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Prediction of gas yield generated by energy recovery from municipal solid waste using deep neural network and moth-flame optimization algorithm

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ABSTRACT

In recent years, the strong development of urban areas and rapid population growth have contributed significantly to environmental pollution issues, especially SW. Of those, municipal solid waste (MSW) is considered a major concern of waste treatment plants. Nowadays, with the development of science and technology, MSW has been treated and recycled to recover energy. However, the issue of energy recovery and optimization from MSW remains a challenge for waste treatment plants. Therefore, a novel artificial intelligence approach was proposed in this study for predicting the gas yield (GY) generated by energy recovery from MSW with high accuracy. Accordingly, a deep neural network (DNN) was developed to predict GY from MSW. Subsequently, the Moth-Flame optimization (MFO) algorithm was applied to optimize the DNN model and improve its accuracy, called MFO-DNN model. The findings revealed that both the DNN and MFO-DNN models predicted GY very well. Of those, the proposed MFO-DNN model provided dominant performance than the DNN model. Based on the proposed MFO-DNN model, the toxic gases can be thoroughly controlled and optimized to recover the gas field from MSW for waste treatment plants, minimizing negative impacts on the surrounding environment.

1. Introduction

SW (SW) is becoming a big concern of the community, and it directly relates to environmental pollution of soil, water, and air (Brunner, 2013). The amount of SW is increasing rapidly due to population growth, urbanization, and the rapid development of industries (Cheng et al., 2020; Malav et al., 2020)(Huan et al., 2020; Thuy et al., 2020). According to a World Bank report, about four billion tonnes of waste are discharged into the environment per year, of which 1.3 billion tonnes is SW. It is forecast that by 2025, the amount of SW discharged into the environment annually will be about 2.2 billion tonnes or more (Hoornweg et al., 2013; Moya et al., 2017). Therefore, SW treatment and management are of particular global concern, especially in low-income countries (Bui et al., 2020; Chen, 2018; Iyamu et al., 2020).

In order to treat SW, only one-fourth of which is recycled, the rest (three-fourths) are directly processed at landfills (Bajracharya et al., 2016). However, municipal solid waste (MSW) is such an acute and not an easy problem in urban areas. MSW includes many different types of waste in urban areas such as food waste, plastic, rubber, wood, cotton, paper, to name a few. Therefore, the treatment of MSW as such can lead to critical environmental problems, seriously affecting human health (Pires et al., 2011). To mitigate these negative impacts, many countries and continents have proposed sustainable development strategies to recover energy from MSW as well as address climate change-related issues (Amigun et al., 2011; Noor et al., 2013; Rajaeifar et al., 2017; Shekdar, 2009; Udomsri et al., 2011; Yi et al., 2018). However, controlling the negative impacts on the environment during energy recovery from MSW is still a big challenge for scientists (Brunner and Rechberger, 2015; Cheng and Hu, 2010; Dalmo et al., 2019).

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Nomenclature

MSW	Municipal solid waste	H	Hydrogen
SW	Solid waste	N	Nitro
GY	Gas yield	S	Sulfur
DNN	Deep neural network	O	Oxygen
MFO	Moth-Flame optimization	MC	Moisture content
ANN	Artificial neural network	ER	Equivalence ratio
AI	Artificial intelligence	Temp	Temperature
FFNN	Feed-forward neural network	MSE	Mean-squared error
MLPNN	Multiple layers perceptron neural network	RMSE	Root-mean-squared error
HANP	Hierarchical analytical network process	MAPE	Mean absolute percentage error
ReLu	Rectified linear unit	VAF	Variance accounted for
C	Carbon	RSE	Root-squared error
		R^2	Determination coefficient
		CV	Cross-validation

In recent years, new technologies for heat treatment from MSW have been proposed to maximize energy recovery and minimize negative impacts on the surrounding environment (Bashir et al., 2019; Dalmo et al., 2019; Ghosh et al., 2019; Liu et al., 2020; Polygalov et al., 2019; Scarlat et al., 2019). The toxic gases (e.g., CO_x, SO_x, and NO_x) and ash were investigated to gasify the MSW for energy recovery. Biomass gasification is also a potential technique to obtain energy from SW, aiming to reduce the local impact and greenhouse gases (Panepinto and Genon, 2011). However, the performance, as well as the ability to recover heating value and gas yield based on those toxic gases, have not been properly predicted and assessed. Panepinto and Genon (2016) indicated that the substrate pretreatments can improve the biomass gasification process's performance, and an extruder was also proposed to improve the electric energy from the methane yield. As an alternative method to improve the performance of gasification processes, Dong et al. (2003) applied a neural network with feed-forward algorithm (FFNN) to predict the heating value recovered from MSW with a promising result. Accordingly, 108 samples were collected from several areas in China (Nanjing city) in their study. In addition, several empirical models were also considered to forecast heating value and compared with that of the FFNN model. The FFNN model's performance showed that it is a good model for forecasting heating value with a sum-squared error (SSE) of 1.7. In another study, Shu et al. (2006) applied a multiple layers perceptron neural network (MLPNN) to predict the energy content of MSW. MSW from 55 sampling sites was collected in various areas of Taiwan (e.g., town, villages, remote islands, cities), and analyzed for two years (04/2002–03/2003) to determine the characteristics of MSW. Different MLPNN models with different input variables were taken into account to estimate the heating value of MSW in their study. They revealed that the elemental analysis model based on MLPNN could predict energy content with the highest accuracy (i.e., $R^2 = 0.930$, MAE = 105.45, and RMSE = 146.75), and it became the best fit model for predicting heating value from MSW. They also claimed that a more appropriate analysis method is necessary for waste treatment operators. A similar study for the prediction of heating value was also conducted by Akkaya and Demir (2010) using a neural network (ANN) with the Levenberg-Marquardt backpropagation algorithm. They found that this ANN model can estimate heating value with high reliability (i.e., MSE of 0.0137 and R^2 of 0.991), and they deduced this model as a robust estimation tool for the determination of heating value from MSW. In another study, Nixon et al. (2013) evaluated the energy recovery ability from MSW in several places in India, using the hierarchical analytical network process (HANP) approach. Their recommendations indicated the alternative technologies that can be applied in India, aiming to recover energy from MSW as best as possible. The HANP method provided a ranking of 24% for anaerobic digestion, and it was indicated as the preferred technology for energy recovery from MSW in this country. Followed by the gasification with a ranking of 23%, and landfill with a ranking of 12%. Pandey et al. (2016) also developed an ANN for modeling the gasification of MSW in a fluidized bed reactor based on the Levenberg-Marquardt backpropagation algorithm, and gas yield is one of the outputs predicted in their research. Their results revealed that ANN is a robust technique to predict gas yield generated by energy recovery from MSW based on two different variants of neural networks (e.g., single layer and double layers). The performance metrics, i.e., R^2 and MSE, indicated that the double layers variant of the ANN model (e.g., 6/logsig/5/logsig/Gas yield) provided the best performance with an R^2 of 0.990 and MSE of 0.00093. Adamović et al. (2018) also developed a GRNN model (general regression neural network) to estimate the efficiency of energy recovery from MSW based on a dataset collected from 16 countries (from 2006 to 2015). They claimed that the GRNN model could predict energy recovery efficiency from MSW with outstanding performance (i.e., MAPE = 7.757 and $R^2 = 0.995$). In a recently published paper, Wang et al. (2021) also applied an ANN model for estimating energy recovery from MSW. To this end, they collected 151 datasets from various countries and developed an ANN model that can represent and predict a globally distributed database. Finally, they found that the developed ANN model was acceptable for the prediction of heating value from MSW with a MAPE of 15.92%. Kardani et al. (2021) also developed an ensemble soft computing model for similar purposes based on various machine learning algorithms, such as decision tree, xgboost (XGB), random forest, ANN, and support vector machine. They were then optimized by an optimization algorithm, i.e., particle swarm optimization (PSO), to estimate the MSW gasification. Eventually, their ensemble model was developed with an R^2 was up to 0.99 for predicting gas yield from MSW.

