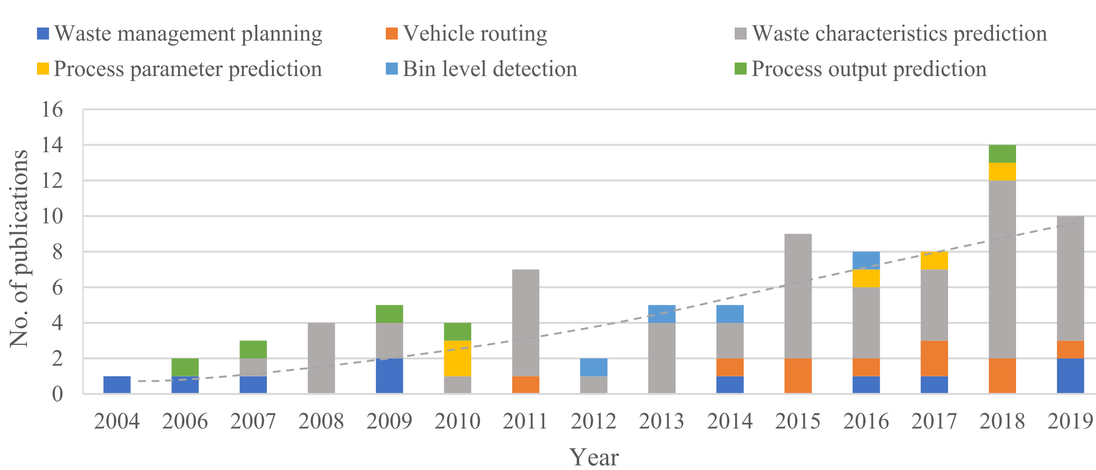

Fig. 2. Number of studies according to publication year and application fields.

Table 3
Summary of reviewed studies under various AI models and application domains.

	Application	ANN	SVM	LR	DT	GA
Waste characteristics	Waste generation	(Golbaz et al., 2019; Milojkovic and Litovski, 2008; R Noori et al., 2009b; Shamshiry et al., 2014; Song et al., 2016)	(Abbasi et al., 2014, 2013; Abbasi and Hanandeh, 2016; Abunama et al., 2018; Dai et al., 2011; Golbaz et al., 2019; Graus et al., 2018; Kumar et al., 2018; R Noori et al., 2009a; Song et al., 2016)	(Abdoli et al., 2011; Azadi and Karimi-jashni, 2015; Chhay et al., 2018; Golbaz et al., 2019; Jahandideh et al., 2009; Montecinos et al., 2018; Wei et al., 2013; Wu et al., 2008)	(Cha et al., 2017; Huang et al., 2011; Kannangara et al., 2017; Ysabel et al., 2008)	(Ferreira et al., 2015; Oliveira et al., 2019; Shamshiry et al., 2014)
	Waste classification	(Singh et al., 2017; Sudha et al., 2016; Tehrani and Karbasi, 2017; Vrancken et al., 2019)	(Kuritcyn et al., 2015; Singh et al., 2017)	–	(Kuritcyn et al., 2015)	(Rajamanikam and Solihin, 2019)
	Waste compression	–	–	–	(R et al., 2015)	–
	Heating value	(Hannan et al., 2016, 2012; Islam et al., 2014; Morison et al., 2013; Rajamanikam and Solihin, 2019)	(Rostami and Baghban, 2018; You et al., 2017)	–	–	(Rostami and Baghban, 2018)
	Co-melting temperature	(Pai et al., 2010)	–	–	–	–
Waste bin	Bin level status	(Hannan et al., 2016, 2012; Islam et al., 2014; Morison et al., 2013; Rajamanikam and Solihin, 2019)	(Morison et al., 2013)	–	–	–
Process output	Biogas generation	(Ozkaya et al., 2007; Qdais et al., 2010)-	–	–	–	(Qdais et al., 2010)
	Leachate formation	(Bayar et al., 2009)	–	(Bayar et al., 2009)	–	–
	Energy recovery	(Shu et al., 2006)	(Graus et al., 2018)			
Vehicle routing	Collection route	(Vu et al., 2019)		(Montecinos et al., 2018)		(Amal et al., 2018; Düzgün et al., 2014; Ferreira et al., 2015; Król et al., 2016; Wichapa and Khokhajaikiat, 2018)
	Collection frequency			Ferreira and Figueiredo, 2017)		
Waste management planning	Illegal dump sites				(Lu, 2019)	
	Waste accumulation					(Toutouh et al., 2019)
	Waste facility siting					(Bautista and Pereira, 2006; Medaglia et al., 2009; Ramasami and Velumani, 2016)
	Management costs					(Shamshiry et al., 2014; Shi et al., 2009)
	Environmental impacts					(Shamshiry et al., 2014)

3.2.1. Artificial neural networks (ANN)

Modelling SWM processes involve multiple variables and can be difficult due to the non-linear behavior exhibited by these variables. ANNs are effective in modelling processes with incomplete or uncertain data sets as well as tackling complicated and imprecise tasks requiring human intuition. ANNs are designed to simulate the reactions of a biological nervous system when faced with real world tasks. Typically, neural networks consist of an input layer, hidden layers, and an output layer, each consisting of a number of nodes linked to every node in the subsequent layer by directed weighted edges (Duda et al., 1998). As shown in Table 3, ANNs have been successfully applied in the prediction of bin level status, waste generation, waste classification, biogas generation, leachate formation, energy recovery, heating value, co-melting temperature of waste, and optimal waste collection routes. Different types of neural networks, including perceptron and BP, have been investigated in the reviewed studies. The tested types of BP algorithms were Levenberg-Marquardt, scaled conjugate gradient, one-step secant, Quasie-Newton, gradient descent with adaptive learning rate, gradient descent with momentum and adaptive learning rate, resilient, batch training with weight and bias learning rules (Ozkaya et al., 2007).

