systems and so on, and disposal of solid waste in municipalities are majorly accountable for environmental pollution. As at 2016, urban location in the world generated 2.01billion tonnes of solid waste, which amount to a footprint of 0.74kg/per person/day. Going by the current rate of urbanization and population growth, the annual waste generation is projected to increase to 3.4billion tonnes in 2050 which represent 70% increase from 2016 [6-8]. About 20-50% of municipal budget is consumed by waste management [7]. The effect of waste management is even more severe in the developing countries where over 90% of waste is usually disposed indiscriminately or incinerated openly [7]. This culminates into health problems, global warming, and urban violence. In order to mitigate the above-mentioned menace, the implementation of waste to energy idea is motivated since it reduces the municipal solid waste landfills and reduces the traditional hydrocarbon fuels consumption [9]. In recent times, energy derived from waste is now being integrated into our energy feedstock. Hence, determination of combustion enthalpy from routine constituents such as Carbon, Moisture, Oxygen, Nitrogen, Sulphur, Ash will ensure rapid decision for the engineers and the policymakers. Also, the development of modern system which can be used to process waste to different energy resources such as electricity, heat and transport fuels requires an accurate understanding of the major properties of MSW such as elemental composition and enthalpy of combustion. Enthalpy of combustion, which is also known as high heating value, HHV is a critical parameter, which determines the energy content of MSW. Such properties constitute the determining factor in the design and operation of biomass combustion systems [10]. In the recent time, artificial intelligence has gained traction as it has been applied in the estimation of the properties of heating systems and biomass feedstocks [11-14]. This is largely due to its ability to accurately predict linear and nonlinear relationships between variables due to its dynamic nature. Fuzzy inference systems (FIS) and artificial neural network (ANN) are very versatile in the estimation of the system behaviour [15, 16]. Optimization of an adaptive neuro-fuzzy inference systems (ANFIS) with particle swarm optimisation (PSO) has been tailored to produce several excellent results for different engineering applications [14, 17, 18]. ANFIS hybridized with PSO optimizes the adaptive ANFIS layers, thus achieving optimal ANFIS parameters. PSO has been credited as a powerful and intelligent population-driven computational algorithm which is able to solve a problem using the population of candidate solutions [19]. PSO acceptance is due to its many benefits which include fast convergence, high performance on nonlinear functions optimisation, simplicity of operation, and ease of realization [17, 20]. PSO has been successfully applied in various field which include engineering, management, medicine, pharmaceuticals, safety and so on [19, 21, 22].

Several correlations have been developed to estimate the HHV of solid waste constituents, but the accuracy of these correlations is not satisfactory as most of them do not take cognizance of nonlinear dependencies of waste constituents. Previous correlations and models were developed by Wilson [23], Lloyd and Davenport [24], Meraz, et al. [25], Boie [26], Khan and Abu-Ghararah [27], Niessen [28], Chang [29], Baghban and Ebadi [11] to estimate the heating value of waste and fossil fuel as shown in Table 1. The correlations by Lloyd and Davenport [24] and Boie [26] were developed based on the elemental properties of fossil fuel and may not be able to generalize the behaviour of MSW constituents. While correlations developed by Chang [29]; Meraz, et al. [25]; Niessen [28]; Ringen, et al. [30]; Wilson [23] did not consider the ash component of the solid waste. In practical sense, it is justifiable to consider the effect of ash and moisture constituents when developing a model to predict the heating value of waste derived fuels. For instance, ash content determines the cost of disposal of combustion waste and may possibly contribute to particle emission while moisture content could affect the shelf life and also contribute to self-ignition of waste-derived fuel [31]. Also, Baghban and Ebadi [11] developed a model based on GA-ANFIS they reported that the model accurately approximated HHV. Table 1 presents a brief review of past studies on the prediction of HHV of biomass feedstock.

