Engineering with Computers
https://doi.org/10.1007/s00366-019-00882-2

ORIGINAL ARTICLE

Nonlinear evolutionary swarm intelligence of grasshopper optimization algorithm and gray wolf optimization for weight adjustment of neural network

Hossein Moayedi[1,2] · **Hoang Nguyen**[3,4] · **Loke Kok Foong**[5]

Received: 22 July 2019 / Accepted: 26 October 2019

Abstract
The advent of new data-mining techniques and, more recently, swarm-based optimization algorithms have antiquated traditional models in the field of energy performance analysis. This paper investigates the potential of two state-of-the-art hybrid methods, namely grasshopper optimization algorithm (GOA) and gray wolf optimization (GWO) in improving the neural assessment of heating load (HL) of residential buildings. To achieve this goal, eight HL influential factors including glazing area distribution, relative compactness, overall height, surface area, roof area, wall area, orientation, and glazing area are considered for preparing the required dataset. A population-based sensitivity analysis is then carried out to use the best-fitted structures of each ensemble. The results showed that utilizing both GOA and GWO algorithms results in increasing the accuracy of the neural network. From comparison viewpoint, it was found that the GWO (error = 2.2899 and correlation = 0.9551) surpasses GOA (error = 2.4459 and correlation = 0.9486) in adjusting the computational parameters of the proposed neural system.

Keywords Energy-efficient building · Heating load · Neural network · Grasshopper optimization

1 Introduction

Heating load (HL) can be affected by different parameters such as the time, season, the supply temperature, climate, wind speed, light rate, water flow, and return water. For HL of the heating system according to a physical model, it is hard to construct a mathematical model. The control influence can act just after a constant time [1]. For obtaining timely as well as precise HL estimation and enhance the of central heating quality, we need to estimate the HL properly and regulate the boiler system factors [2]. In the literature, different approaches have been suggested as mathematical-based estimation, such as the method of gray theory estimation [2], traditional estimation, prediction method of regression analysis [3–7], wavelet algorithm [8], fuzzy theory [9], time series [10], and so on. These methods have various defects in feasible usages as: (a) the factors of the model are hard to indicate since the estimation approach is nonlinear and (b) forecast parameters cached from the related evaluation are commonly fuzzy as well as uncertain. Therefore, it is difficult to obtain desirable outcomes with high precision in predicting HL.

In this regard, there are different traditional approaches to predict HL. However, due to data limitations in the case of older buildings, scholars have suggested modeling approaches [11]. In the case of building heat load, building information modeling (BEM) systems-recorded data have been suggested for estimating heat loads. Such information

✉ Hossein Moayedi
hossein.moayedi@tdtu.edu.vn

✉ Loke Kok Foong
lokekokfoong@duytan.edu.vn

1 Department for Management of Science and Technology Development, Ton Duc Thang University, Ho Chi Minh City, Vietnam

2 Faculty of Civil Engineering, Ton Duc Thang University, Ho Chi Minh City, Vietnam

3 Department of Surface Mining, Hanoi University of Mining and Geology, 18 Vien Street, Duc Thang Ward, Bac Tu Liem District, Hanoi, Vietnam

4 Center for Mining, Electro-Mechanical Research, Hanoi University of Mining and Geology, 18 Vien Street, Duc Thang Ward, Bac Tu Liem District, Hanoi, Vietnam

5 Institute of Research and Development, Duy Tan University, Da Nang 550000, Vietnam

may be provided to the algorithms of data mining. For generating accurate predictions, these algorithms were suggested for an extensive assessment of variables in input and output [12]. In 1970, Justel et al. [13] conducted a sensitivity evaluation for undetermined parameters in inputs for a building and determined that the energy consumption of the building was dramatically sensitive to various elements such as heating, ventilation and air conditioning (HVAC) system performances, and inside temperature.

Up to now, many intelligent predictive models have been widely used to model the heating load and cooling load (CL) of different buildings [14, 15]. In this regard, Castelli et al. [16] employed a model of genetic programming (GP) to analyze building energy efficiency (EEB) systems in terms of energy efficiency and HL. They examined different GP forms in comparison to other different approaches, such as HYBRID that had linear scaling. Their outcomes indicated that, in comparison to the other methods such as GP and HYBRID, the method of HYBRID-LIN obtained promising results. In addition, in Ref. [17] deep learning approaches were investigated in the case of prediction tasks of the energy performance of EEB apparatuses and showed that these approaches have an accurate result. Xie [18] suggested the prediction model of BP neural network-Markov for estimating the Hl. In addition to the accurate estimation of the BP neural network, this algorithm can employ the model of Markov to estimate volatility information. Finally, they have found that the introduced approach has desirable benefits in comparison to other methods of HL prediction.

Moreover, their method has a suitable influence in the HL estimation task In addition, for predicting HL as well as CL in the case of building design, Chou and Bui [19] employed a novel method named ANN–SVR (a combination of support vector regression (SVR) and ANN) by considering 17 buildings as database. Additionally, different approaches were taken into account for comparing the suggested ANN–SVR, such as general linear regression, SVR, Chi squared automatic interaction detector, ANN, as well as classification and regression tree. They concluded that in optimizing systems of EEB, AI methods have good outcomes with an average absolute percentage error (MAPE) under around 4% and root mean-squared error (RMSE) below 39–65.9% compared to the previous studies [20, 21].

Gray wolf optimization (GWO) and grasshopper optimization algorithm (GOA) are two recently developed notions of metaheuristic algorithms which have shown high robustness for various engineering modelings [22–25]. Barman and Choudhury [26] used the GOA algorithm for optimizing the parameters of the SVR model in short-term load estimation during periods with substantial weather changes. This algorithm was also used by Liu et al. [27] along with the linear weighted sum for coordinated operation of multi-integrated energy system. Kahla et al. [28] applied a multi-objective GWO to wind energy conversion system for tracking the maximum power point.