ANNs have been widely used to model various SWM processes due to their robustness, fault tolerance, and suitability at depicting the complex relationships between variables in multivariate systems. Moreover, the calibration process of ANN systems typically requires fewer parameters than deterministic models, thereby making those algorithms preferable in such cases. On the other hand, ANNs are weak at handling logical and arithmetic problems necessitating high accuracy and is prone to overfitting. Moreover, ANNs are incapable of determining the relative importance of the numerous factors involved in the analysis, i.e., which input characteristic has the highest impact on the output.

3.2.2. Support vector machines (SVM)

SVMs are supervised machine learning algorithms useful for data analysis (Dixon and Candade, 2013; Hasituya et al., 2016). They function as non-parametric classifiers capable of solving classification problems due to their proficiency at maximizing the class separations while minimizing the classification errors. Although initially intended to tackle classification problems, SVM has been evolved to solve regression problems as it was found to outperform several classical regression techniques. Support vector regression algorithms are less susceptible to overfitting and is adept at simultaneously reducing error estimates and model dimensions, unlike statistical procedures like principal component analysis (PCA) which address only the dimensionality of the model (Li et al., 2010). SVMs generate low generalization error and computational costs, and solution analysis is simple (Harrington, 2012). However, SVMs are highly sensitive to the selected kernel and tuning variables. Nevertheless, due to the multiple advantages of SVM, this technique has been widely applied in the SWM field as shown in Table 3. It was found to be especially useful for the prediction of bin fill level, waste generation, waste classification, energy recovery, and waste heating value.

3.2.3. Linear regression analysis (LR)

LR analysis of data is a supervised technique used to model a target value on the basis of independent predictors (Abdi, 1974). SWM models can be modelled based on one variable (single regression) or numerous variables (multiple linear regression (MLR)). The SWM models are typically dependent on numerous parameters, hence, multiple (or multivariate) LR is more appropriate to simulate these processes. The results obtained from LR are easy to interpret and the computational costs are low. However, this method is generally considered unsuitable for modelling nonlinear data. As shown in Table 3, LR is often used to predict waste generation and leachate formation. It has also been applied to optimize waste collection routes and frequencies.

3.2.4. Decision trees (DT)

DT is a supervised classification technique efficient at extracting a set of rules from unfamiliar data. It is particularly useful for expert systems, capable of generating results similar to those from a human specialist in a given field. The advantages of using DTs include easy interpretation of results, low computational costs, and ability to process data with missing values and irrelevant features. However, this method has a tendency for data overfitting. As shown in Table 3, DTs have been utilized for the prediction of waste generation, waste compression, and waste classification, as well as the detection of waste generation behavior patterns and illegal waste dumping sites.

3.2.5. Genetic algorithm (GA)

GA is a class of metaheuristic algorithms that mimic natural evolution (Yang and Alavi, 2013). GAs execute optimization technique in a binary search space where instead of enhancing a single solution, they improve a set of solutions or hypotheses (Meyer-Baese and Volker Schmid, 2014). The primary components of GA are crossover, mutation, and selection of the fittest. Crossover is the process of exchanging information between two strings, where each string represents a binary or decimal solution. Alternatively, mutation is executed by switching certain digits of the string thereby creating new solutions. The solutions created are evaluated against the objective function of the optimization problem to determine the overall fitness of each solution. Best solutions among these are selected for the next series of optimization. The advantages of GA include efficiency, robustness of input data, and easy programmability. On the other hand, GAs require meticulous construction, wherein incorrect selection of operators may adversely affect the results generated by the model. As shown in Table 3, GAs were widely applied in solving SWM problems including waste classification, waste generation forecasting, prediction of waste accumulation and facility siting, and estimating the waste heating value and biogas generation. Further, they are useful for the optimization of collection routes, management costs, and environmental impacts associated with waste handling.

3.2.6. Hybrid models

The hybrid models involve the combination of different AI systems with each other or with metaheuristic algorithms in order to eliminate the shortcomings associated with implementing those systems separately. Hybrid models are generally aimed at integrated problem solving or accomplishing distinct tasks within the same problem. A detailed discussion of the hybrid models used in the literature is presented in Table 4. It is clear that combining AI models has constantly improved the performance of the original non-hybrid models. It can be noticed that each hybrid model was only used in a single research study. This represents one of the main drawbacks in the AI literature which grows horizontally in most SWM applications and AI models.

3.2.7. Critical analysis

Several studies have compared the performance of various AI algorithms with each other as well as with non-AI models. Critical analyses of those comparative studies are presented in Table 5.

Overall, based on the studies discussed in Table 5, ANN demonstrated several advantages including higher explanatory power and low sensitivity to outliers compared to regression techniques. However, dealing with ANN was challenging due to its higher input variable requirement and the difficulty encountered during model development and result elucidation. Noori et al. (2010) combined

Table 4
Analyses of hybrid AI models in the SWM literature.