Table 1. Correlations for the prediction of HHV

References	**Equation HHV (MJ/kg)**	**Sample size**	**Feedstock class**
Meraz et al [25]	$\left(1-\frac{H_2O}{100}\right)\left((-0.3708C) - 1.1123H + 0.1391O - 0.3178N - 0.1391S\right)$	100	MSW
Wilson [23]	$\left(1-\frac{H_2O}{100}\right)\left((-0.3279C) - 1.5330H + 0.1668O - 0.0242N - 0.0928S\right)$	100	Organic waste
Boie [26]	$0.3517C + 1.1626H - 0.1047S - 0.111O$	-	Fossil fuel
Lloyd and Davenport [24]	$\left(1-\frac{H_2O}{100}\right)\left((-0.3578C) - 1.1357H + 0.0845O - 0.0594N - 0.1119S\right)$	138	Fossil fuel
Chang [29]	$35.8368 + 0.7523H - 0.2674S - 0.4654) - 0.3814Cl - 0.2802N$	150	Organic waste
Niessen [28]	$0.2322C + 0.7655H - 0.0698S - 0.072O - 0.0262Cl - 0.1814P$	80	Waste water sludge

C=Carbon; H=Hydrogen; O=Oxygen; S=Sulphur; N=Nitrogen; Cl=Chlorine; P=Phosphorous (on dry basis in % weight); H_2O=Moisture content (as discarded, in % weight).

From the literature survey to the best of information available to the authors, there is no model which has predicted the High Heating Value of MSW based on PSO-ANFIS. Bearing this in mind, this current study introduces a PSO-ANFIS model aimed at predicting the enthalpy of combustion of waste-derived fuel based on the moisture content (H_2O), Carbon C, Hydrogen H, Oxygen O, Nitrogen N, Sulphur S, and Ash contents.

This study is aimed at estimating the combustion enthalpy of MSW for the purpose of energy recovery. The rest of this article is as structured: section 2 presents the materials and methods used, section 3 discusses the results obtained, and section 4 concludes the work.

2 Materials and Methods

A dataset comprising of 123 different waste samples of municipal origin which have been experimentally characterized were taken from Meraz, et al. [25] and Phyllis2, database for biomass and waste [32]. The major classification of municipal solid waste involved are; food waste, municipal woods, tree, and plants residue, plastic, paper, wood, textiles, solid waste incinerator samples, refuse-derived fuel, domestic waste. The input variables were the major components of MSW such as C, O, H, N, S, Ash on dry basis and moisture content (weight percentage calculated as discarded), while the output parameter was the HHV(MJ/kg). The 123 datasets were randomized and then divided into two subsets with 70% of the data used for training while 30% was used for model testing. The coverage of the data points and statistical analysis of the ultimate constituents and HHV is as shown in Table 2.

Table 2. Statistical analysis of MSW experimental dataset

Constituents	min	max	mean	Std
H_20 (%)	0.20	78.7	20.4	22.5
C (%)	0.50	87.1	42.8	18.3
H (%)	0.08	14.2	5.7	2.7
O (%)	0.23	47.8	27.1	13.8
N (%)	0.04	10.0	1.2	1.7
S (%)	0.01	1.5	0.3	0.3
Ash (%)	0.26	98.9	23.2	28.9
HHV(MJ/kg)	0.14	45.9	16.2	9.6

2.1 Fundamental Principles of ANFIS

Takagi-Sugeno fuzzy model is the most applied fuzzy inference system (FIS) due to its adaptive framework [33-35]. It provides a systematic approach to develop fuzzy rules from given input and output variables. The data elements are classified into different categories through data clustering process. The optimal estimation of the membership function parameters is achieved by dual advantages of fuzzy logic and artificial neural network. This enable the ANFIS to be able to solve complex and nonlinear problems [34, 36]. The fuzzy rules are based on first order Takagi-Sugeno fuzzy inference as follows:

Rule 1: If J_1 is A_1 AND J_2 is C_1 then $F_1 = b_1J_1 + c_1J_2 + k_1$.

Rule 2: If J_1 is A_2 AND J_2 is C_2 then $F_2 = b_2J_1 + c_2J_2 + k_2$.

where A_1, C_1, A_2, C_2, are nonlinear parameters and membership functions for input (J_1 and J_2) and b_1, c_1, k_1, b_2, c_2, k_2 and output function parameters. In this article, the above two rules were adapted with input $J_i\ (i = 1 \dots 7)$, output $F_i(i = 1)$ and cluster $C_j(j = 1 \dots 10)$ with equal weights using fuzzy c-means clustering technique.

In general, ANFIS model is a five-layered network comprising of the fuzzy layer, product layer, normalization layer, de-fuzzification layer, and summation layer. For the prediction of the enthalpy of combustion, which is of interest in this study, ANFIS model maps the seven inputs (H_2O, O, H, C, S, N, Ash) to the output (High heating value, HHV). It is established in the literature that ANFIS model formulated based on Gaussian principle gives a better performance in comparison with other models. Therefore, fuzzy rules for the antecedents in this study were formulated based on Gaussian membership function. Further information about ANFIS can be found in [37, 38] [34, 39].