Due to some drawbacks of the typical predictive models (like getting trapped in local minima), the scholars are motivated to improve their efficiency by using other complementary methods [4, 29, 30]. Hybrid metaheuristic algorithms are capable of optimization techniques which have been effectively used for enhancing the accuracy of models such as ANN, SVR, and adaptive neuro-fuzzy inference system (ANFIS). In the field of HL simulation, although well-known optimization methods such as genetic algorithm (GA) and imperialist competition algorithm (ICA) have been sufficiently used [31–34], not employing more state-of-the-art techniques is an appreciable gap of knowledge. Hence, the main purpose of this paper lies in proposing two novel optimization techniques of GWO and GOA for enhancing the neural estimation of the HL in HVAC systems.

2 Methodology

The overall steps taken to achieve the goal of this study are shown in Fig. 1. According to this figure, after providing the required dataset, it is randomly divided into the training and testing samples with the well-known ratio of 80:20, respectively. More clearly, out of whole 768 samples, 614 were used for discerning the relationship between the HL and its influential factors, and the remaining 155 samples were set aside, as stranger conditions, to evaluate the generalization capability of the developed algorithms. Three predictive models, namely typical multilayer perception (MLP), the ensemble of MLP and WOA (WOA–MLP), and the ensemble of MLP and GWO (GWO–MLP) were developed to predict the HL. Finally, the accuracy of the mentioned models was measured by means of three well-known criteria, namely, root mean-square error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2).

The description of the used models is presented in the following.

2.1 Multilayer perceptron neural network

Multilayer perceptron (MLP) [35–40] is known to be one of the most commonly held types of feedforward neural networks for minimizing the error function based on the performance of some synaptic weights. With a learning approach to estimate the target variable, synaptic weight values are adopted in the case of given training information such as input–output data. It is commonly done by taking into account the back-propagation (BP) of the error signal through the layers. An MLP can be introduced as a network, which can progressively map input information on a collection of outputs in a constant manner. This tool consists of

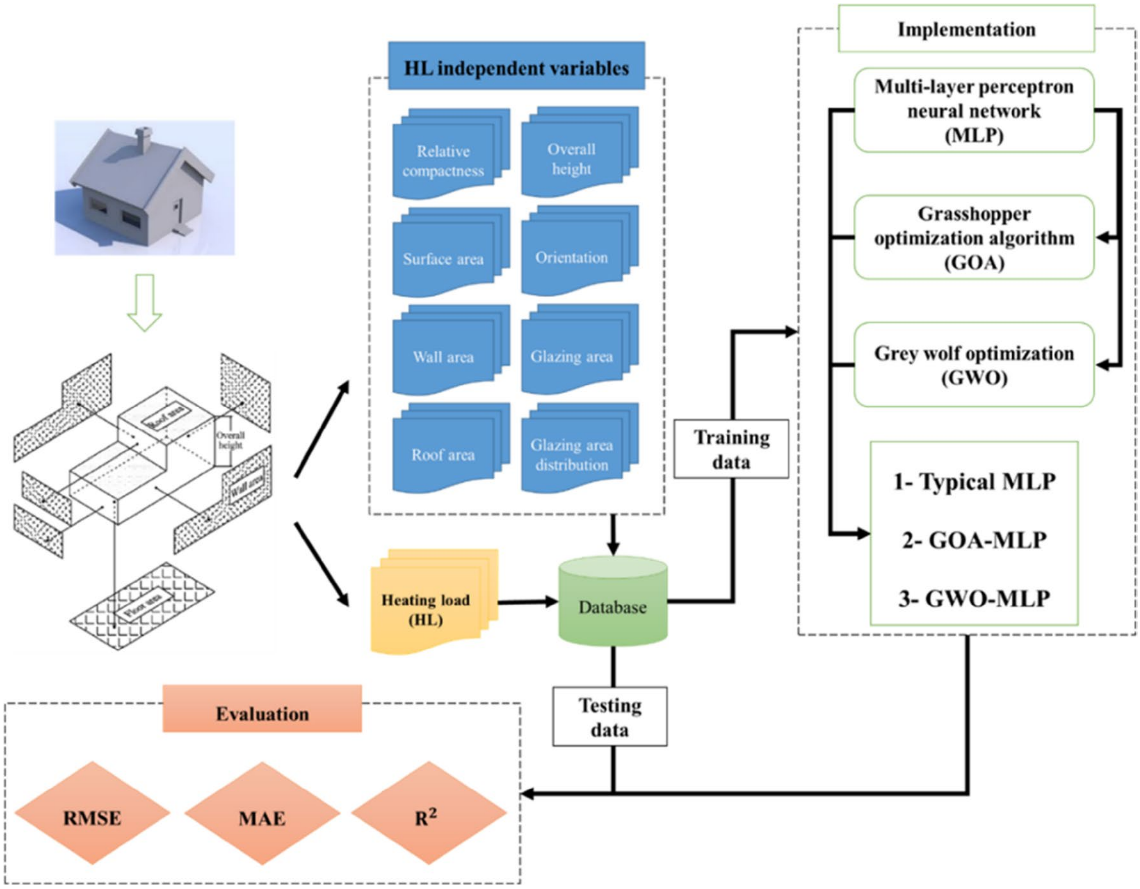


Fig. 1 The graphical methodology of this study

computational nodes within the input and output layers, as well as one or more hidden layer(s). Note that the hidden nodes are completely linked to the preceding and subsequent layers. For analyzing not linearly separable information, the response of each unit should be weighted using nonlinear activation function [41]. Commonly, at layer $k+1$, the output activation of $f^{(k+1)}$ can be calculated using the following relationship:

$$f^{(k+1)} = \partial\left(w^{(k)}a^{(k)} + b^{(k)}\right). \tag{1}$$

In the above relation, ∂ indicates the type of nonlinear activation operation, and $w^{(k)}$, $b^{(k)}$, and $a^{(k)}$ indicate the weight, bias, and the input of layer k.

