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Research article

Early energy performance analysis of smart buildings by consolidated artificial neural network paradigms

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ABSTRACT

The assessment of energy performance in smart buildings has emerged as a prominent area of research driven by the increasing energy consumption trends worldwide. Analyzing the attributes of buildings using optimized machine learning models has been a highly effective approach for estimating the cooling load (C_L) and heating load (H_L) of the buildings. In this study, an artificial neural network (ANN) is used as the basic predictor that undergoes optimization using five metaheuristic algorithms, namely coati optimization algorithm (COA), gazelle optimization algorithm (GOA), incomprehensible but intelligible-in-time logics (IbIL), osprey optimization algorithm (OOA), and sooty tern optimization algorithm (STOA) to predict the C_L and H_L of a residential building. The models are trained and tested via an Energy Efficiency dataset (downloaded from UCI Repository). A score-based ranking system is built upon three accuracy evaluators including mean absolute percentage error (MAPE), root mean square error (RMSE), and percentage-Pearson correlation coefficient (PPCC) to compare the prediction accuracy of the models. Referring to the results, all models demonstrated high accuracy (e.g., PPCCs >89%) for predicting both C_L and H_L. However, the calculated final scores of the models (43, 20, 39, 38, and 10 in H_L prediction and 36, 20, 42, 42, and 10 in C_L prediction for the STOA, OOA, IbIL, GOA, and COA, respectively) indicated that the GOA, IbIL, and STOA perform better than COA and OOA. Moreover, a comparison with various algorithms used in earlier literature showed that the GOA, IbIL, and STOA provide a more accurate solution. Therefore, the use of ANN optimized by these three algorithms is recommended for practical early forecast of energy performance in buildings and optimizing the design of energy systems.

1. Introduction

1.1. Background

The world of engineering has observed significant advances that have led to creating new methods/tools for dealing with complicated problems with higher efficiency [1–5]. These problems are drawn within various engineering domains such as civil and structural engineering [6–8]. Sustainable development and energy management form similar research hotspots in the relevant literature [9–13]. Focusing on the energy sector, experts have suggested various solutions (e.g., enhancing energy efficiency, integrating

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renewable energy, developing energy storage technologies, improving energy management policies, etc.) to better deal with the challenges associated with production, distribution, and consumption of energy worldwide [14–16]. Despite various measures established in many countries, a significant level of energy consumption persists and is anticipated to rise globally. This trend is often attributed to increasing living standards. In Europe, for instance, buildings consume approximately 40% of energy, while there are specific requirements for energy efficiency in building construction. Similarly, in the United States and China, buildings contribute to around 39% of the total primary energy requirement (PER) and above 27% of the total national energy use, respectively [17,18]. Leveraging state-of-the-art technologies in modern construction projects, the use of heating, ventilation, and air conditioning (HVAC) systems and the internet of things (IoT) have been popular ideas for optimizing building energy consumption [19–23]. However, conducting a comprehensive evaluation of energy performance of buildings (EPB) remains critical to enhance sustainable energy consumption [24–26]. For this purpose, engineers have recently focused on developing predictive and evaluation tools to better estimate building energy consumption [27,28].

1.2. Literature review

Many earlier efforts have been made in this regard that consist of both forward and inverse modeling [29]. Some examples of popular forward simulation tools are DOE-2 [30], Energy Plus [31], and DeST [32]. However, several drawbacks that are associated with forward techniques (e.g., requiring high time and precision in energy simulation packages) call for tending towards inverse approaches including data-driven modeling [33–35]. These approaches have been extensively applied to building-related analysis such as big data analytics, anomaly detection in EPB, and power consumption [36–39]. Detection of anomalies in energy consumption patterns of buildings is another interesting domain that has been recently more developed using intelligent models [40–43]. Further applications in this regard (e.g., building occupancy detection and prediction) can be sufficiently found in earlier literature [44–46].