Study	Hybrid model	Objective	Key findings
(Abbasi et al., 2014)	Wavelet denoising method with SVM(WT-SVM)	Enhancement of SVM model performance by eliminating the noise and outliers from the time series data using Wavelet denoising method.	• Pre-processing of input data by WT reduced the MARE from 0.051 to 0.038, improved the R^2 from 0.702 to 0.813, and decreased inputs sensitivity to variations.
(Abbasi et al., 2013)	Partial least square with SVM (PLS-SVM)	Utilization of SVM model using time series and improving the accuracy of the model by PLS method.	• PLS-SVM achieved better prediction accuracy (R^2 = 0.87) compared to the non-hybrid model (R^2 = 0.76). • PLS enhanced the predictive abilities, handled complex and non-linear input variables of SVM models, and reduced computation time (from 42 to 29 s).
(Roohollah Noori et al., 2009)	WT-ANFIS	Preprocessing using WT to improve the input variables and long-term forecasting of ANFIS model.	• WT-ANFIS demonstrated the second best fit with the original data (R^2 = 0.84), whereas non-hybrid showed poor fit (R^2 = 0.34).
(Roohollah Noori et al., 2009)	WT-ANN	Effectiveness of ANN model to handle non-stationery data when combined with WT following the preprocessing of inputs and outputs.	• WT improved preprocessing techniques of the ANN input variables. • WT-ANN demonstrated the best fit with original data (R^2 = 0.91), compared to non-hybrid (R^2 = 0.40).
(Song et al., 2016)	GM-SVR	Improving the prediction efficiency of SVR by modifying the residual series through GM.	• GM model had a 76% higher error rate than the GM-SVR hybrid model.
(Soni et al., 2019)	GA-ANN	Comparison of GA-ANN and non-hybrid ANN model to assess the efficiency of handling high inputs.	• GA improved the prediction of ANN and increased the R^2 of ANN from 0.13 to 0.78 for GA-ANN.
(Golbaz et al., 2019)	Least square support vector machine (LSSVM)Fuzzy logic - support vector regression (FSVM)	Comparing MLR with ANN, ANFIS, SVM, LSSVM and FSVM.	• FSVM demonstrated best performance among the examined hybrid models (R^2 = 0.92, MSE = 0.002), whereas non-hybrid SVM produced better fit to original data (R^2 = 0.90–0.98, MSE = 0.001–0.002). • Hybrid SVM models achieved better results compared to ANN and ANFIS, indicating that the intricate nonlinear relationships between input and output variables can be appropriately modelled using LSSVM and FSVM.
(Chu et al., 2018)	Multilayer hybrid deep learning system	Evaluating a multilayer hybrid deep learning system composed of conventional ANN image processing system, a numerical sensor system, and an MLP system.	• Compared to conventional ANN for image classification, the hybrid model showed 11% better performance.
(Shamshiry et al., 2014)	Response surface model (RSM) with ANN and GA	Assessing the optimization efficiency of RSM combined with ANN and GA.	• Cost reductions up to 11% were observed when the hybrid RSM was implemented. • Test results proved 71% fit of the predicted values with the original data at an MSE of 0.036.

ANN with PCA and Gamma test (GT) methods to decrease the number of input variables. The study indicated that PCA-ANN and GT-ANN methods performed slightly better than ANN, while simultaneously reducing the number of input variables from 13 (for ANN) to 7 and 5, respectively. Another study proved MLR to be highly sensitive to outliers, with low processing capability at high input variable count (Golbaz et al., 2019). Finally, Montecinos et al. (2018) developed a model based on Theil-Sen constrained regression to reduce errors and reject outliers. Compared to LR, the prediction error observed was significant. An overall summary of the advantages and limitations of each AI model is compiled in Table 6.

Fig. 4 depicts the range of accuracies of different AI models. ANN, being the most commonly used AI algorithm, demonstrated a wide range of accuracy (between 37 and 99%). ANN, ANFIS, GM and SVM achieved high accuracies (up to 99%), whereas studies using CNN reported very low accuracy (71%).

3.3. Simulation tools

Several AI software platforms and libraries have been utilized to solve SWM problems. Table 7 summarizes the simulation platforms in terms of their advantages and disadvantages, as well as SWM application fields and they are freeware or open source software. The table intends to guide researchers in the selection of the most suitable tool for their study. MATLAB was the most common simulation software utilized, particularly in the training and testing of neural networks and MLP algorithms (Chhay et al., 2018; Jahandideh et al., 2009; Jalili Ghazi Zade and Noori, 2008; Korhonen and Kaila, 2015; Shamshiry et al., 2006; Shu et al., 2006; You et al., 2017). Another commonly used simulation tool was SPSS, an IBM software used to simulate MLR models, perform Q-clustering of different SWM characteristics, and correlate between attributes such as population density and waste generation (Golbaz et al., 2019; Lu, 2019; Pan et al., 2019). R software was adept at eliminating outliers from datasets, particularly in waste generation simulations (Kumar et al., 2018; Lu et al., 2015). In the reviewed studies, C++ and Python languages were used to simulate AI models. C++ has multiple AI libraries including OpenNN, OpenCV, BOOST, gflags, glog, and Tensor Flow. Similarly, Python contained Tensor Flow along with other libraries such as, Spyder, Matplotlib, and Utils.

4. Application domains

4.1. Prediction of solid waste characteristics

Efficient collection, treatment and disposal of MSW are dependent on accurate prediction of waste characteristics, which are largely affected by various technical, socioeconomic, legal, environmental, political, and cultural elements. Due to the interdependence between these elements as well as insufficient data and associated uncertainties, unconventional modelling techniques were expected to account for these factors. Majority of the studies that explored the applications of AI in waste management analyzed the prediction of solid waste characteristics. Among these

Table 5
Comparative studies of various AI applications in the SWM literature.