Literature review shows that although some of the advanced technologies have been applied to predict the energy contents of MSW. However, they are very rare, and most of them are the ANN models. Furthermore, the gas yield is one of the important productions of MSW gasification (He et al., 2010; Jun et al., 2017; Luo et al., 2012); however, it was only predicted by Pandey et al. (2016) and Kardani et al. (2021) based on ANN and PSO-XGB models, and some drawbacks of them were not addressed. Therefore, this paper aims to develop and propose a novel approach based on artificial intelligence techniques to predict the gas yield of MSW, namely MFO (moth-flame optimization) -DNN (deep neural network). Also, some drawbacks of the previous studies were also addressed and the MFO-DNN model was developed based on those fixed problems.

2. Methodology

2.1. Deep neural network (DNN)

ANN is one of the famous tools in terms of artificial intelligence (AI), which was inspired by the biological structure of the human brain, and it

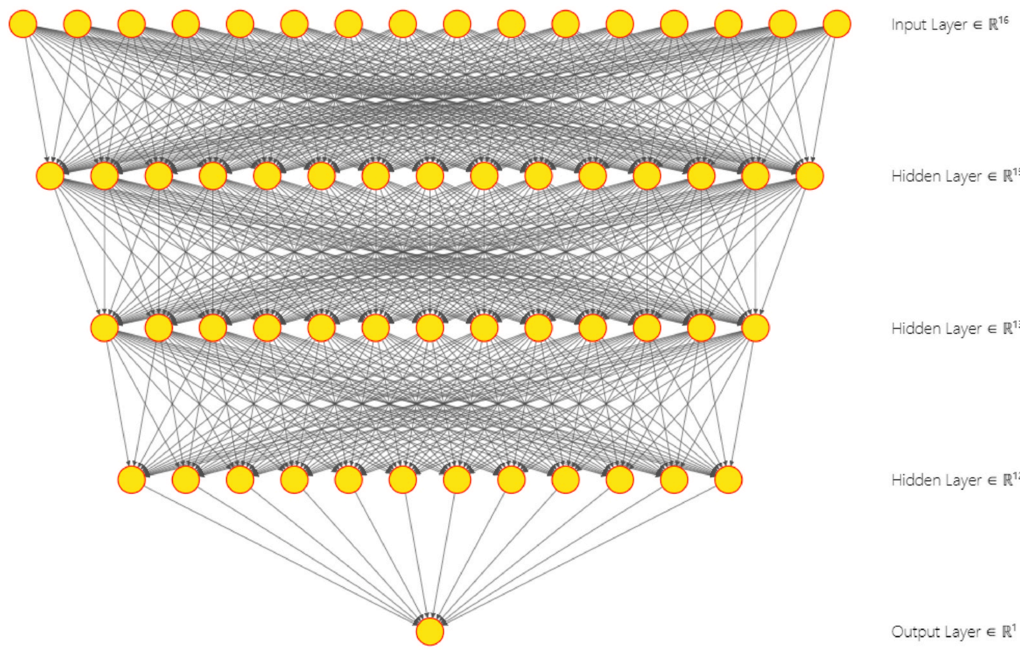


Fig. 1. General structure of a DNN model.

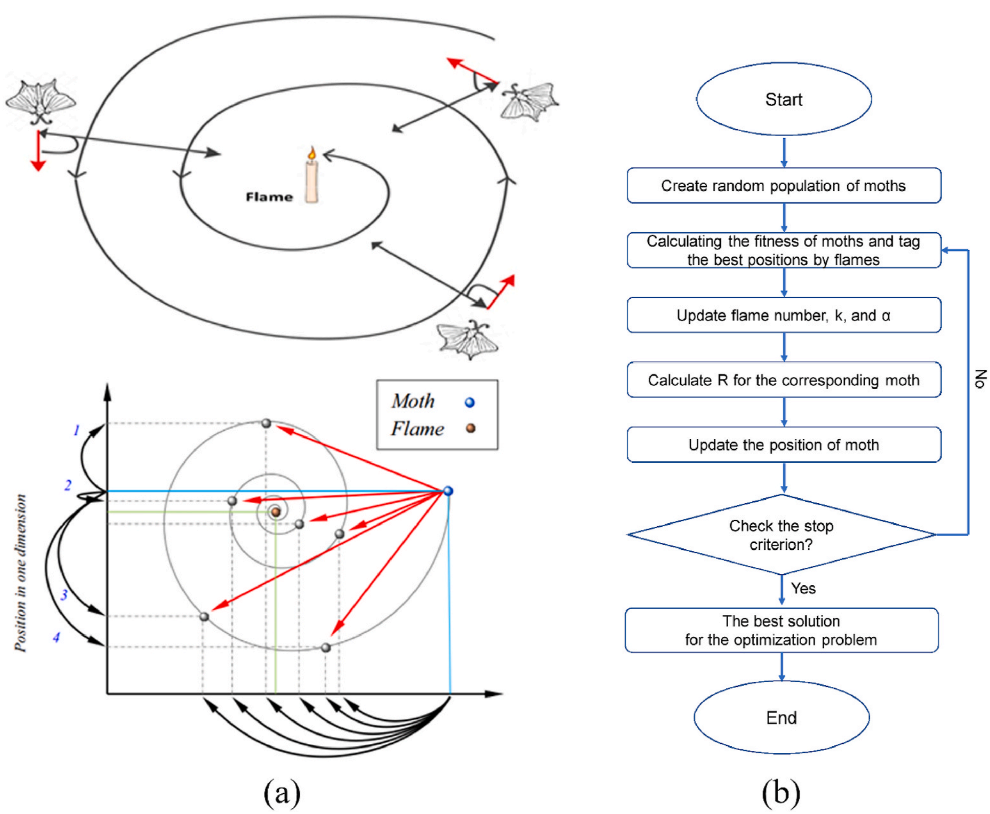


Fig. 2. Mechanism and framework of the MFO algorithm (Ghobaei-Arani et al., 2020; Mehne and Mirjalili, 2020) (a) Mechanism of the moths; (b) Framework of the MFO algorithm.