Machine learning techniques are eminent examples of these data-driven models that have garnered significant attention in assessing building energy consumption [47–50]. Random forest [51], artificial neural networks (ANN) [52], and support vector machine (SVM) [53] are famous examples of the techniques used in this domain. Jihad and Tahiri [54] employed ANN to forecast heating and cooling energy requirements in buildings with residential use. The study focused on three specific types of residential buildings, namely the "economic villa, middle-class building, and economic building". The findings demonstrated that ANN exhibited strong predictive performance in this context. Moradzadeh, Mansour-Saatloo [55] support vector regression (SVR) and multilayer perceptron (MLP) to forecast cooling load (C_L) and heating load (H_L). The results indicated that the highest R-values achieved by the MLP and SVR were 0.9993 and 0.9878 for predicting H_L and C_L, respectively, suggesting their superior performance. In a research by Roy, Samui [56], a deep neural network (DNN) was applied to forecast the buildings' heating and cooling requirements. The competency of the DNN was compared to other models including gaussian process regression (GPR), gradient boosted machine, and minimax probability models, machine regression. The findings revealed that the DNN and GPR stood out, due to the best achieved variance accounted for (VAFs) in estimating the C_L and H_L. Further comparative efforts can be pursued in the previous literature [57–61].

More recently, metaheuristic algorithms (MAs) have been hired in the domain of machine learning, which exhibit the ability to optimize intricate problems [62,63]. By incorporating these algorithms into generic machine learning models, challenges like local minima can be effectively addressed, leading to the development of optimal networks with optimal components. Lin and Lin [64] introduced a novel technique for analyzing the EPB of residential buildings using a water cycle algorithm (WCA) combined with a double-target MLP). The model simultaneously predicts two energy performance metrics, enhancing the overall accuracy and effectiveness of the analysis. Alkhazaleh, Nahi [65] optimized an adaptive neuro-fuzzy-inference system (ANFIS) using four MAs, namely equilibrium optimization (EO), Harris hawks optimization (HHO), slap swarm algorithm (SSA), and grey wolf optimizer (GWO). ANFIS-EO with a root mean square error (RMSE) of 6.43 kWh.m^{-2}.year^{-1} versus ANFIS-HHO, ANFIS-GWO, and ANFIS-SSA with respective RMSEs equal to 6.90, 9.01, and 11.80 kWh.m^{-2}.year^{-1}. Jahanafroozi, Shokrpour [66] used an electrostatic discharge algorithm (ESDA) to optimize an MLP for estimating the C_L of residential buildings. The suggested ESDA was compared to five similar MAs, namely chimp optimization algorithm (ChOA), satin bowerbird optimization (SBO), future search algorithm (FSA), symbiotic organism search (SOS), and seeker optimization algorithm (SOA). They applied these models to a dataset developed by Tsanas and Xifara [67] and concluded that while all used models have the competency to predict the C_L with high accuracy, the MLP-ESDA presents the highest accuracy with mean absolute percentage error (MAPE) around 7%. Nejati, Zoy [68] presented an ANN based on the symbiotic organism search (SOS) algorithm for estimating buildings' thermal load. The proposed approach achieved a high prediction accuracy, with an average MAPE of around 8.2%. Gong, Zoltán [69] optimized an ANN using the multi-tracker optimization algorithm (MTOA) for estimating the EPB of residential buildings. The proposed approach achieved high accuracy, with a coefficient of determination (R^2) value of 0.92, indicating a strong correlation between predicted and actual energy performance. Peng and Chen [70] tested transient search algorithm (TSO), forensic-based investigation (FBI), Beluga whale optimization (BWO), snake optimizer (SO), and Archimedes optimization algorithm (AOA) in combination with an ANN for estimating the required annual thermal energy in a residential building. According to their analysis, while the FBI presented the best training and the AOA provided the best prediction, the BWO - with Pearson correlation coefficient (PCC) of 0.996 and an MAPE of 1.99%- was introduced as the most accurate optimizer considering both phases.