2.2 Optimisation of ANFIS model with PSO

The objective of the PSO is the optimization of the adaptive layers in the ANFIS model such that optimal membership function parameters are obtained. The stopping criterion was selected in such a way that premature convergence and overfitting is avoided [40, 41]. The PSO is terminated if maximum number of iterations is exceeded, satisfactory solution is obtained based on the set conditions, or if there is no further improvement in the objective function over a specific number of iterations. Fuzzy c-means (FCM) clustering method is applied to minimize error in ANFIS and subsequently, the ANFIS is trained with PSO algorithm. Conventional ANFIS model proceeds with an integration of the gradient descent backpropagation algorithm and the least square method for the optimization of the adaptive layers [42]. However, recent studies in this domain have shown that optimization of the adaptive layers in ANFIS model with evolutionary algorithm increases ANFIS prediction accuracy [43, 44]. This study optimizes the ANFIS model with PSO.

PSO begins with a random set of initial solution and evolves toward the optimal solutions, just like other evolutionary algorithms. Each particle within the solution space possess a random velocity value. When the previous generation of information is updated, a new generation is produced. The best solution is attained as the particle search through the solution space according to equation 1 and 2. Once the fitness of the particles has been established, the velocity of the particles is estimated according to equation 1. The position of the particles is updated based on their present position and velocity as shown in equation 2. The iteration proceed until the stopping conditions are attained. The position and velocity of the particle are updated using a population topology functions as defined in [19, 45] as:

$$V_j^d = \left[w \times V_j^d\right] + \left[b_1 \times rand1_j^d\left(P_j^d - X_j^d\right)\right] + \left[b_2 \times rand2_j^d\left[P_g^d - X_j^d\right]\right] \quad (1)$$

$$X_j^d = X_j^d - V_j^d \quad (2)$$

such that each particle j in M population possesses X_j^d position component and V_j^d velocity component at dth dimension. P_j signifies the best position of the jth particle and P_g the global best position. The acceleration coefficients are defined by b_1 and b_2, w is the linearly decreasing inertia weight. The $rand1_j^d$ and $rand2_j^d$ components of the equation are randomly generated numbers within the range of 0 and 1. The readers may refer to [17, 34, 35, 43, 46, 47] for more information and further reading on PSO and ANFIS.

The flow diagram of PSO technique used as the optimisation algorithm for ANFIS is as shown in Figure 1. The model was used to predict the HHV of MSW based on their ultimate constituents.

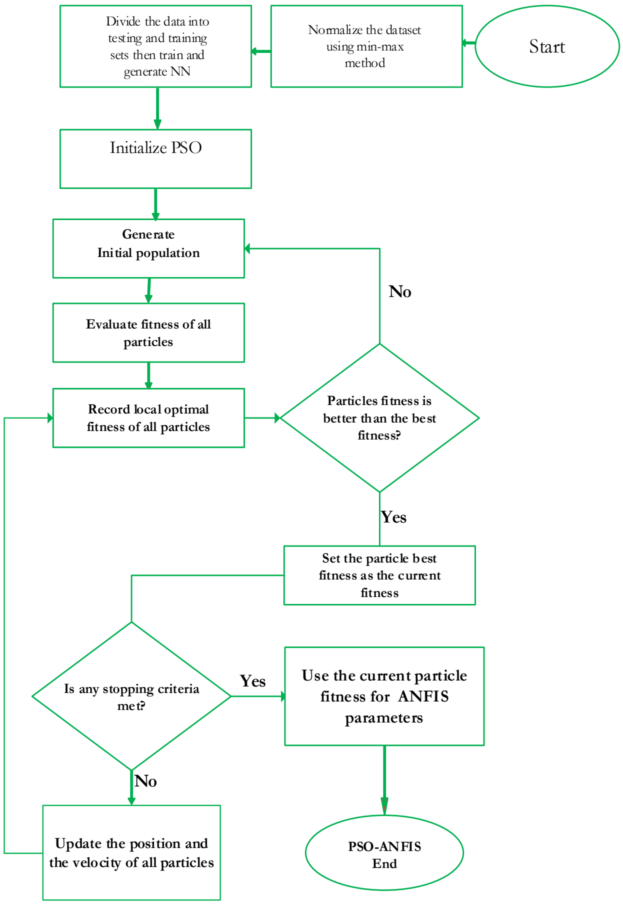

Figure 1. Flow diagram of PSO-ANFIS Algorithm

The relationship between the ultimate composition and HHV of MSW can be mathematically expressed as follows

$$HHV = f\,(H_2O, C, H, O, N, S, Ash) \quad (3)$$

In general term, the principle guiding the PSO-ANFIS is as outlined in the steps below:

Step 1: Prepare the data for the input and the corresponding output.
Step 2: Generate initial FIS structure using Fuzzy C-means clustering technique
Step 3: Generate the first particle swarm and do random initialization of variables.
Step 4: Determine the initial location of the particles.
Step 5: Generate the next generation of the particles
Step 6: Estimate the fitness value of all the particles
Step 7: Evaluate the cost of particles and update personal best
Step 8: If the stopping criteria is not met, update the velocity and position of the particles then compute the particle fitness again
Step 9: Use the global optimal value for the ANFIS parameters then end PSO-ANFIS, Output results and terminate the algorithm

The PSO script was written in MATLAB (R2015a) installed on a desktop computer workstation with configuration 64 bits, 32GB RAM Intel (R) Core (TM) i7 5960X. An initial population of 20, local and global learning efficiencies of 2 each and the initial weight damping ratio of 0.8 was used for all ultimate constituents and HHV. A total of 48 premise parameters were optimized using the PSO. A maximum iteration of 400 and the convergence values which minimizes the training error objective function were made the stopping criteria. The specification of the PSO learning parameters are shown in Table 1. Minimization of the training error objective function was made a stopping criterion. The training stops when no further improvement is recorded in the value of the objective function:

Table 3. The specification of the PSO learning parameters

User-defined Parameters	Value
Input/output	7/3
Swarm size	20
Input MF type	Gaussian
Output MF type	Linear
Inertia damping ratio	0.8
Number of iterations	400
Personal learning coefficient	2
Global learning coefficient	2
Inertia weight	0.5
FIS type	Takagi-Sugeno
FIS clustering	Fuzzy C-means
Number of rules	20
Stopping criteria	Minimum training error

2.3 Model performance evaluation

Statistical estimation of errors was performed to evaluate the effectiveness of the model. These include; Mean Absolute Deviation (MAD), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The Coefficient of Correlation (CC) was estimated to determine the degree of fitness of the proposed model. The choice of MAD and RMSE is based on their use in numerous related studies as an effective means of determining the eligibility of the model for prediction. MAPE estimate the degree of accuracy and coverage of the model. The Log accuracy ratio (LAR) was calculated for the testing phase only since it is most expedient to establish if the developed model satisfactorily predicts the HHV. LAR was also introduced as a measure of error in order to address the asymmetric nature of MAPE with respect to over-forecasting and under-forecasting and also non-resistance to outliers [48, 49] Computation time (CT) was estimated as a measure of the overall prediction time as a measure of time cost of the forecasting and to further underline the economic significance of this model.

Correlation Coefficient (CC)

$$CC = 1 - \frac{\sum_{i=1}^{n}(y_k - \widehat{y_k})^2}{\sum_{i=1}^{n}(y_k - \overline{y_k})^2} \tag{4}$$

Root Mean square Error (RMSE):

$$RMSE = \sqrt{\frac{\sum_{k=1}^{N}\left[y_k - \widehat{y_k}\right]^2}{N}} \tag{5}$$

Mean Absolute Deviation (MAD):

$$MAD = \frac{1}{N}\sum_{k=1}^{N}\left|y_k - \bar{y}_k\right| \tag{6}$$

Mean Absolute Percentage Error (MAPE)

$$MAPE = \left[\frac{1}{N}\sum_{k=1}^{N}\left|\frac{y_k - \bar{y}_k}{y_k}\right|\right] \times 100 \tag{7}$$

Log Accuracy ratio, LAR

$$LAR = Log(AR) = \log\left(\frac{\overline{y_k}}{y_k}\right) \tag{8}$$

3 Results and Discussion

The prediction ability of the model developed for MSW was evaluated at training and testing phases as shown in Figure 2 and Figure 3. However, most of the discussion is centred around the testing phase since the objective is to determine if the model can predict the experimental results with minimum error. To gain better insight into the performance of the model, the predicted and actual HHV were plotted against the data index. Also, Figure 4 illustrate the correlation between the experimental and the observed HHV. The CC was determined to be 0.87. A good dispersion around the best line of fit from the regression plot was observed. Also, satisfactory fitness and predictive capability with the actual data at both the training and testing stages was established. As obtainable in most linear correlations in MSW studies, the dependencies among the constituents are not expected to be linear, therefore a ‘propose and test’ method may not be able to give an accurate prediction. Rather than applying linear regression, where each correlation was proposed, the corresponding coefficient of regression calculated and the error estimated, this study presents an optimized ANFIS model with new correlation and better predictive capacity compared to existing linear models.