2.2 Grasshopper optimization algorithm

Grasshoppers are known to be insects which feed on plants and may be seen individually or in a swarm in nature. As is known, these insects are considered as a pest because they damage the pasture and crops severely [42]. Inspired by the herding behavior of grasshoppers, Saremi et al. [43] introduced the grasshopper optimization algorithm (GOA) for solving continuous optimization issues. Like many naturally inspired algorithms, the GOA draws on two major stages, namely exploration and exploitation in seeking a food source. During these stages, it is aimed to remedy the computational drawbacks (e.g., local optima) and/or enhancing the convergence speed [44].

Figure 2 illustrates the behavior of grasshoppers. During the implementation, some search agents locally fly over the search space. This is while these relations are motivated for an abrupt movement in the other phase. Considering X_i as the position of the i th insect, Eq. 3 expresses the swarming action of grasshoppers:

$$X_i = r_1S_i + r_2G_i + r_3A_i, \tag{2}$$

in which S_i denotes the social relationship, G_i symbolizes the gravity force, and A_i is the wind advection. Also, r_1, r_2, and r_3 are random values ranging from 0 to 1. More mathematical details about the algorithm can be found in [45, 46].

2.3 Gray wolf optimization

To perform an efficient optimization, gray wolf algorithm (GWO) was introduced as a novel metaheuristic nature-inspired method [47]. In nature, the gray wolves commonly

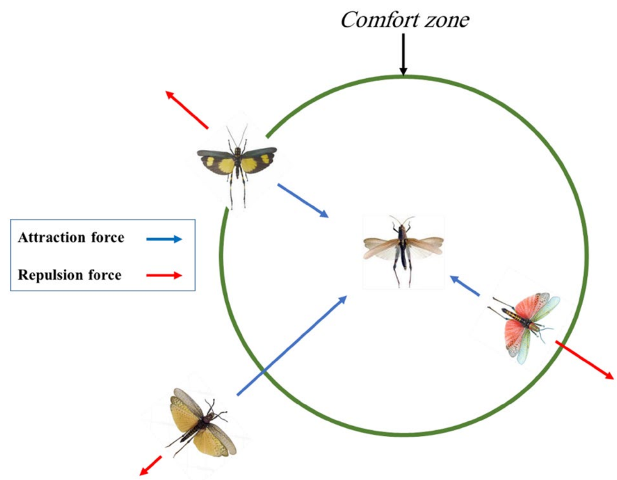


Fig. 2 The primitive corrective patterns in the GOA method

pursue a collective hierarchy strictly. In the leader group of wolves, a couple of female and male exist, called alpha (α). They make the major decision during hunting and other behaviors. Beta (β) wolves are the subsequent level and assist alpha wolves for making decisions. However, they have to obey the alpha wolves. The β wolves may be female and their role is to adjust the flock. To substitute the alpha (while they get older or even die), they are the most appropriate candidates. The subsequent level of the flock is named delta (δ). They hunt and play the role of scouts, sentinels, etc. The last group of individuals is named omega (ω) and are also known to be the weakest level. They play the role of babysitters. Without omega wolves, some fights can be seen in the flock. The gray wolves hunt, and this is their major social conduct. The flowchart of the GWO can be seen in Fig. 3. Muro et al. [48] introduced three stages of GW hunting manner which are (1) recognizing, following, and nearing the prey, (2) circling the prey, and (3) rushing the prey. These two different social conducts have been considered in the algorithm of GWO [49]. In the modeling stage of this algorithm, α is the best solution. In the subsequent steps, β, δ, and ω are proper solutions. The mathematical modeling of encompassing can be shown as:

$$\vec{D} = \left| \vec{C} \cdot \overrightarrow{X_p(t)} - \overrightarrow{X(t)} \right|, \tag{3}$$

$$\vec{X}(t+1) = \overrightarrow{X_p(t)} - \vec{A} \cdot \vec{D}, \tag{4}$$

in which $\vec{A}$ and $\vec{C}$ are coefficient vectors. In addition, $\overrightarrow{X_p}$ shows the prey location and $\overline{X}$ stands for the location of wolves. $\vec{D}$ is a vector that specifies a novel location of GWs. The term t stands for the time of iteration. The GWO is better detailed in [47, 48, 50].