has been successfully applied to various problems (Çolak, 2021; Özdoğan, 2021; Praveen et al., 2021; Sang et al., 2021). Theoretically, an ANN consists of three types of layers: input, hidden, and output (Xu et al., 2021). In its topology, each layer is connected through neurons/nodes and exposed by their weights. In which, the input layer contains the input neurons that are observations or information measured/recorded. Subsequently, they are transferred to the hidden layer(s) using transfer functions or active functions. Herein, neurons in the hidden layer(s) process the input data and calculate them under the training algorithms (e.g., feedforward, backpropagation, Levenberg-Marquardt backpropagation, to name a few) (Wali and Tyagi, 2020). Finally, their results are transferred to the output layer, where the

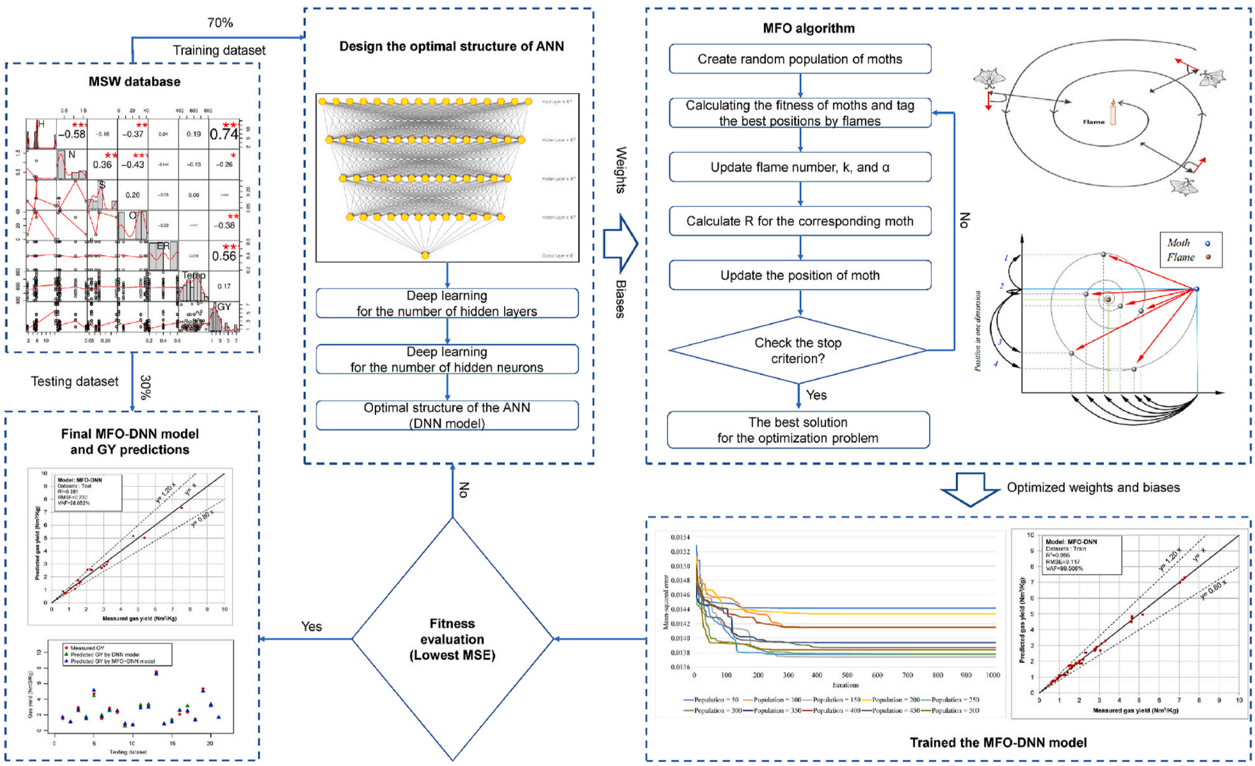


Fig. 3. Proposed framework of the MFO-DNN model for predicting GY.

output neuron will process and present the outcomes.

In real-life problems, many complex problems require an ANN with a complex structure, as well as various variants of ANN. Indeed, an ANN model with multiple hidden layers is called a DNN since it has to train and process through multiple layers (Liu et al., 2017). Furthermore, a DNN is often trained by deep learning tasks (Kumarasinghe et al., 2020). In general, the structure of DNN and ANN is similar, and their training algorithm is not different. However, it can find better mathematical manipulation to explain the relationship between inputs and output even though they have non-linear relationships (Zhang et al., 2020), and the structure of DNN is a more obvious hierarchy (Feng et al., 2019). Therefore, DNN tends to provide better performance and accuracy than conventional ANN models. A structure of DNN is illustrated in Fig. 1.

Nowadays, DNN is often used for many complexed problems that require high accuracy and reliability. It can model non-linear and convoluted relationships; then, generating models in which the object is conducted oneself toward as a layered formation of primitives (Dargan et al., 2019). For a regression problem, DNN have to face to the vanishing gradients, such as poor local minimums and depth of the network (Du et al., 2019; Goodfellow et al., 2016a; LeCun et al., 2015). It is challenging to know/define the network's moving direction to optimize the loss function. Nevertheless, the rectified linear unit (ReLU) active function was proposed to overcome this problem, and it can learn faster with many hidden layers (Glorot et al., 2011; Truong et al., 2020).

It is the fact that DNN has been successfully applied in many fields, such as prediction ore production (Baek and Choi, 2019), cardiology and arrhythmia issues (Hannun et al., 2019), environment perception of intelligent vehicles (Yan et al., 2017), marine environment monitoring (Reddy et al., 2020), energy (Du and Li, 2019; Eshratifar and Pedram, 2018; Li et al., 2019), to name a few. However, it has not been applied to predict the energy content of MSW, especially the gas yield. Therefore, it was investigated and developed to predict the gas yield of MSW in this study. Furthermore, it was taken into account to be optimized by an optimization algorithm to boost the DNN model's accuracy for predicting the gas yield of MSW in this study.