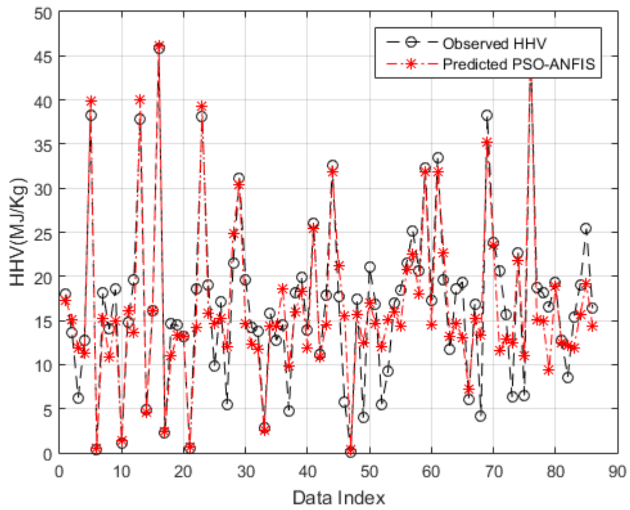

Figure 2. Comparison of experimental and predicted HHV for PSO-ANFIS at training stage

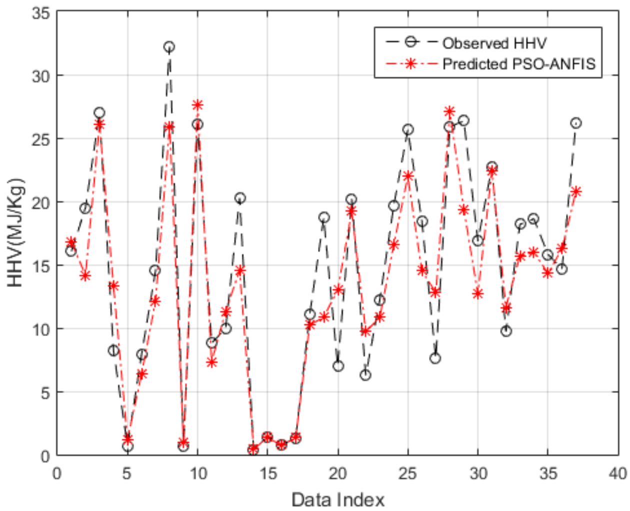

Figure 3. Comparison of experimental and predicted HHV for PSO-ANFIS at testing stage

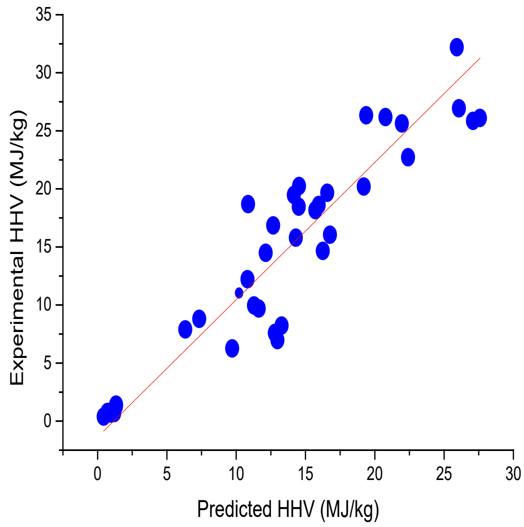

Figure 4. Regression plot of experimental and predicted HHV(MJ/kg) by PSO-ANFIS

RMSE and MAD revealed the variability between the experimental and estimated data, but the RMSE is more sensitive to extreme data compared to MAD due to the squared term. Table 4 shows the estimation of errors for HHV developed for MSW. The value of R^2 and RMSE may have improved if the moisture content were ignored in the development of the model, however, the significance of moisture variable makes it vital to be considered for practical purpose. The computation time (CT) which is a measure of the cost-effectiveness of the MSW prediction model was evaluated. The CT results shows that the model predict the HHV in less than 60seconds. This is quite an important outcome in term of energy recovery from MSW.