1.3. Motivation and contribution

The previous section addresses promising usages of MAs in the literature of EPB analysis [71]. However, there are still some limitations to be addressed. While many new MAs are developed regularly, most studies that are contained in this literature are bound to old well-tried algorithms (including particle swarm optimization (PSO) [34], genetic algorithm (GA) [72], GWO [73], etc.). On the other hand, the existing literature lacks comparative studies to compare the efficiency of new MAs which is helpful for practical applications and proper method selection. Moreover, each new MA requires evaluating key parameters (e.g., population size) to perform the optimization at its best. Considering these points, this research focuses on introducing various novel MAs for EPB analysis. More clearly.

- five MAs, namely coati optimization algorithm (COA) [74], gazelle optimization algorithm (GOA) [75], incomprehensible but intelligible-in-time logics (IbIL) [76], osprey optimization algorithm (OOA) [77], and sooty tern optimization algorithm (STOA) [78] are applied to optimize an ANN model for predicting the H_L and C_L in a residential building.
- The hybrid models are optimized with regard to population size through an extensive trial-and-error effort.
- The pivotal role of these five MAs in solving the problem at hand can be expressed as weight and bias adjustment in the ANN for establishing the non-linear relationship between the thermal loads (i.e., H_L and C_L) and buildings' characteristics.
- This research applies these algorithms to EPB analysis for the first time and presents a comprehensive comparison to identify the most potential ones.
- The findings of the present research can contribute to both (i) the body of knowledge by enriching the relevant literature and (ii) real-world EPB analysis by providing optimal hybrid models.

2. Materials and methods

2.1. Dataset

A well-known dataset is considered for enabling the intelligent models offered in this study. It is known as the energy efficiency dataset that is downloaded from the UCI Repository [79]. This data was created in a study by Tsanas and Xifara [67] and provides 768 records of H_L and C_L as interrelated functions of eight building characteristics. Therefore, it has eight inputs and two targets and is tabulated in a 768 × 10 Excel file.

In the machine learning general context, the model tries to understand and predict the behavior of the target(s) by analyzing the variation in the inputs. Hence, the inputs are considered influential parameters of the thermal energy targets in this study.

The dataset parameters are introduced in Table 1 along with their acronyms and value ranges. In order to evaluate the performance of the models in the purest form, the original dataset is used (without normalization). It is worth noting that there were not any nulls, missing values, and invalid/outliers records in the dataset. Fig. 1 (a)-(j) show the boxplot of the mentioned parameters.

As a prerequisite for machine learning implementation, the dataset needs to be split into two separate subsets. One subset with most of the records is consumed by the models in the early stage (called the training phase) for discovering the interrelated relationship between the inputs and target(s). This subset is called train data. Once training data is separated, the remaining records are set aside to be used in the post-training stage (called the testing phase). This subset is called test data.

The most common ratio for doing this split is 80:20 indicating that 80% of records construct the training subset and the remaining 20% construct the testing subset. It is important for both subsets to have samples from all over the original dataset. Hence, it is subjected to a random permutation before splitting. Hereby, the selection of train and test data is random. Table 2 denotes the splitting parameters and results.

2.2. MA description

The coati optimization algorithm (COA) [74] is a nature-based optimizer based on the coatis' behavior, which are small mammals known for their cooperative foraging and social behavior. COA aims to solve optimization problems by mimicking the coati's search strategy, which involves exploration, exploitation, and communication among individuals. It is a metaheuristic algorithm that has been promisingly used for various optimization problems and has high potential regarding the quality of solution and convergence.

The gazelle optimization algorithm (GOA) [75] is a nature-inspired optimization algorithm that is based on the social behavior and

Table 1
Dataset parameters, abbreviations, and statistical analysis results.