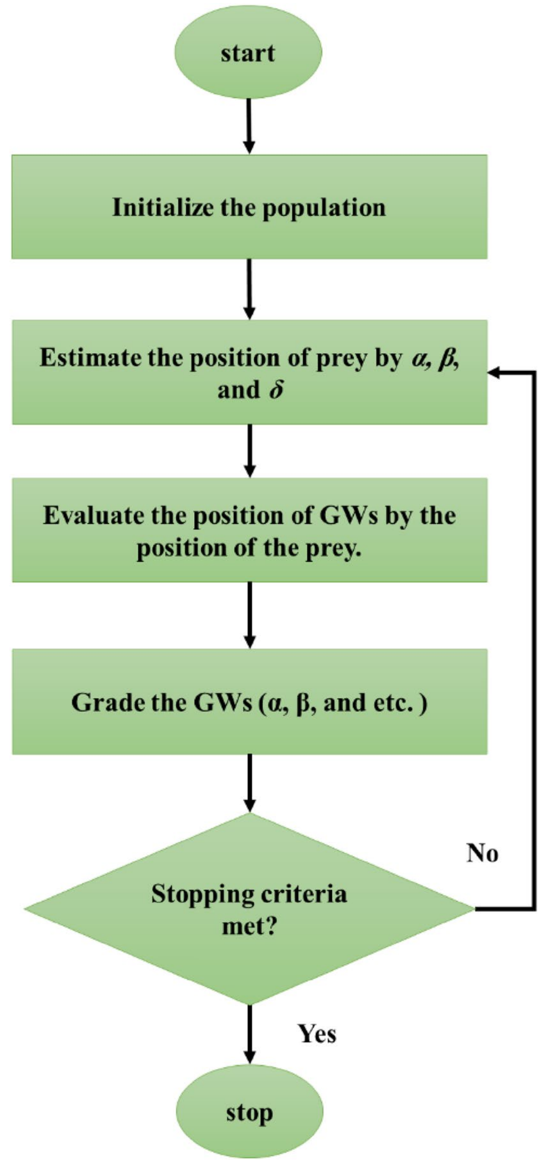


Fig. 3 The flowchart of the GWO algorithm (after [47])

3 Data collection and statistical analysis

Based on a research by Tsanas and Xifara [21], the database used for this research was obtained through analyzing 768 residential buildings (with respect to 12 buildings, 5 distribution scenarios, 4 glazing areas, and 4 orientations) using Ecotect computer software. It consists of 8 HL independent factors, namely relative compactness, surface area, wall area, roof area, overall height, orientation, glazing area, and glazing area distribution, where the HL is considered as the target variable. The database is available on https://cml.ics.uci.edu/. The results of the statistical analysis of the HL and its influential parameters are presented in Table 1.

Table 1 Statistic analysis of the heating load and key factors

Features	Descriptive index									
	Mean	SE	Median	Mode	SD	Sample variance	Skewness	Minimum	Maximum	Count
Relative compactness	0.76	0.00	0.75	0.98	0.11	0.01	0.50	0.62	0.98	768
Surface area	671.71	3.18	673.75	514.50	88.09	7759.16	−0.13	514.50	808.50	768
Wall area	318.50	1.57	318.50	294.00	43.63	1903.27	0.53	245.00	416.50	768
Roof area	176.60	1.63	183.75	220.50	45.17	2039.96	−0.16	110.25	220.50	768
Overall height	5.25	0.06	5.25	7.00	1.75	3.07	0.00	3.50	7.00	768
Orientation	3.50	0.04	3.50	2.00	1.12	1.25	0.00	2.00	5.00	768
Glazing area	0.23	0.00	0.25	0.10	0.13	0.02	−0.06	0.00	0.40	768
Glazing area distribution	2.81	0.06	3.00	1.00	1.55	2.41	−0.09	0.00	5.00	768
Heating load	22.31	0.36	18.95	15.16	10.09	101.81	0.36	6.01	43.10	768

4 Results

The specific objective of the current study is to examine the applicability of two state-of-the-art metaheuristic techniques, namely grasshopper and gray wolf optimization algorithms for simulating the heating load of residential buildings. To achieve this goal, the mentioned algorithms are coupled with a multi-layer perceptron neural network for adjusting its computational parameters. Utilizing the programming language of MATLAB v.2014, the proposed GOA–MLP and GWO–MLP models are developed. Out of 768 data, 80% (i.e., 614 samples) were randomly selected and used to train the proposed predictive models and the remaining 20% (i.e., 154 samples) were devoted to validating their prediction of the buildings with unseen conditions. In this way, two well-known error criteria, namely root mean-square error (RMSE) and mean absolute error (MAE) are used to measure the error of the performance, as well as the coefficient of determination (R^2) for measuring the correlation between the predicted and observed HLs. Eqs. 5–7 define the formulation of the R^2, MAE, and RMSE indices.

$$\mathrm{R}^2 = 1 - \frac{\sum_{i=1}^{N}\left(Y_{i_{\text{predicted}}} - Y_{i_{\text{observed}}}\right)^2}{\sum_{i=1}^{N}\left(Y_{i_{\text{observed}}} - \overline{Y}_{\text{observed}}\right)^2}, \tag{5}$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{I=1}^{N}\left|Y_{i_{\text{observed}}} - Y_{i_{\text{predicted}}}\right|, \tag{6}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left[\left(Y_{i_{\text{observed}}} - Y_{i_{\text{predicted}}}\right)\right]^2}, \tag{7}$$