2.2. Moth-flame optimization (MFO)

MFO is a nature-inspired heuristic algorithm that was proposed by Mirjalili (2015). Based on the moths' navigational behavior at night, they always seek to maintain a fixed angle to the moon and create a spiral scrolling path (Frank et al., 2006). Accordingly, moths can fly in one, more, or hyperdimensional based on the exchanging the position vectors (Fig. 2a). In those dimensional, the spatial position of a moth is considered as a variable, and a set of all spatial positions is a potential solution of MFO. Fig. 2b illustrates the framework of the MFO algorithm.

For performing the algorithm, a population is necessary, and it can be set up by the following matrix:

$$M = \begin{bmatrix} m_{1,1} m_{1,2} \ldots\ldots m_{1,d} \\ m_{2,1} m_{2,2} \ldots\ldots m_{2,d} \\ \vdots \vdots \vdots \vdots \vdots \\ m_{n,1} m_{n,2} \ldots\ldots m_{n,d} \end{bmatrix} \tag{1}$$

where n denotes the number of moths, and the dimensions (variables) are represented by d.

To sort the fitness of moths based on the objective function, an array is assumed, as follow:

$$FitnessM_{obj\_func} = \begin{bmatrix} FitnessM_1 \\ FitnessM_2 \\ \vdots \\ FitnessM_n \end{bmatrix} \tag{2}$$

Since the moths fly around the flames, therefore, a matrix of flames is necessary like to the matrix of the moths, and it is one of the main components of the MFO algorithm:

$$F = \begin{bmatrix} F_{1,1} F_{1,2} \ldots\ldots F_{1,d} \\ F_{2,1} F_{2,2} \ldots\ldots F_{2,d} \\ \vdots \vdots \vdots \vdots \vdots \\ F_{n,1} F_{n,2} \ldots\ldots F_{n,d} \end{bmatrix} \tag{3}$$

And similar to the fitness of the moths, an array to sort the fitness of

Table 1
Characteristics of the MSW database used.

Elements	C	H	N	S	O	MC	Ash	ER	Temp	GY
Min.	11.15	1.47	0.16	0.04	0	0	0.15	0.2	400	0.58
1st Qua.	42.27	4.62	0.18	0.07	6.9	0.02	0.6	0.2	503.5	1.385
Median	43.73	5.3	0.27	0.11	38.43	6.96	2.0	0.4	602	1.98
Mean	44.45	5.946	0.6036	0.1301	26.97	17.66	4.36	0.403	582.7	2.415
3rd Qu.	46.8	5.63	1.1	0.14	40.95	8.42	6.72	0.6	653	2.88
Max.	85.83	14.38	1.65	0.3	40.96	78.12	17.1	0.6	798	7.51

Table 2
Correlation matrix of the dataset collected for GY prediction.

	C	H	N	S	O	MC	Ash	ER	Temp	GY
C	1	0.969	−0.723	−0.148	−0.136	−0.770	−0.054	0.038	0.190	0.701
H	0.969	1	−0.575	−0.159	−0.370	−0.604	−0.111	0.040	0.186	0.744
N	−0.723	−0.575	1	0.363	−0.430	0.806	0.208	−0.041	−0.132	−0.259
S	−0.148	−0.159	0.363	1	0.197	−0.174	0.885	−0.050	0.060	−0.009
O	−0.136	−0.370	−0.430	0.197	1	−0.494	0.320	−0.020	−0.008	−0.383
MC	−0.770	−0.604	0.806	−0.174	−0.494	1	−0.343	−0.008	−0.163	−0.396
Ash	−0.054	−0.111	0.208	0.885	0.320	−0.343	1	−0.065	0.014	0.017
ER	0.038	0.040	−0.041	−0.050	−0.020	−0.008	−0.065	1	0.019	0.562
Temp	0.190	0.186	−0.132	0.060	−0.008	−0.163	0.014	0.019	1	0.169
GY	0.701	0.744	−0.259	−0.009	−0.383	−0.396	0.017	0.562	0.169	1

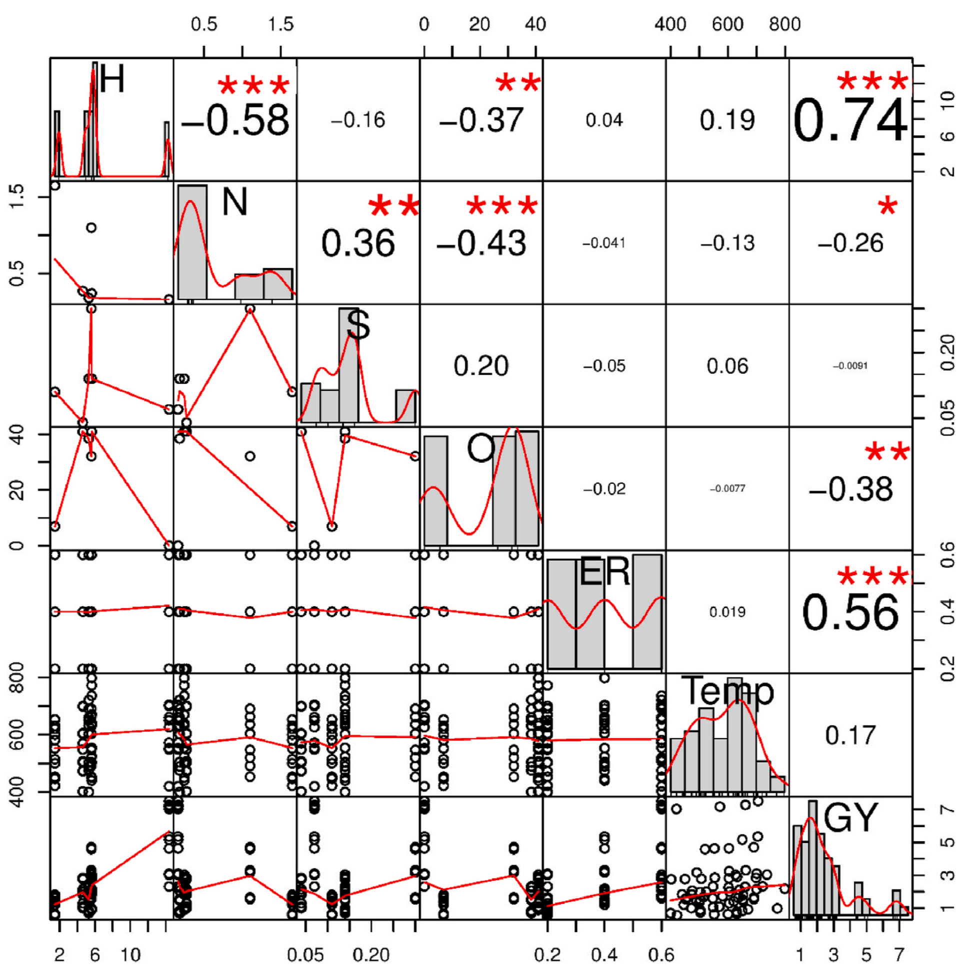


Fig. 4. Visualization of the dataset used and its distribution, correlation, and density.