Study	Objectives	Key Findings
(Abbasi et al., 2018)	Analyzing distinguished features of RBF neural network compared to ANN and ANFIS techniques.	• RBF performed better due to its forward network architecture that enables processing noisy data and non-linear patterns. • Performance of RBF was compared to ANN and ANFIS models based on R^2 values (0.68,0.53, and 0.43, respectively)
(Abbasi and Hanandeh 2016)	Comparing ANFIS performance to SVM, ANN and KNN models in monthly waste generation forecasting.	• ANFIS had the best fit and highest performance compared to SVM, ANN and KNN (R^2 = 0.98, 0.71, 0.46 and 0.51, respectively). • SVM tended to underestimate peak values and projected volumes.
(Abdoli et al., 2011)	Developing a waste generation forecasting model using ANN, and evaluating the accuracy compared to MLR model.	• ANN models outperformed those based on MLR, in terms of MAE, RMSE and R^2, due to the capability of ANN to non-linearly associate independent variables to dependent ones. • ANN performed better than MLR based on R^2 values (0.66 and 0.79, respectively).
(Azadi and Karimi-jashni, 2015)	Evaluating the accuracy of seasonal waste generation prediction using MLR and ANN.	• ANN produced accurate results and showed lower error compared to MLR (R^2 of 0.86 and 0.70, respectively).
(Jahandideh et al., 2009)	Assessing the performance of ANN against MLR for prediction of waste generation	• ANN showed superior performance with R^2 = 0.99 compared to MLR (R^2 = 0.24).
(Abunama et al., 2018)	Comparing ANN-MLP with double hidden layers to single layer and SVM models for the prediction of leachate generation.	• ANN-MLP with double hidden layers had lower error and higher correlation (R^2 = 0.96) compared to single layer and SVM models (R^2 = 0.89).
(Morison et al., 2013)	Assessing the performance of different supervised (MLP, logistic model tree, K nearest neighbor (KNN), J48, SVM, Naïve Bayes) and non-supervised (single threshold, FL) classifiers for bin level detection.	• MLP classifier demonstrated maximum accuracy of 97%, followed by logistic model tree (94%). • 2-NN and single threshold produced equal performance (92%). • Accuracy of FL was around 90%, whereas SVM (Puk Kernel) and J48 had lower performance compared to other models (87%). • Naïve Bayes had the least accuracy (80%).
(Noori et al., 2009b)	Developing principal component regression analysis (PCA) MLR.	• Multicollinearity issue of independent variables by PCA was eliminated. • ANN model demonstrated better performance (R^2 = 0.84, MAE = 4.4%) than the PCA-MLR model (R^2 = 0.45, MAE = 6.6%).
(Oliveira et al., 2019)	Comparing the performance of ANN to multiple nonlinear regression.	• ANN achieved superior performance compared to multiple nonlinear regression models (R^2 = 0.98 and 0.73, respectively).
(You et al., 2017)	Comparing the performance of MLP, SVM, ANFIS, and RF models for the prediction of lower heating value of waste.	• ANFIS achieved the highest accuracy (94%) and outperformed RF, SVM and MLP by 4.2, 6.9 and 21.8% respectively. • SVM had the fastest training time followed by RF, MLP and ANFIS (0.2, 2.5, 4.8 and 223.2 s, respectively). • MLP was inefficient at expressing rule-based knowledge due to the inherent limitation of gradient-descent-based learning algorithms.

studies, waste generation forecasting was the most widely investigated application. ANNs were widely implemented in those applications, followed by SVMs; refer to Table 3. Spectral analysis, correlation analysis, response surface model, GM, gene expression programming, partial least square, hybridized wavelet de-noising, Gaussian mixture model, hidden Markov model, Viterbi algorithms, and principal component analysis were some of the techniques used in combination with the AI models. As shown in Table 8, different short- and long-term prediction periods were modeled for waste generation. The limited number of studies simulating the daily waste generation is likely due to the scarcity of such detailed data. The reviewed studies covered a wide range of input variables affecting waste generation.

Several other studies focused on the classification of waste materials to be used in automated sorting systems that eliminate manual waste segregation. Majority of these studies used ANNs for the identification of different waste fractions. One such study used hyperspectral imaging and multi-layer ANNs to recognize various types of plastics in e-waste (Tehrani and Karbasi, 2017). The proposed methodology demonstrated high accuracy (99%) at identifying these materials. Sudha et al. (2016) attempted to automate the garbage sorting process using deep CNNs. The automated process enhanced the waste sorting and classification time compared to manual sorting. Similarly, deep CNNs were used to separate different types of paper and cardboard (Vrancken et al., 2019). The mean accuracy of the model ranged between 61.9 and 77.5%; these low values were attributed to the limited size of the training database (24 images). Chu et al. (2018) used CNNs for feature extraction and MLP for waste segregation into recyclables and non-recyclables. The hybrid methodology demonstrated a maximum accuracy of 98.2% which was approximately 10% higher than that when only CNNs were used. Few studies also tested the efficiency of other machine learning algorithms in waste classification (Kuritcyn et al., 2015; Singh et al., 2017). Kuritcyn et al. (2015) showed that RF, the Nu- and C-LibSVM were excellent at classification, with accuracy greater than 90%. On the other hand, Naïve Bayes and nearest neighbor performed poorly at an accuracy of 44.8 and 84.8%, respectively. Very few studies explored the effects of various parameters on waste generation. Ysabel et al. (2008) correlated sociodemographic and behavioral attributes with waste generation using data mining techniques such as cluster analysis and DT classifier. The tree classifier demonstrated good performance, producing an error rate as low as 3.6%. Another study used data mining techniques to determine waste generation trends based on housing type and seasonal variations (Korhonen and Kaila, 2015). Finally, DT using Quinlan's M5 algorithm was utilized to forecast the MSW compression ratio, which is useful to assess waste settlement during the design of municipal landfills (R et al., 2015). The model was trained and tested using various constituents and characteristics of solid waste such as dry density, water content, and biodegradable fraction. Performance of the model was satisfactory with a correlation coefficient of 0.92 during the testing phase.