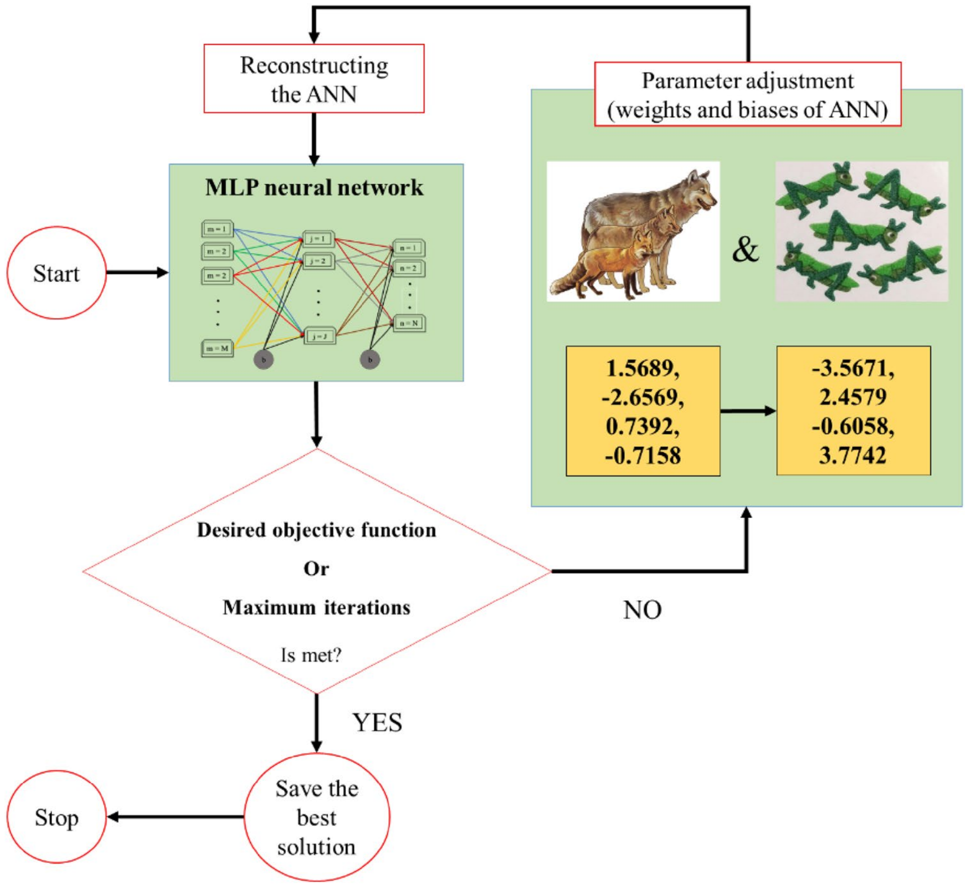
where $Y_{i_{\text{predicted}}}$ and $Y_{i_{\text{observed}}}$ represent the predicted and actual HLs, and the number of instances is shown by N. Also, $\overline{Y}_{\text{observed}}$ denotes the average of the actual HLs.

4.1 Optimizing the MLP using GOA and GWO conventional algorithms

At the first stage, a trial and error procedure was carried out to determine the best structure of the MLP. The tangent sigmoid (i.e., Tansig) was set as the activation function, based on its good performance in many previous attempts [37, 51, 52]. The number of hidden neurons was considered to range from 1 to 15, and it was shown that the MLP which contains nine computational units presents the most consistent results. Therefore, the proposed MLP took the structure $8 \times 9 \times 1$ indicating 8 and 1 nodes in the input and output layer, respectively. In the following, the MLP approximation of the HL was mathematically introduced to the GOA and GWO metaheuristic algorithms as the problem function. The optimization process is depicted in Fig. 4.

To determine the best structure of the GOA–MLP and GWO–MLP ensembles, a population-based sensitivity analysis was carried out. Within 1000 repetitions, both models were tested with 7 different population sizes, including 10, 50, 100, 200, 300, 400, and 500. Note that the RMSE (of the training samples) was considered as the objective function to measure the error of the performance at the end of each try. The convergence curves of the implemented GOA–MLP and GWO–MLP models are shown in Fig. 5a, b, respectively. As illustrated in these figures, all implemented GWO–MLP networks have similar behavior in decreasing the RMSE over 1000 iterations, while the GOA shows higher sensitivity to the population size. In this sense, the convergence curve of the GAO–MLP with population size = 10 remained steady over time. Likewise, the network with population size = 50 decreased the RMSE less considerably than others. Finally, the elite structure of the GOA–MLP (RMSE = 2.371500249)

Fig. 4 The steps for optimizing the ANN parameters using the GWO and GOA



and GWO–MLP (RMSE = 2.295899401) networks was found to have 300 and 400 population sizes, respectively. The parameters of the MLP, GOA, and GWO are summarized in Table 2.

The performance of the proposed GOA–MLP and GWO–MLP is evaluated in terms of complexity and time-effectiveness. In this sense, Fig. 6 illustrates the required computation time for each tested structure of both neural ensembles. Based on this figure, there is a slight difference between the computation time of these models for the first population sizes (i.e., 10, 50, 100). An upward trend was observed for this difference, and peaked for the population size = 500. Remarkably, the best networks of the GOA and GWO algorithms took nearly 4852 and 5549 s, respectively.

4.2 Accuracy assessment of the MLP, GOA–MLP, and GWO–MLP predictive models

The prediction results (i.e., graphical comparison between the predicted and actual values of the HL) are presented in Figs. 7 and 8, respectively, for the training and testing samples. According to these figures, it can be seen that the HL pattern in both training and testing samples is better recognized by the hybrid ensembles in comparison with the unreinforced MLP.

As explained previously, the RMSE and MAE error criteria were used to measure the error of the predictions in this study. Besides, the R^2 index was calculated to evaluate the correlation between the predicted and observed values of HL. The obtained values are presented in Table 3 for both training and testing phases. Accordingly, applying the GOA and GWO optimization techniques has led to enhancing the performance of the MLP in both training and testing phases. More clearly, the training RMSE leveled off by 16.53% (i.e., from 2.8411 to 2.3715) and 19.19% (i.e., from 2.8411 to 2.2959), respectively, by synthesizing the GOA and GWO evolutionary algorithms. As well as the RMSE, the MAE of this phase was reduced by 13.46% (i.e., from 1.9568 to 1.6934) and 15.81% (i.e., from 1.9568 to 1.6475). Moreover, increasing the R^2 from 0.9223 to 0.9432 and 0.9468 indicated a higher correlation of the products of hybrid models and, consequently, improvement of the learning potential of the MLP. For the testing phase, the RMSE experienced a decrease from 2.9859 to 2.4459 (i.e., by 18.08%) and 2.2899 (i.e., by 23.31%), which shows a higher generalization power of the proposed neural ensembles. Likewise, the testing MAE decreased from 2.0830 to 1.7373 (i.e., by 16.60%)