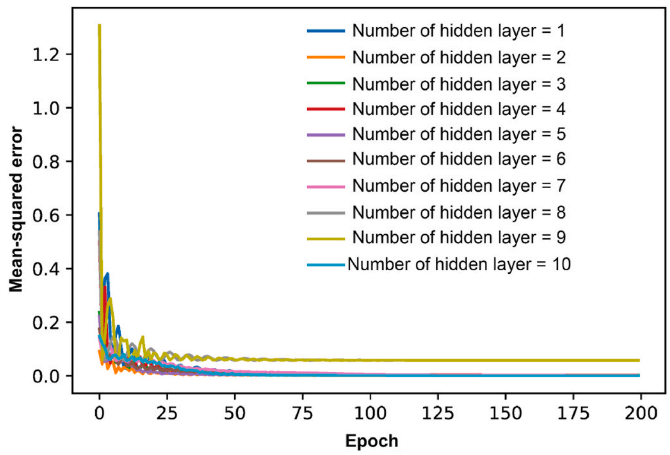
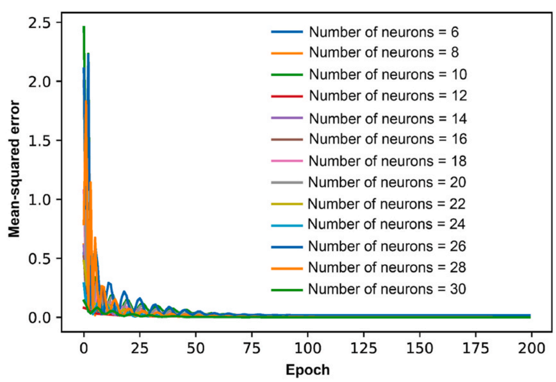
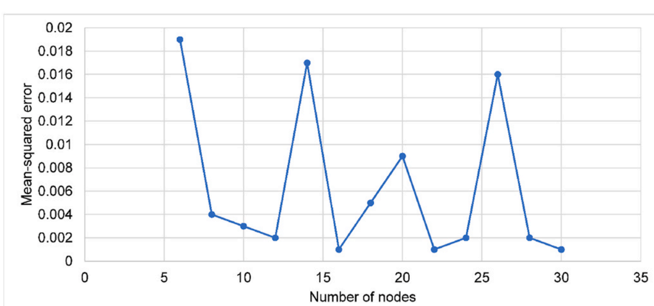


Fig. 5. Determination of the number of hidden layers using deep learning.



(a)



(b)

Fig. 6. Determination of the number of neurons using deep learning
(a) Training process to determine the number of neurons using deep learning;
(b) Zoom-out of the DNN performance with different number of neurons.

flames based on the objective function is also assumed, as follows:

$$FitnessF_{obj\_func} = \begin{bmatrix} FitnessF_1 \\ FitnessF_2 \\ \vdots \\ FitnessF_n \end{bmatrix} \tag{4}$$

It is worth mentioning that both flames and moths are the solutions, and the main difference is the update and treatment at each iteration. For each iteration, moths fly around the search space with many spatial positions, whereas flames are the best spatial position of moths during searching, and moths mark them to avoid losing their best solution. During searching, moths continuously exchange their experiences and update the better positions.

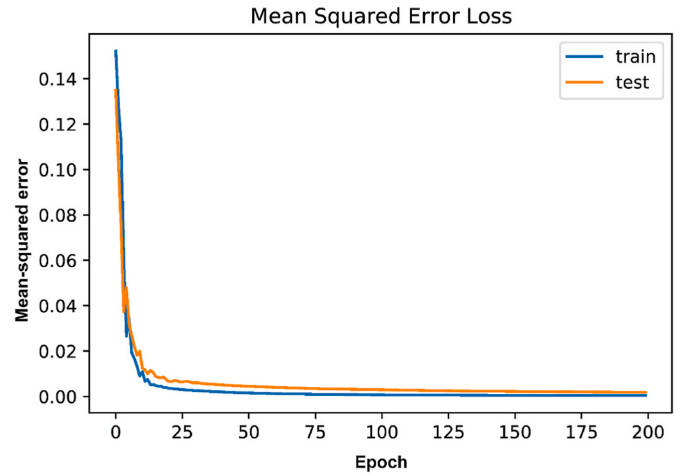
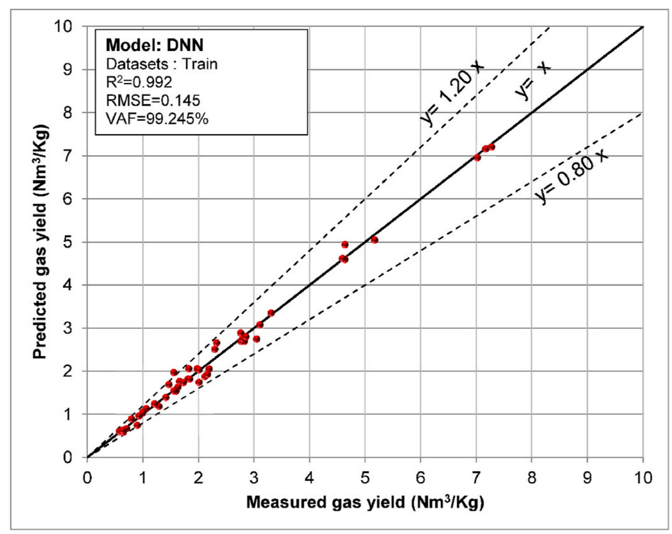
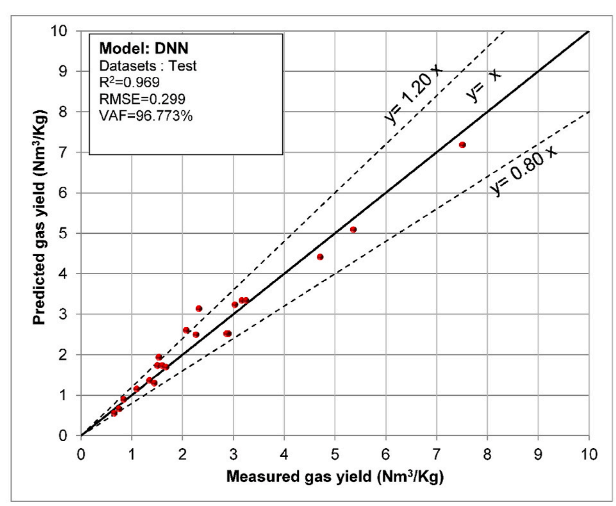


Fig. 7. Performance curves of the DNN model for predicting GY.