4.2. Bin level detection

Bin level detection models are developed to predict the fill level of waste bins, which can be effectively used to tackle improper waste disposal and overloading of waste bins. The performance of smart waste collection systems is affected by the temporal variations in the disposed quantities. The algorithms are typically fed with real-time data from level or image sensors installed in smart

Table 6
Advantages and limitations of the most frequently used AI models.

AI model	Advantages	Disadvantages	Reference
Artificial neural networks	• Fault tolerance. • Simulation ability of complex and non-linear relationships between variables in multivariate systems. • Calibration requires fewer parameters than deterministic models.	• Weak at handling logical and arithmetic problems necessitating high accuracy. • Pre-processing of data is necessary. • Imprecise analysis of non-stationery datasets. • Prone to overfitting. • Incapable of determining the correlations of numerous factors involved.	(Abbasi et al., 2013; Roohollah Noori et al., 2009;Goel et al., 2017; Abunama et al., 2018; Bayar et al., 2009)
Support vector machines	• Proficiency in maximizing the class separations while minimizing the classification errors. • Less susceptibility to overfitting. • Adept at simultaneously reducing error estimates and model dimensions. • Low generalization error. • Low computational costs.	• Highly sensitive to the selected kernel and tuning variables.	(Lanorte et al. 2017; Abbasi and Hanandeh 2016)
Linear regression analysis	• Easy interpretation of results. • Low computational costs.	• Unsuitable for modelling nonlinear data.	(Azadi and Karimi-jashni, 2015)
Decision trees	• Easy interpretation of results. • Low computational costs. • Ability to deal with missing values and irrelevant features.	• Data overfitting. • Poor generalization of trained datasets.	(R et al., 2015; Johnson et al., 2017)
Genetic algorithm	• High accuracy. • Easy programmability.	• Require meticulous construction, wherein incorrect selection of operators may adversely affect the generated results.	(Oliveira et al., 2019; Düzgün et al., 2014)

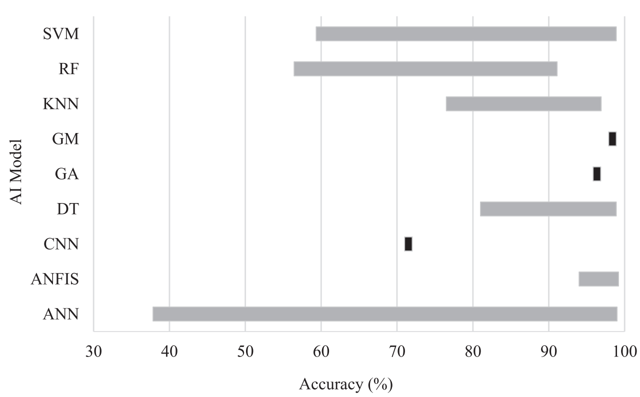

Fig. 4. Range of accuracies reported for different AI models.

waste bins (Abdallah et al., 2019). Few research studies have incorporated AI in real-time monitoring of waste level within the bins to enhance the solid waste collection process (Hannan et al., 2016, 2012; Islam et al., 2014; Morison et al., 2013; Rajamanikam and Solihin, 2019). Hannan et al. (2012) used gray level aura matrix (GLAM) to generate the image texture of a 120L waste bin and compared the performance of an MLP BP neural network with KNN algorithm for waste level classification. The GLAM system exhibited more than 95% efficiency in generating image textures of the bin. Similarly, both algorithms achieved accuracy level greater than 95%, with MLP demonstrating higher performance than KNN (98.9 and 96.9%, respectively). Increasing the training dataset size was suggested to reduce misclassification by the KNN model. However, another study by Hannan et al. (2016) reported better accuracy by the KNN classifier compared to MLP for bin level classification (95 and 97%, respectively). The study used various feature extraction techniques such as Gabor wavelet (GW) filter, gray level co-occurrence matrix (GLCM), and GLAM to determine bin level with accuracies up to 87.5% accuracy. Moreover, Islam et al. (2014) assessed MLP for bin level identification and waste quantification. Dynamic time warping (DTW) and GW were utilized for bin area recognition and texture extraction to train the MLP. The proposed methodology was successful at bin level status prediction and generated highly accurate results (98.5%). Finally, Morison et al. (2013) studied bin status in terms of wall entropy perturbation, which is the gradual entropy reduction estimated by observing how internal wall gets hidden by waste. Several classifiers were analyzed including MLP, logistic model tree, KNN, single threshold, FL, J48, SVM (Puk Kernel), and Naïve Bayes. MLP showed the highest performance with an accuracy of 97.4%, whereas Naïve Bayes achieved the least performance (79.5%).

4.3. Process output prediction

Quantifying useful by-products such as biogas and energy, as well as harmful by-products such as leachate and fugitive emissions is essential for optimal waste management. Various studies have developed models to predict the quantity and composition of different by-products generated from waste management processes. Ozkaya et al. (2007) compared different BP ANN algorithms to predict biogas generation from bioreactor landfills. The examined algorithms included Levenberge-Marquardt, scaled conjugate gradient, one-step secant, quasie-newton, gradient descent with adaptive learning rate, gradient descent with momentum and adaptive learning rate, resilient, batch training with weight and bias learning rules, gradient descent, and gradient descent with momentum. Levenberge-Marquardt was proven to be the best training algorithm with an MSE of 0.0025, which was 99.8% better than the gradient descent with momentum BP algorithm which had an error of 1.2622. Moreover, Abdallah et al. (2011) developed an ANFIS model to estimate landfill gas production, and reported high correlation of 0.98 and 98% confidence level. A similar study was conducted by Qdais et al. (2010), which discussed the simulation and optimization of methane generation using BP ANN and GA. The predicted values had a coefficient of determination of 0.87 and an MSE of 6×10^{-5}, suggesting good correlation between the modelled and measured data. Furthermore, optimizing the operational variables of the biogas digester using GA resulted in 6.9% increase in the methane yield.