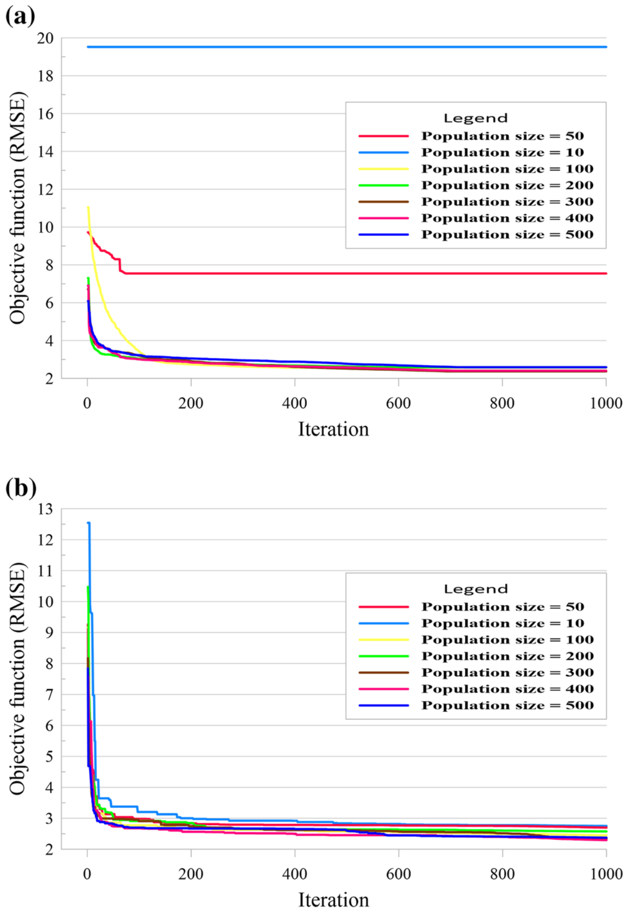


Fig. 5 Executed population-based sensitivity analysis for the **a** GOA–MLP and **b** GWO–MLP

and 1.6514 (i.e., by 20.72%). Furthermore, the R^2 value rose from 0.9328 to 0.9486 and 0.9551.

5 Discussion

As derived, the incorporation of both metaheuristic techniques led to increasing the accuracy of the ANN in both learning and generalization phases. In this part, a score-based ranking system was used to compare the overall performance of the models. In this sense, the higher the accuracy of the results, the larger would be the acquired score. Finally, a total ranking score (TRS) was calculated as the summation of the partial scores to determine the most successful model. The results of the ranking system show that the GWO algorithm outperformed the GOA in optimizing the computational parameters of the MLP. In detail, the GWO–MLP, with TRS = 18, gained the first rank in terms of all three RMSE, MAE, and R^2 measures in both training and testing stages. After that, the GOA–MLP, with TRS = 12, featured as the second accurate model in all positions. Moreover, it was observed that there was no discrepancy between the training and testing results of the models. In other words, a better-trained network presented more accurate prediction. This claim can be also supported by the calculated values of mean absolute percentage error (MAPE). Accordingly, the obtained MAPEs were 9.01%, 7.82%, and 7.66% in the training phase, and 10.04%, 8.16%, and 7.89% in the testing phase of the MLP, GOA–MLP, and GWO–MLP, respectively.

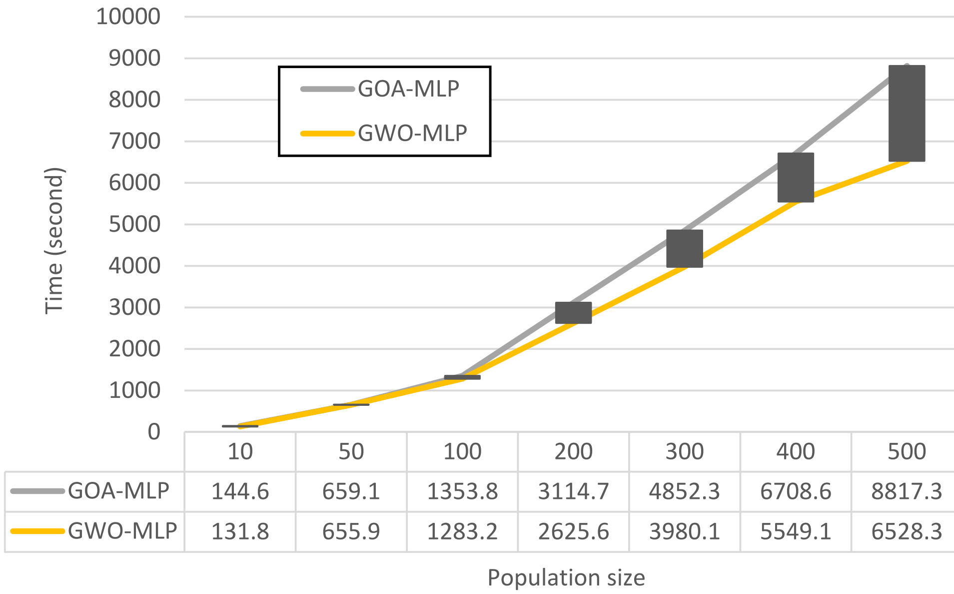
The GOA and GWO constructed strong ensembles of artificial neural network which showed higher robustness than many conventional models (e.g., extreme learning machine used by Roy et al. [53]). Moreover, in comparison with popular hybrid algorithms which have been used in previous studies, the ensemble models of this study presented more accurate prediction of the HL. The GA and ICA employed by Tien Bui et al. [34], for example, achieved a good optimization of the ANN through enhancing the learning capability of it (i.e., decreasing the training error from 3.6535 to 2.9986 and 2.8050, respectively). But as is seen, both GWO and GOA algorithms that are presented in this study performed more efficiently in this task. There is also a considerable distinction between the testing results (i.e., predicting the HL for unseen building conditions) of the proposed models in these two studies. More clearly, the R^2 of ICA and GA was around 0.91, while it was nearly 0.95 for the GWO and GOA.