(a)



(b)

Fig. 8. Results of the DNN model and the correlation between measured vs. predicted GY values.

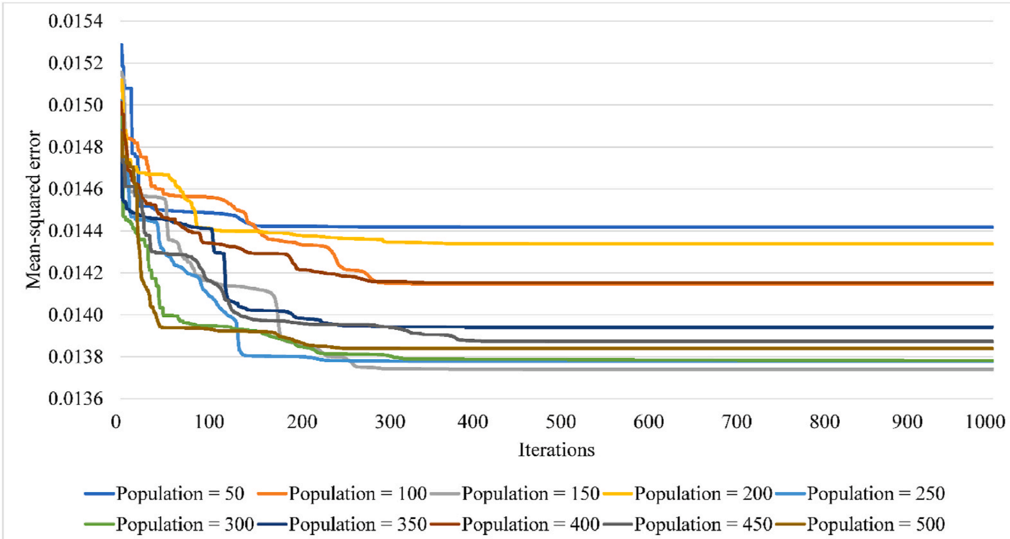


Fig. 9. MFO optimizer for optimization of the DNN model through weights and biases (MFO-DNN).

As presented by Mirjalili (2015), MFO contains three optimization problems (steps) based on global optimization, including (i) random population of moths and their fitness, (ii) the search space, and the way moths move around the search space (exchanging experiences and update the positions), (iii) checking the stop criterion whether it is satisfied or not.

In step 2, moths update their position using the following equation:

$$M_i = P(M_i, F_j) = R_j \exp^{\alpha k}.\cos(2\pi k) + F_j \tag{5}$$

where P denotes the spiral function of moths; M_i and F_j are the ith moth and jth flame; R_j is the distance between ith moth and jth flame ($R_j > 0$); α stands the coefficient of the spiral function; and k is a random number in the range of -1 to 1.

Further details of the MFO algorithm can be read and referred to the literature (Abd El Aziz et al., 2017; Allam et al., 2016; Bahrami et al., 2018; Mirjalili, 2015; Wang et al., 2017; Yamany et al., 2015)

2.3. Hybridization of DNN and MFO for predicting gas yield

As stated earlier, this study's primary purpose is to develop and propose a novel AI model for predicting GY based on the MFO algorithm and DNN model. The idea of this study is based on the disadvantage of DNN and the advantage of the MFO algorithm. Whereas the DNN can overcome the local minimum and improve the accuracy of an ANN model since it can find a better way to train the network, the selection and calculation of the optimal weights and biases still are challenging of DNN (Uddin et al., 2017). In contrast, the MFO algorithm can perform a global optimization for optimization problems (Mehne and Mirjalili, 2020; Mirjalili, 2015). Therefore, the MFO algorithm was used to optimize weights of the DNN model, called MFO-DNN model. The framework of the MFO-DNN model for predicting GY is proposed in Fig. 3.

Accordingly, the database is divided into two sections, one for training with 70% of the whole dataset, one for testing with the remaining 30% of the dataset. At the first step, an initial ANN model is necessary for the optimization step. However, it is hard to design an optimal structure of the ANN model. Therefore, deep learning techniques were applied to find the optimal number of hidden layers and hidden neurons, such as configure capacity with layers and neurons (evaluate deeper and wider network topologies), configure gradient precision with batch size, optimization of loss functions, and configure speed of learning with learning rate (Goodfellow et al., 2016b; Shamshirband et al., 2019; Shickel et al., 2017; Wang et al., 2019). Finally, a DNN (deep neural network) is developed.

Although a DNN model is developed with the optimal structure; however, the weights still are random, and different performances can be generated with many runs. In other words, the weights of the DNN model need to be optimized to have an optimal DNN model with the accuracy improved. To this end, the MFO algorithm is applied. Mean-squared error (MSE) is used as the objective function for the optimization process with the lowest MSE, and the best MFO-DNN model is selected. Ultimately, the testing dataset is applied to evaluate the optimized MFO-DNN model's accuracy for predicting GY.

3. Municipal solid waste gasification database

In this study, an MSW database from different sources, such as wood, paper, kitchen garbage, PE plastic, textile, to name a few, were collected with 67 observations, and it is available in (Choy et al., 2004; Pandey et al., 2016). Based on that, carbon (C), hydrogen (H), nitro (N), sulfur (S), oxygen (O), moisture content (MC), ash, equivalence ratio (ER), and temperature (Temp) were taken into account to estimate the gas yield (GY) during gasification in a fluidized bed reactor. The mechanism of the fluidized bed reactor was described by Choy et al. (2004). Of those, the content of C is in the range of 11.15%–85.83%; $1.47 < H < 14.38$; $0.16 < N < 1.65$; $0.04 < S < 0.3$; $0 < O < 40.96$; $0 < MC < 78.12$; $0.15 <$ Ash <17.1; $0.2 < ER < 0.6$, and the Temp increase from 400 to 798 °C (^{o}C). The details of the collected MSW database were summarized in Table 1.

Before developing the models, in order to get most of the dataset, it must be well-prepared, including data cleaning, feature selection, and data transforms (Liu and Motoda, 2012; Zhang et al., 2003)(Hoang, 2020; Jian et al., 2021; Tinh et al., 2020). Therefore, a correlation matrix of the collected dataset was computed to discover the relationship between variables, as shown in Table 2.