Other studies focused on the prediction and optimization of the energy produced from solid waste fractions. One such study developed four MLP neural network prediction models, each with differ-

Table 7
Summary of simulation platforms used in the reviewed studies.

Software	Application Fields	Advantages	Disadvantages	Open Source	Cost	No. of studies
MATLAB	Route optimization, prediction of waste generation, waste heating value, energy content, biogas production and co-melting temperature	• Can handle different data types such as images, sound, signals and sensor data • Wide range of useful libraries	• Difficult to cross compile or convert to other coding languages	–	Paid	11
IBM SPSS	Locating illegal disposal sites, waste generation forecasting	• User friendly interface • No coding knowledge required	• Cannot handle large datasets	–	Paid	7
R	Waste generation forecasting	• Good for statistics-heavy projects and exploring datasets • Performs time series analysis, panel data and data mining • Large number of repositories in GitHub	• Difficult without coding knowledge	✓	Free	4
WEKA	Locating illegal disposal sites, waste classification, prediction of waste generation behavior patterns, optimization of cost and environmental impacts of MSW management	• Easy to use • Can be integrated with other java platforms	• Memory intensive	✓	Free	4
Scikit-learn	Waste generation forecasting	• Easy to use • Suitable for simple data analysis tasks	• Not suitable for deep learning • Limited efficiency with GPU	✓	Free	3
Caffe	Waste classification	• Suitable for feed-forward networks, image processing and improving existing networks • No coding required to train models	• Not suitable for recurrent networks or big networks • Slow software development	✓	Free	2
KNIME	Waste generation forecasting	• Easy to use and learn • Can be integrated with other platforms such as Python, R and Spark • No coding knowledge required for data mining	• Difficult to create complex models • Limited data visualization and exporting capabilities • Knowledge of R/Python required for statistical analysis	✓	Free	1
Microsoft Azure	Waste generation forecasting	• No coding knowledge required for data analysis • User-friendly interface	• Does not break down data comprehensively	–	Paid	1
Neural Designer	Waste classification	• Simple interface • Several tools available for data analysis and predictive analysis • Can handle big data • High analytical speed	• Inability to integrate with cloud-based system	–	Free	1
Tableau	Waste generation forecasting	• No coding knowledge required • Can handle large datasets • Can integrate with Python or R • Good visualization capabilities	• Limited large-scale reporting, building of data tables and static layouts	–	Paid	1

ent input variables such as elemental compositions, physical compositions, and proximate analysis (Shu et al., 2006). The model based on elemental compositions reported highest the accuracy (R^2 = 0.93), while that based on proximate analysis demonstrated 13% lower performance (R^2 = 0.81) during the testing phase. Finally, Bayar et al. (2009) attempted to model the leachate content of solidified wastes using LR. However, due to its poor performance, the model was replaced by an ANN with a single hidden layer and four neurons. High accuracy was reported during the evaluation phase (R^2 = 0.99).

4.4. Process parameter prediction

Sustainable energy can be derived from MSW, using waste conversion systems such as gasification, pyrolysis, and combustion (Dong et al., 2003). Modelling and optimization of process variables are crucial in the design and operation of waste-to-energy technologies. Over the last decade, few studies have explored the use of AI in the prediction of high/low heating value and co-melting temperature of solid wastes. Shankar et al. (2016) predicted the low heating values and syngas yield in a fluidized bed reactor gasification process using single/double layer neural network models. The models were trained using Levenberg-Marquardt BP algorithm. The predictive performance of MIMO model was higher compared to single output model with MSE as low as 0.00074. The study reported longer computational time for ANNs with double layer (8 days), which was more than 10 times higher than that of single layer ANN models. Another study examined the efficiency of ANNs for the prediction of low heating values of solid waste (Ogwueleka and Ogwueleka, 2010). Feed forward ANN using waste composition inputs, trained using BP algorithm, was found to have high accuracy. The R^2 and average error values during training and testing phases were 0.992 and 0.0913, and 0.981 and 0.096, respectively. Rostami and Baghban (2018) developed an LS-SVM with GA optimization for the prediction of the high heating value of solid wastes. The study reported an abso-

Table 8
Various attributes of AI models used to predict waste generation.