This study also had some limitations. Above all, the used dataset consists of a limited range of HL, and the predictive models can be applied only for 12 types of residential building with a controlled experimental setup. Additionally, the authors believe that optimizing the configuration of HL effective factor may lead to a more reliable approximation of this parameter, which could be a good subject for further studies. Also, due to the high capability of various

Table 2 The optimal parameters of the used models

MLP	GWO–MLP	GOA–MLP
Number of hidden neurons = 9	Population size = 300	Population size = 400
Activation function = Tansig	Number of iterations = 1000	Number of iterations = 1000
Training algorithm = Levenberg–Marquardt	lb* = – 1 ub** = 1	lb = – 1 ub = 1

lb lower bound of decision variables, *ub* upper bound of decision variables



	10	50	100	200	300	400	500
GOA-MLP	144.6	659.1	1353.8	3114.7	4852.3	6708.6	8817.3
GWO-MLP	131.8	655.9	1283.2	2625.6	3980.1	5549.1	6528.3

Fig. 6 The computation time of the used GOA–MLP and GWO–MLP ensembles

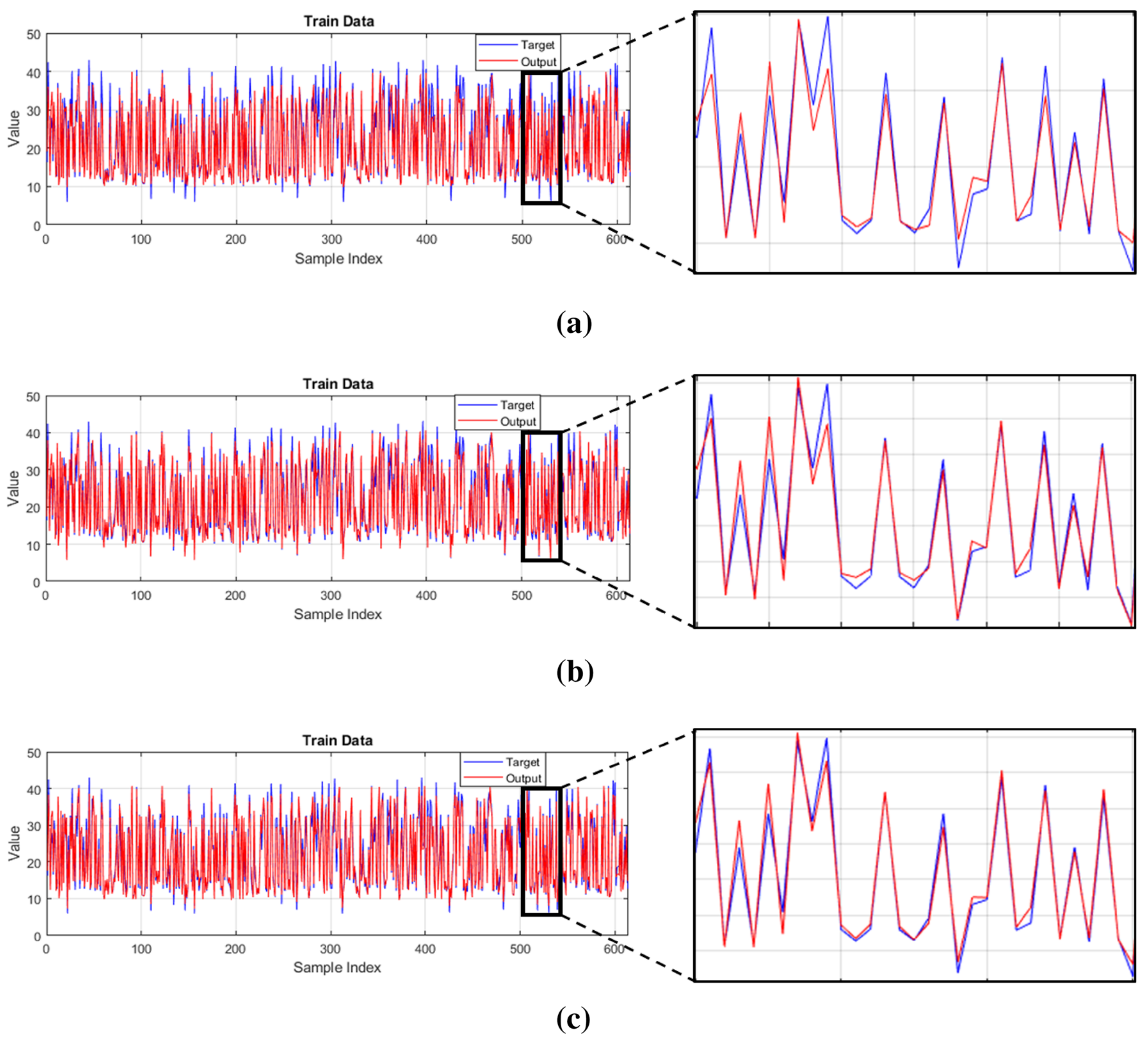


Fig. 7 The training results obtained for **a** MLP, **b** GOA–MLP, and **c** GWO–MLP predictions