Table 4. Estimation of errors for HHV of MSW

	Training	Testing
MSE	13.1603	11.8634
RMSE	3.6277	3.4443
MAD	2.7058	2.562
MAPE	29.0494	22.6202
Error STD	3.63	3.3141
CC		0.867
Computational Time(s)		36.964
LAR		0.0337

The model developed in this study was compared to the existing models. Meraz *et al* [25] and Wilson *et al* [23] were selected since they were originally used to predict MSW and Organic waste respectively. All models were applied to the data which was used in this study so that the data was kept the same for each of the models evaluated. The predicted results of each model are as compared in Table 5.

Table 5. Experimental and Predicted HHV based on different models

Experimental HHV (MJ/kg)	Wilson et al. [23] (MJ/kg)	Meraz et al.[25] (MJ/kg)	This study (MJ/kg)
26.3400	27.5805	27.1253	26.0702
20.2490	20.1251	20.8074	20.2708
19.6610	19.5083	20.4102	19.3810
17.0700	15.9383	16.5805	16.7671
14.4950	13.9645	14.4361	14.4605
12.7470	12.4326	12.8900	12.6678
6.5130	7.3915	8.0940	6.3316
5.5120	5.7759	6.1709	5.5314
0.6980	1.6254	1.7166	0.7180
0.3880	0.2431	0.2673	0.3914

Conclusion

Sustainable and renewable energy sources which are technologically feasible, environmentally friendly and economically viable, are been explored using waste-to-fuel technologies. This study introduced an ANFIS model optimised with PSO aimed at predicting the enthalpy of combustion of MSW based on the moisture content (H_2O), Carbon, Hydrogen, Oxygen, Nitrogen, Sulphur and Ash contents. The study establishes the viability of PSO-ANFIS model in predictive analysis in MSW studies. The performance metrics in this study compared with other existing models proved that this model will be useful in municipal solid waste management to predict expected HHV of the waste collected from the municipalities. Future research will model the effect of the predicted properties of biomass on the MSW energy recovery technologies to establish the optimum energy recovery condition.

Conflict of Interest

The authors acknowledge that there is no conflict of interest as regards this article.

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References

[1] WorldNuclearAssociation, "World Energy Needs and Nuclear Power," http://www.world-nuclear.org/information-library/current-and-future-generation/world-energy-needs-and-nuclear-power.aspx *accessed on 8th December 2018,* 2018.

[2] Y. D. Singh, P. Mahanta, and U. Bora, "Comprehensive characterization of lignocellulosic biomass through proximate, ultimate and compositional analysis for bioenergy production," *Renewable Energy,* vol. 103, pp. 490-500, 2017.

[3] S. Singh, C. Wu, and P. T. Williams, "Pyrolysis of waste materials using TGA-MS and TGA-FTIR as complementary characterisation techniques," *Journal of Analytical and Applied Pyrolysis,* vol. 94, pp. 99-107, 2012.

[4] J. Singh, N. Mishra, S. Banerjee, and Y. C. Sharma, "Comparative studies of physical characteristics of raw and modified sawdust for their use as adsorbents for removal of acid dye," *BioResources,* vol. 6, no. 3, pp. 2732-2743, 2011.

[5] WHO, "Air pollution and health:Summary," https://www.who.int/airpollution/ambient/about/en/ *accessed on 20th December, 2018,* 2018.

[6] D. Hoornweg and P. Bhada-Tata, "What a waste: a global review of solid waste management," 2012.

[7] WorldBank, "Solid Waste Management," http://www.worldbank.org/en/topic/urbandevelopment/brief/solid-waste-management *accessed on 20th December 2018,* 2018.

[8] WorldBank, "World Bank Group Announcements at One Planet Summit," https://www.worldbank.org/en/news/press-release/2017/12/12/world-bank-group-announcements-at-one-planet-summit *accessed on 18th January 2019,* 2017.

[9] M. S. Vlaskin, "Municipal solid waste as an alternative energy source," *Proceedings of the Institution of Mechanical Engineers, Part A: Journal of Power and Energy,* p. 0957650918762023, 2018.

[10] S. B. Ghugare, S. Tiwary, and S. S. Tambe, "Computational intelligence based models for prediction of elemental composition of solid biomass fuels from proximate analysis," *International Journal of System Assurance Engineering and Management,* vol. 8, no. 4, pp. 2083-2096, 2017.

[11] A. Baghban and T. Ebadi, "GA-ANFIS modeling of higher heating value of wastes: Application to fuel upgrading," *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects,* vol. 41, no. 1, pp. 7-13, 2019.