Type	Full name	Acronym	Range	Mean	Standard Error	Sample Variance
Input	Relative compactness	C_R	[0.6, 0.9]	0.76	0.00	0.01
	Surface area	S_A	[514.5, 808.5]	671.71	3.18	7759.16
	Wall area	S_W	[245.0, 416.5]	318.50	1.57	1903.27
	Roof area	S_R	[110.2, 220.5]	176.60	1.63	2039.96
	Overall height	H_T	[3.5, 7.0]	5.25	0.06	3.07
	Orientation	O	[2.0, 5.0]	3.50	0.04	1.25
	Glazing area	S_G	[0.0, 0.4]	0.23	0.00	0.02
	Glazing area distribution	DS_G	[0.0, 5.0]	2.81	0.06	2.41
Target	Heating load	H_L	[6.0, 43.1]	22.31	0.36	101.81
	Cooling load	C_L	[10.9, 48.0]	24.59	0.34	90.50

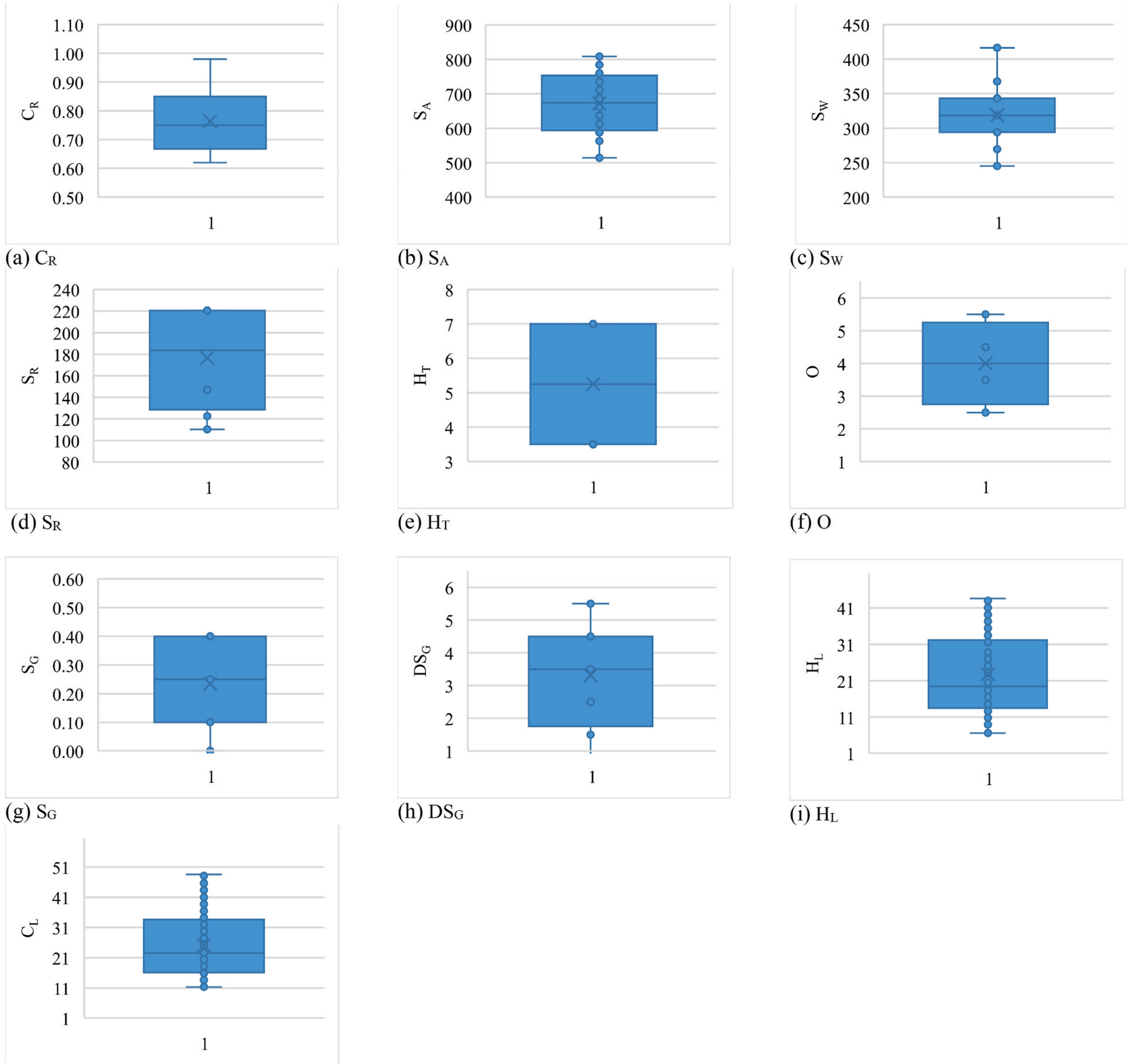


Fig. 1. Boxplots of the dataset parameters - 8 inputs (a)–(h) + 2 outputs (i) and (j).

Table 2
Data split policy for constructing training and testing subsets.

Dataset	Number of records	Subset	Ratio	Number of records
UCI energy efficiency dataset	768	Train	80%	$0.8 \times 768 = 614$
		Test	20%	$0.2 \times 768 = 154$

movement patterns of gazelles, which are agile and fast-running animals. GOA mimics the gazelle's characteristics, such as their ability to detect predators, avoid obstacles, and coordinate their movements within a group. The algorithm utilizes a population of candidate solutions that iteratively search for the optimal solution by imitating the gazelle's foraging and evasion strategies.

The concept underlying the Incomprehensible but Intelligible-in-time logics (IbIL) [76] algorithm is derived from the theory of IbI logic, aiming to identify a highly competent IbI logic that represents the logic at a specific future time. The IbIL algorithm consists of a preparatory phase followed by three distinct phases: (i) exploration, (ii) integration, and (iii) exploitation. Each phase serves a unique purpose and operates independently from one another, ensuring that once a phase is accomplished, the solutions progress to the subsequent phase without revisiting the previous phase during subsequent iterations. This design sets IbIL apart from other algorithms and contributes to its effectiveness in problem-solving tasks.