Accordingly, the input variables with high correlation should be eliminated to ensure the generalization of the predictors and model. In other words, the inputs that have similar characteristics and roles should be considered carefully. In Table 2, it is clear that C and H are the variables with the highest correlation (i.e., 0.969–1). Therefore, one of them must be removed from the collected dataset. Considering the correlation between C, H and the output variable, i.e., GY, it can be seen that the correlation between H and GY is higher than those of C and GY. Thus, C variable should be removed in this study. By the similar technique, MC and Ash variables were also removed from the collected dataset since their correlation is very high (>0.8). This problem is a drawback of the previous study (Pandey et al., 2016) as well, where they have not yet fully evaluated the correlation of the variables. Therefore, this study considered the drawbacks of the previous study and used only six input variables instead of nine input variables. Finally, H, N, S, O, ER, and Temp are the remaining variables used to predict GY in this study. The distribution, density, and correlation of the variables are illustrated in Fig. 4.

4. Results and discussion

Once the dataset was well-prepared, it was divided into two sections, as mentioned in section 2.3. Aiming to prevent over-fitting, the MinMax scaling method with the range of [-1, 1] and 5-fold cross-validation (CV) technique were applied during the development of the models (Dung and Chi, 2020; Jian et al., 2021; Yingui et al., 2021). The python environment (version 3.7.9) was used to program and develop the mentioned models in this work.

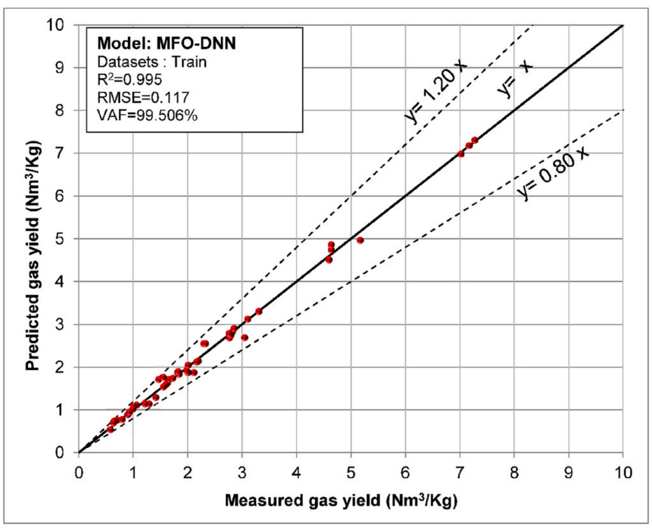
As shown in Fig. 3, an initial ANN model is necessary for predicting GY before optimizing and improving its performance. However, it is hard to design an optimal structure of an ANN model. Therefore, deep learning techniques were applied to find an optimal topology network (e.g., hidden layers, neurons) with the performance improved, as shown in Figs. 5 and 6. It is worth noting that in order to define the optimal number of hidden layers, the trial-and-error technique with a fixed number of neurons (i.e., 10 neurons). The results showed that the optimal network topology is of two hidden layers. Once the optimal number of hidden layers was defined, the number of neurons in the hidden layers were defined based on the errors of the network topology (i.e., MSE). The number of neurons with the lowest MSE were selected for the second hidden layer, followed by the number of neurons with a slightly higher MSE for the first hidden layer. Eventually, an optimal structure of DNN was defined with 2 hidden layers, and 22 neurons in the first hidden layer, 16 neurons in the second hidden layer, respectively.

Once the DNN structure was defined to predict GY, it was built, and its performance was computed based on both training and testing process, as shown in Fig. 7. Herein, the DNN performance is very well in predicting GY, and the train line and test line are very close. Finally, the predictions of GY by the DNN model were reported and shown in Fig. 8.

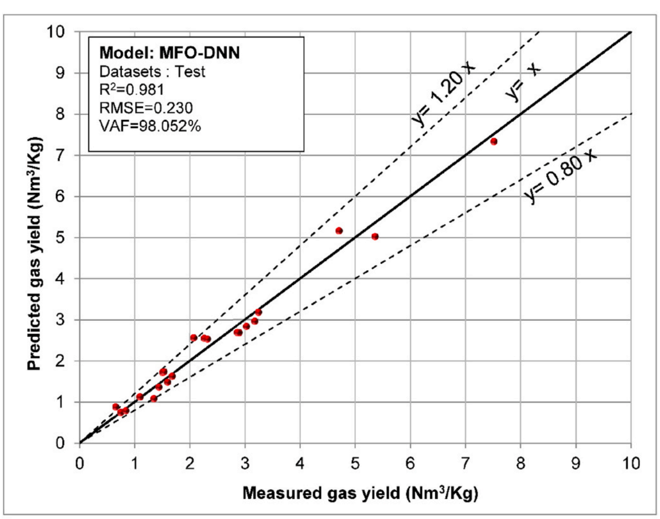
Although the performance of the DNN model for predicting GY is good, as mentioned above. However, the weights of the DNN model have not been yet optimized. Therefore, we tried our best to optimize the weights of the developed DNN model and discover whether the performance of the DNN model can be further improved or not. And the MFO algorithm was used for this aim.

To optimize the DNN model by the MFO algorithm, the parameters of the MFO must be set up first. For instance, the number of moths and flames are necessary for the global search and they have a great impact on the accuracy of the model. Therefore, they were selected as 50, 100, 150, 200, 250, 300, 350, 400, 450, 500, respectively, to check the different random population's performance. Also, the number of features and dimensions was selected as 6, the number of iterations was set as equal to 1000, and the other coefficients were selected in the range of −1 to 1. MSE was selected to evaluate the optimization process. The MFO-DNN training performance is shown in Fig. 9. Once the weights of the DNN were optimized by the MFO algorithm, the predictions of the optimized DNN model (i.e., MFO-DNN) was re-computed, and they are shown in Fig. 10. For further assessment of the DNN and MFO-DNN models, RMSE, MAPE, R^2, VAF, and RSE, were used and computed, as listed in Table 3.

The performance metrics in Table 3 show that both DNN and MFO-DNN performed very well in predicting GY. Remarkably, the MFO-DNN performance is more superior than the DNN model on all the performance indices. In other words, the MFO algorithm improved the DNN performance based on the optimization of the weights. Considering the testing dataset and the correlation between measured and predicted GYs (Fig. 8b), it is clear that although the DNN model performed very well; however, there are some data points that outside of the 80% confidence level of the model. Those data points were performed better by the MFO-DNN model, and they are inside the 80% confidence level of the model (Fig. 10b). These results interpreted that the MFO algorithm contributed a significant role in reducing the DNN model's violation. The proposed MFO-DNN model accuracy compared with the DNN model and measured GYs is further demonstrated in Fig. 11.



(a)



(b)

Fig. 10. Results of the MFO-DNN model and the correlation between measured vs predicted GY values from the MFO-DNN model
(a) Training dataset; (b) Testing dataset.