[12] D. Petković, M. Protić, S. Shamshirband, S. Akib, M. Raos, and D. Marković, "Evaluation of the most influential parameters of heat load in district heating systems," *Energy and Buildings,* vol. 104, pp. 264-274, 2015.

[13] S. Shamshirband *et al.*, "Heat load prediction in district heating systems with adaptive neuro-fuzzy method," *Renewable and Sustainable Energy Reviews,* vol. 48, pp. 760-767, 2015.

[14] M. Suleymani and A. Bemani, "Application of ANFIS-PSO algorithm as a novel method for estimation of higher heating value of biomass," *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects,* vol. 40, no. 3, pp. 288-293, 2018.

[15] E. Akkaya, "ANFIS based prediction model for biomass heating value using proximate analysis components," *Fuel,* vol. 180, pp. 687-693, 2016.
[16] R. D. Behrooz, A. Esmaili-Sari, N. Bahramifar, and D. Kaskaoutis, "Analysis of the TSP, PM10 concentrations and water-soluble ionic species in airborne samples over Sistan, Iran during the summer dusty period," *Atmospheric Pollution Research,* vol. 8, no. 3, pp. 403-417, 2017.
[17] M. Hajihassani, D. J. Armaghani, and R. Kalatehjari, "Applications of particle swarm optimization in geotechnical engineering: a comprehensive review," *Geotechnical and Geological Engineering,* vol. 36, no. 2, pp. 705-722, 2018.
[18] J. Lauwers, L. Appels, I. P. Thompson, J. Degrève, J. F. Van Impe, and R. Dewil, "Mathematical modelling of anaerobic digestion of biomass and waste: Power and limitations," *Progress in Energy and Combustion Science,* vol. 39, no. 4, pp. 383-402, 2013.
[19] R. Eberhart and J. Kennedy, "A new optimizer using particle swarm theory," in *Micro Machine and Human Science, 1995. MHS'95., Proceedings of the Sixth International Symposium on*, 1995, pp. 39-43: IEEE.
[20] S. Cheng, H. Lu, X. Lei, and Y. Shi, "A quarter century of particle swarm optimization," *Complex & Intelligent Systems,* pp. 1-13, 2018.
[21] Y. Zhang *et al.*, "Tissue intrinsic fluorescence recovering by an empirical approach based on the PSO algorithm and its application in type 2 diabetes screening," *Biomedical optics express,* vol. 9, no. 4, pp. 1795-1808, 2018.
[22] J. H. Tam, Z. C. Ong, Z. Ismail, B. C. Ang, and S. Y. Khoo, "A new hybrid GA− ACO− PSO algorithm for solving various engineering design problems," *International Journal of Computer Mathematics,* pp. 1-37, 2018.
[23] D. L. Wilson, "Prediction of heat of combustion of solid wastes from ultimate analysis," *Environmental Science & Technology,* vol. 6, no. 13, pp. 1119-1121, 1972.
[24] W. G. Lloyd and D. A. Davenport, "Applying thermodynamics to fossil fuels: Heats of combustion from elemental compositions," *Journal of chemical education,* vol. 57, no. 1, p. 56, 1980.
[25] L. Meraz, A. Domínguez, I. Kornhauser, and F. Rojas, "A thermochemical concept-based equation to estimate waste combustion enthalpy from elemental composition☆," *Fuel,* vol. 82, no. 12, pp. 1499-1507, 2003.
[26] W. Boie, "Fuel technology calculations," *Energietechnik,* vol. 3, pp. 309-316, 1953.
[27] M. A. Khan and Z. H. Abu-Ghararah, "New approach for estimating energy content of municipal solid waste," *Journal of environmental engineering,* vol. 117, no. 3, pp. 376-380, 1991.
[28] W. R. Niessen, *Combustion and incineration processes: applications in environmental engineering*. CRC Press, 2002.
[29] Y. Chang, "Estimating heat of combustion for waste materials," *Pollut. Eng.;(United States),* vol. 14, no. 11, 1982.
[30] S. Ringen, J. Lanum, and F. P. Miknis, "Calculating heating values from elemental compositions of fossil fuels," *Fuel,* vol. 58, no. 1, pp. 69-71, 1979.