	Factor	Reference	Model
Prediction periods	Annual	(Antanasijević et al., 2013; Dai et al., 2011; Jiang and Liu, 2015; Kannangara et al., 2017; Oliveira et al., 2019; Shamshiry et al., 2014; Soni et al., 2019; Wei et al., 2013; Younes et al., 2015)	ANN, ANFIS, DT, GA, MLR, SVR
	Monthly	(Abbasi et al., 2018; Abbasi and Hanandeh, 2016; Abdoli et al., 2011; Abunama et al., 2018; Golbaz et al., 2019; Niska and Serkkola, 2018; Shamshiry et al., 2014; Singh and Satija, 2016)	ANN, ANFIS, FL, GA, MLR, LSSVM, RBF, KNN, SVM
	Weekly	(Abbasi et al., 2014, 2013; Jalili Ghazi Zade and Noori, 2008; Johnson et al., 2017; Noori et al., 2010; R Noori et al., 2009b, 2009a; Roohollah Noori et al., 2009; Shahabi et al., 2012; Vu et al., 2019)	ANN, DT, MLP, PCA, SVM, WT, WT-ANFIS
	Daily	(Kontokosta et al., 2018; Montecinos et al., 2018; Shamshiry et al., 2014)	ANN, GA, LR
Factors affecting waste generation	Population growth	(Abdoli et al., 2011; Chhay et al., 2018; Dai et al., 2011; Kannangara et al., 2017; Oliveira et al., 2019; Pan et al., 2019; Younes et al., 2015)	ANN, DT, GA, LR, SVR
	Income	(Abbasi et al., 2018; Abdoli et al., 2011; Johnson et al., 2017; Kannangara et al., 2017; Kumar et al., 2018; Niska and Serkkola, 2018)	ANN, ANFIS, DT, RBF, RF, SVM
	Level of education	(Abbasi et al., 2018; Johnson et al., 2017; Kannangara et al., 2017; Kumar et al., 2018; Oliveira et al., 2019)	ANN, ANFIS, DT, MLR, RBF, RF, SVM
	Economic trends	(Abbasi et al., 2018; Chhay et al., 2018; Dai et al., 2011; Pan et al., 2019; Younes et al., 2015)	ANN, ANFIS, LR, RBF, SVR
	Household size	(Abbasi et al., 2018; Kannangara et al., 2017; Niska and Serkkola, 2018)	ANN, ANFIS, DT, RBF
	Occupational status	(Kannangara et al., 2017; Kumar et al., 2018; Younes et al., 2015)	ANN, DT, RF, SVM
	Temperature	(Abbasi et al., 2018; Johnson et al., 2017)	ANN, ANFIS, RBF
	Precipitation	(Abbasi et al., 2018; Johnson et al., 2017)	ANN, ANFIS, RBF
	Energy consumption	(Chhay et al., 2018; Younes et al., 2015)	ANN, LR
	Household type	(Kumar et al., 2018)	ANN, RF, SVM
	Holidays	(Johnson et al., 2017)	DT
	Consumption levels	(Dai et al., 2011)	SVR

lute average error of 0.327 and an R^2 of 1, indicating high prediction accuracy. Finally, a single study used GM and ANN in the prediction of co-melting temperatures of sewage sludge ash and fly ash generated from an incinerator fed with MSW (Pai et al., 2010). The lowest MAPE reported with GM was 0.0131, which was 97% higher than the error observed using the ANN model (0.0004). Nevertheless, the study concluded that in case of insufficient data, GM can successfully predict outcomes as it requires only a minimum of four data points.

4.5. Vehicle routing

Adequate waste collection routing is an essential part of a successful integrated SWM strategy; collection works typically constitute 70 to 85% of the overall SWM costs (Singh et al., 2011). Unorganized collection schedules and inadequate allocation of trucks result in unnecessary vehicular emissions and traffic congestions, in addition to increasing the operating costs (Salhofer et al., 2007). Several studies have developed optimization models for the waste collection frequency and route planning; majority of which used GA and its hybrid versions. Król et al. (2016) implemented GA for route optimization during the collection of electrical and electronic household wastes. Utilizing GA decreased collection costs due to optimized route distance, number of collection vehicles and employees. The methodology proposed user participation in scheduling waste collection requests to generate optimized routes. Analysis results showed that although the AI-optimized route length was shortened, the average service time was longer than the non-optimized solution by 85%. Another study developed a software that integrated GIS with hybrid GA to optimize vehicle routing taking into account path constraints such as road inclinations, traffic directions and U-turns (Düzgün et al., 2014). Although optimization resulted in longer routes compared to the initial travel distance, steep roads were served at low truckloads to reduce fuel consumption. Validation results indicated that the routes proposed by GA were closely correlated to the optimal values, with low error values (up to 3.15%). Similarly, Amal et al. (2018) integrated GA with GIS for optimized waste collection routing. The study utilized a modified Dijkstra algorithm in GIS for optimal route options, and further assimilated the obtained solutions in GA to determine the optimum route. The proposed approach improved operating distance, travel time, and fuel consumption by 8, 28 and 3%, respectively. Another study compared hybrid fuzzy AHP and goal programming with hybrid GA, and observed that hybrid GA was efficient at optimizing the transportation cost and number of vehicles for the collection and disposal of waste (Wichapa and Khokhajaikiat, 2018). Similarly, Ferreira et al. (2015) used cellular GA to maximize the amount of waste collected and the locations served while simultaneously minimizing the travel distance and the number of vehicles used.

Few other studies implemented ANN and regression models in waste collection routing. Vu et al. (2019) combined nonlinear autoregressive neural networks with GIS route optimization to study the impact of waste composition and weight on the optimized vehicle routes and emissions. Ferreira and Figueiredo (2017) used MLR and ANN models to predict the required collection frequency at different locations. By incorporating socio-economic and demographic factors into the model, a 10% decrease in the collection frequency was observed. The methodology avoided serving locations with empty bins, thereby reducing environmental damage and collection costs. A similar study compared Theil-Sen constrained regression with LR to the optimize collection frequency in terms of sustainability and environmental factors (Montecinos et al., 2018). LR demonstrated 19% higher performance than Theil-Sen regression, in terms of RMSE and MAE. The proposed methodology was estimated to potentially decrease the greenhouse gas emissions by 940 tCO_2 equivalent per year.