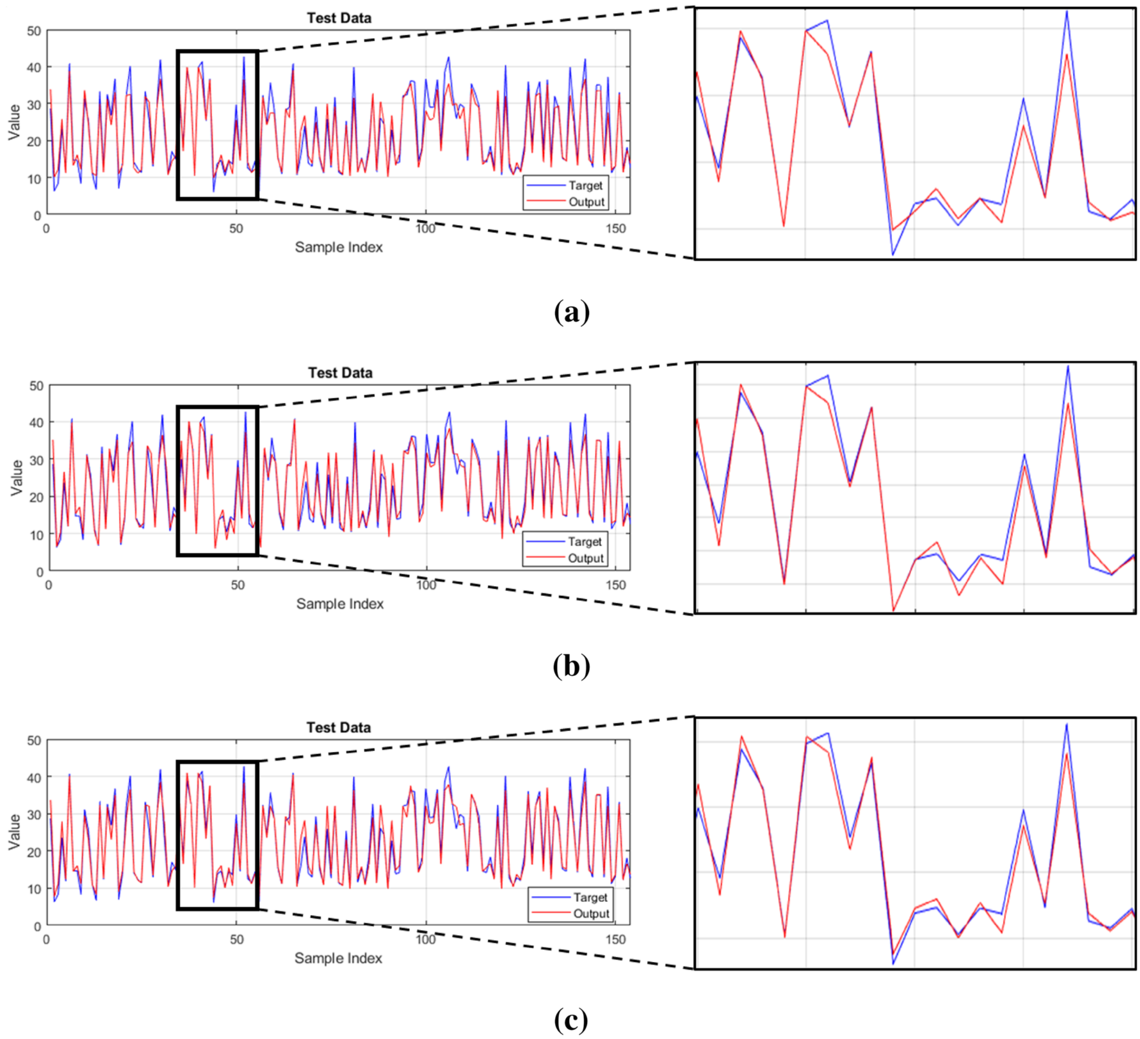


Fig. 8 The testing results obtained for **a** MLP, **b** GOA–MLP, and **c** GWO–MLP predictions

optimization techniques in prediction aims, conducting comprehensive comparative studies seems a very helpful task for determining the most appropriate models in HL estimation.

6 Conclusions

Due to the significance of analyzing energy performance in the building sector, scholars have developed various predictive and evaluative models for this aim. In this paper, two novel optimization techniques motivated by the herding behavior of grasshoppers and gray wolves were applied to improve the efficiency of multilayer perceptron neural network in predicting the HL in residential buildings. The proposed GOA and GWO metaheuristic algorithms were mathematically coupled with the MLP to seek the most appropriate computational parameters of this method, including the connecting weights and biases. The results of the sensitivity analysis showed that the GOA–MLP and GWO–MLP with the population sizes of 300 and 400 outperformed other tested networks. Notably, the GWO-based ensemble needed more computation time. Evaluation of the results revealed that both applied algorithms help the MLP to have a better approximation of the HL. It was also deduced that the GWO performs more efficiently than GOA.

Table 3 The developed ranking system based on the obtained accuracy criteria

Ensemble models	Network results									Ranking score						Total ranking score (TRS)	Rank
	Training phase			Testing phase			Average value			Training phase			Testing phase				
	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2		
MLP	2.8411	1.9568	0.9223	2.9859	2.0830	0.9328	2.9135	2.0199	0.9275	1	1	1	1	1	1	6	3
GOA–MLP	2.3715	1.6934	0.9432	2.4459	1.7373	0.9486	2.4087	1.7153	0.9459	2	2	2	2	2	2	12	2
GWO–MLP	2.2959	1.6475	0.9468	2.2899	1.6514	0.9551	2.2929	1.6494	0.9509	3	3	3	3	3	3	18	1

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