5. Sensitivity analysis

The obtained results demonstrated the accuracy and agreement of the proposed MFO-DNN model in predicting GY generated by energy recovery from MSW. This model is helpful for improving the performance of the gasification process by adjusting the input parameters (i.e., C, H, N, S, O, MC, ER, and Temp). Nevertheless, the problem now is which parameters should be adjusted? The answer for this question was interpreted by a sensitivity analysis to calculate the importance of the input variables (Fig. 12). To this end, the Olden method (Olden et al.,

Table 3
The accuracy and errors of the DNN and MFO-DNN models for predicting GY.

Model	Training dataset					Testing dataset				
	R^2	RMSE	MAPE	VAF	RSE	R^2	RMSE	MAPE	VAF	RSE
DNN	0.992	0.145	0.056	99.245	0.003	0.969	0.299	0.101	96.773	0.001
MFO-DNN	0.995	0.117	0.045	99.506	0.001	0.981	0.230	0.090	98.052	0.0004

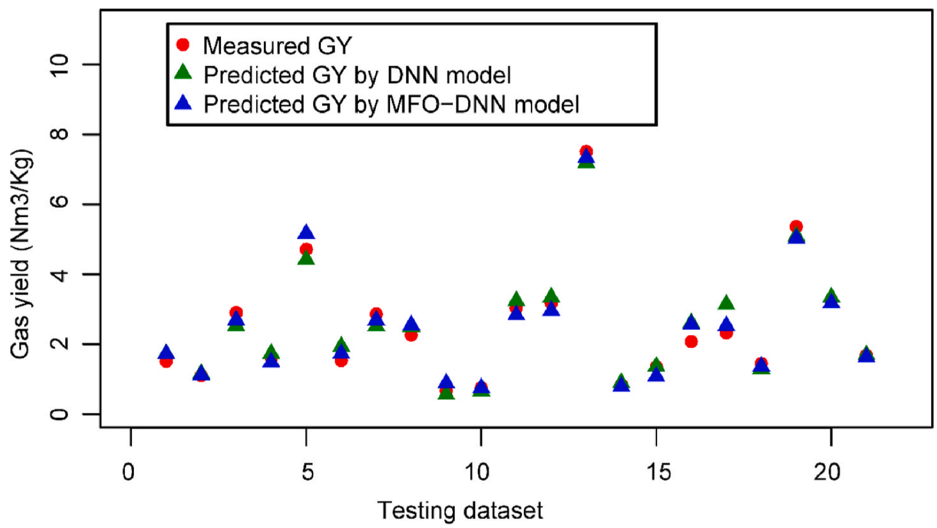


Fig. 11. Measured vs predicted GY by DNN and MFO-DNN models (testing).

2004) was applied for such a DNN model. Based on the importance scores of the inputs in Fig. 12, Temp and H are the highest importance. Followed by the variables O, S, and N. The ER variable seems to be of very low importance for the gasification process. Based on these analyses, the gasification performance can be improved by adjusting the input variables with high importance scores.

6. Conclusion

MSW is a big concern of countries and urban areas. It severely affects the environment and people if not handled properly. The recycling and recovery of energy from MSW is considered an effective solution for cleaner production, minimizing negative impacts on the surrounding environment, and contributing more renewable energy to the countries. However, the recycling and recovery of energy from MSW should be accurately predicted to minimize excess harmful gases, such as C, H, O, N, S, and increase energy efficiency. Therefore, this study developed and proposed a novel hybrid AI model (i.e., MFO-DNN) for predicting GY generated by energy recovery from MSW with high accuracy. This model allows MSW processing plants to accurately predict the amount of gas yield collected from MSW sources to have a plan for rational adjustment and distribution of energy. Also, the proposed MFO-DNN model can be

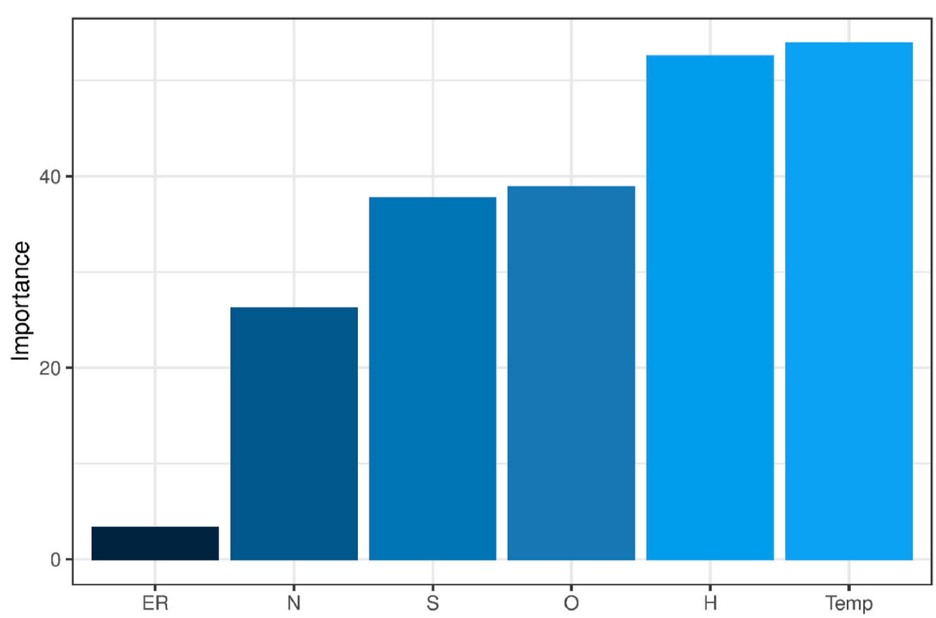


Fig. 12. Importance of the input variables in the proposed MFO-DNN model using the Olden sensitivity analysis method.

considered to adjust the components aiming to create the most optimal GYs, avoiding the generation of excess harmful gases into the surrounding environment.

Although the findings of this study are meaningful and the contributions and insights into the gasification process are valuable for the scientific community. Nevertheless, its limitations still need further researcher in the future, including:

A larger database with different MSW types and furnaces is better to explain and develop a predictive model for gasification processes.

- The performance of the proposed MFO-DNN model for other waste treatment technologies (e.g., biological gasification) needs to be investigated and discussed.
- This study just solved the first phase of the problem, i.e., predicting GY generated by energy recovery from MSW. The second phase of this problem should be further researched in the future, aiming to optimize the input variables to achieve the highest performance in the gasification process.

CRediT authorship contribution statement

Libing Yang: Conceptualization, Methodology, Software, Validation, Formal analysis, Writing – original draft, Writing – review & editing. **Hoang Nguyen:** Conceptualization, Methodology, Software, Validation, Formal analysis, Writing – original draft, Writing – review & editing. **Xuan-Nam Bui:** Conceptualization, Methodology, Software, Validation, Formal analysis, Writing – original draft, Writing – review & editing. **Trung Nguyen-Thoi:** Validation, Formal analysis, Writing – original draft, Writing – review & editing, Visualization.

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.

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