Alternatively, an AIS model was implemented to optimize the waste collection time with vehicular workload based on hauling truck capacity and collection requirement of various locations (Hsieh and You, 2014). Another study proposed the use of AIS for the optimization of route planning and bin location (Nowakowski and Mrówczy, 2017). Several assessment constraints were considered including parking facilities, busy streets, and narrow pavements.

4.6. Waste management planning

SWM planning includes the decision-making and optimization of management practices in order to accomplish strategic objectives and goals. It is a broad domain that includes developing waste collection strategies, siting SWM facilities, preventing illegal disposal, and optimizing costs and environmental impacts during waste collection, transportation, treatment and disposal. Several studies have implemented AI methods for waste management planning. One study implemented DTs to detect illegal waste disposal and was successful at determining more than 500 trucks potentially engaged in illegal dumping (Lu, 2019). Lanorte et al. (2017) used SVMs and satellite data to locate agricultural plastic waste, and aid in waste facility siting and route mapping. SVM was used to classify images and distinguish between crops and plastic waste, with an accuracy of 94.5%. Another study applied rough sets to determine the optimal cost-based waste allocation strategy to be implemented for the available waste processing and disposal facilities (Warren et al., 2004). Other machine learning algorithms, including rule mining (Apriori and Tertius) and clustering algorithms (K-means) were utilized in a multi-criteria decision analysis towards a cost-effective and environmentally safe management of MSW (Kaplan and Ranjithan, 2007).

Several other researchers studied GA-based models for SWM planning. Bautista and Pereira (2006) used GA and greedy randomized adaptive search procedure (GRASP) heuristic in order to develop a well distributed network of waste collection locations. Results indicated that, in terms of the distance to the collection location, GRASP heuristics outperformed GA which may be attributed to the randomness of the dataset used in the study. The heuristics of GA have higher parametric sensitivity compared to GRASP heuristics, which potentially affected the solution. However, it should be noted that the computational time required by GRASP heuristics was approximately 29% higher than that of GA. A similar study used GA to determine optimal facility siting of landfills (Ramasami and Velumani, 2016). Various constraints, such as highly populated areas, vicinity of schools, buildings, airports, water bodies and transportation paths, were applied. The predicted locations were validated using google maps. Another study used GA with hybrid encoding to optimize the costs of medical waste reverse logistics networks, including waste allocations from hospitals, collection and processing units, and factories (Shi et al., 2009). Transportation fees, capital and operation costs of collection and processing units were incorporated in the model. Toutouh et al. (2019) compared PageRank schema and non-dominated sorting genetic algorithm (NSGA II) to determining waste accumulation locations. The study aimed to improve the accessibility of the public to waste bins at low installation costs. This algorithm exhibited higher performance in terms of distance and cost. The solution provided by the evolutionary algorithm was up to 40% more accurate than its alternative and the cost improvements were 38% higher. Furthermore, Medaglia et al. (2009) integrated NSGA II with a mixed-integer program for the siting of infectious waste management facilities. The trade-off criteria included the cost of transport and the exposed population. The proposed algorithm performed better compared to NISE method, in terms of speed, space requirements and the former's ability to determine non-supported solutions. However, the results generated by the latter were more cost-effective.

5. Conclusions

This systematic review focused on assessing the various AI models used in SWM applications, extracted from 85 studies published between 2004 and 2019. The performance of AI algorithms was compared, and the strengths and limitations of AI applications in waste management were discussed. The findings of this SLR study indicated that several types of AI models, stand-alone and hybrid, have been utilized to predict, model, simulate and optimize SWM systems. Overall, as most waste management problems are inherently complex and ill-defined, it is evident that traditional methods - based on mechanistic models and strict algorithms - do not seem to provide an adequate solution in many cases, particularly those suffering from lack of data. AI models offer an alternative effective approach which has gained significant attention in the scientific community. Although research in this field is rapidly advancing, AI-based SWM systems are still mostly in the research and development (R&D) phase. Identifying the limitations of these techniques is crucial for future planning of robust AI-based SWM applications; key examples of those challenges are as follows:

1. *Insufficient data is a major obstacle affecting the implementation of AI systems*. AI models are mainly driven by extensive data sets for training and calibration purposes. Current research is often plagued by the lack or incompleteness of waste data. This is partially due to the fact that SWM industries are mostly outdated with limited reliable records and scarce sensory data, especially in developing countries.
2. *The numerous AI models and their rapid evolution distract the efforts of incorporating AI in SWM*. The reviewed literature showed an abundant number of models, each reporting successful results compared to conventional methods. However, with very few exceptions, there was no thread of progressive research work in specific areas. In other words, the overall progress does not seem to be significant as expected, given the number of studies.
3. *The black box nature of AI models is a key issue in the wide implementation of such techniques*. It is difficult to replicate most AI models as they are mainly based on large datasets that are either protected or hidden in publications. This is one of the main reasons behind the lack of continuation in many of the AI application efforts in the SWM field.
4. *Most studies were direct applications of AI models to solve specific waste problems*. It was rare to find tailored AI solutions addressing the unique features and properties of SWM systems. This can be realized through in-depth collaborative research between multidisciplinary teams of computer science and waste management, with an emphasis on highly-qualified AI technical personnel.
5. *The SWM business entities are slowly adopting the shift towards AI versus the traditional methods*. Such transition can be achieved by bridging the gap between the research and industry, e.g., by fostering start-up technology companies and collaboration between research institutes and small and medium-sized enterprises (SEMs), or through the R&D departments in large SWM companies.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

We would like to thank the University of Sharjah and OpenUAE Research and Development Group for funding this research study.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.wasman.2020.04.057.

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