[31] J. S. Tumuluru, C. T. Wright, R. D. Boardman, N. A. Yancey, and S. Sokhansanj, "A review on biomass classification and composition, co-firing issues and pretreatment methods," in *2011 Louisville, Kentucky, August 7-10, 2011*, 2011, p. 1: American Society of Agricultural and Biological Engineers.
[32] ECN, "Phyllis2, database for biomass and waste " *https://phyllis.nl/Browse/Standard/ECN-Phyllis accessed on 20th Novemebr 2018,* 2018.
[33] M. Sugeno and G. Kang, "Structure identification of fuzzy model," *Fuzzy sets and systems,* vol. 28, no. 1, pp. 15-33, 1988.
[34] J.-S. Jang, "ANFIS: adaptive-network-based fuzzy inference system," *IEEE transactions on systems, man, and cybernetics,* vol. 23, no. 3, pp. 665-685, 1993.
[35] D. Karaboga and E. Kaya, "Adaptive network based fuzzy inference system (ANFIS) training approaches: a comprehensive survey," *Artificial Intelligence Review,* pp. 1-31, 2018.
[36] A. Yaghoobi, M. Bakhshi-Jooybari, A. Gorji, and H. Baseri, "Application of adaptive neuro fuzzy inference system and genetic algorithm for pressure path optimization in sheet hydroforming process," *The International Journal of Advanced Manufacturing Technology,* vol. 86, no. 9-12, pp. 2667-2677, 2016.
[37] T. Takagi and M. Sugeno, "Fuzzy identification of systems and its applications to modeling and control," *IEEE transactions on systems, man, and cybernetics,* no. 1, pp. 116-132, 1985.
[38] M. Rezakazemi, A. Dashti, M. Asghari, and S. Shirazian, "H2-selective mixed matrix membranes modeling using ANFIS, PSO-ANFIS, GA-ANFIS," *International Journal of Hydrogen Energy,* vol. 42, no. 22, pp. 15211-15225, 2017.
[39] W. Suparta and K. M. Alhasa, *Modeling of tropospheric delays using ANFIS*. Springer, 2016.
[40] C. W. Cleghorn and A. P. Engelbrecht, "Particle swarm variants: Standardized convergence analysis," *Swarm Intelligence,* vol. 9, no. 2-3, pp. 177-203, 2015.
[41] J. Fulcher, "Computational intelligence: an introduction," in *Computational intelligence: a compendium*: Springer, 2008, pp. 3-78.
[42] E. Essien, H. Ibrahim, M. Mehrandezh, and R. Idem, "Adaptive neuro-fuzzy inference system (ANFIS)–based model predictive control (MPC) for carbon dioxide reforming of methane (CDRM) in a plug flow tubular reactor for hydrogen production," *Thermal Science and Engineering Progress,* vol. 9, pp. 148-161, 2019.
[43] B. Ordóñez-De León, M. Aceves-Fernandez, S. Fernandez-Fraga, J. Ramos-Arreguín, and E. Gorrostieta-Hurtado, "An improved particle swarm optimization (PSO): method to enhance modeling of airborne particulate matter (PM10)," *Evolving Systems,* pp. 1-10, 2019.
[44] J. Farzaneh, R. Keypour, and A. Karsaz, "A novel fast maximum power point tracking for a PV system using hybrid PSO-ANFIS algorithm under partial shading conditions," *International Journal of Industrial Electronics, Control and Optimization,* vol. 2, no. 1, pp. 47-58, 2019.
[45] Y. Shi and R. Eberhart, "A modified particle swarm optimizer," in *Evolutionary Computation Proceedings, 1998. IEEE World Congress on Computational*

Intelligence., The 1998 IEEE International Conference on, 1998, pp. 69-73: IEEE.

[46] Y. K. Semero, D. Zheng, and J. Zhang, "A PSO-ANFIS based hybrid approach for short term PV power prediction in microgrids," *Electric Power Components and Systems,* vol. 46, no. 1, pp. 95-103, 2018.

[47] H. Moayedi, M. Raftari, A. Sharifi, W. A. W. Jusoh, and A. S. A. Rashid, "Optimization of ANFIS with GA and PSO estimating α ratio in driven piles," *Engineering with Computers,* pp. 1-12, 2019.

[48] C. Tofallis, "A better measure of relative prediction accuracy for model selection and model estimation," *Journal of the Operational Research Society,* vol. 66, no. 8, pp. 1352-1362, 2015.

[49] R. J. Hyndman and A. B. Koehler, "Another look at measures of forecast accuracy," *International journal of forecasting,* vol. 22, no. 4, pp. 679-688, 2006.