The osprey optimization algorithm (OOA) [77] is a metaheuristic optimization algorithm inspired by osprey bird's hunting behavior. It employs exploration and exploitation techniques to seek optimal (or near-optimal) solutions to optimization problems. The algorithm utilizes mechanisms (e.g., crossover and mutation) to enhance the search process and maintain a diverse population of candidate solutions. Through fitness evaluation, selection, reproduction, and replacement, the OOA evolves the population towards improved solutions over iterations.

The sooty tern optimization algorithm (STOA) [78] is a nature-inspired metaheuristic algorithm inspired by the foraging behavior of sooty tern birds. It mimics the movement and search patterns of the birds to efficiently explore solution spaces and find optimal (or near-optimal) solutions. The algorithm utilizes techniques such as randomization, local search, and global search to balance exploitation and exploration during the optimization process. By iteratively updating the population based on fitness evaluation, selection, and reproduction, the STOA improves the quality of solutions over time.

These techniques have shown promise in tackling optimization problems in engineering, operations research, and other domains [80–83]. Further explanations and mathematical details of these algorithms can be found in their relevant literature ([84,85] for the COA [86,87], for the GOA [76,88], for the IbIL [89,90], for the OOA, and [91,92] for the STOA).

2.3. Algorithms combination

This study uses hybrid methodologies for the EPB prediction task. These types of hybrids are known as neural-metaheuristic models which represent an ANN model driven by an MA. The pivotal role of the MA is to determine optimum values for the ANN internal parameters (i.e., weights and biases) that constitute the model rules [93]. This optimum solution is sought by the search agents (i.e., the population) of the involved MA within the search space. In the algorithms which are designed based in foraging behaviors, the solution may be represented by a food source sought by the animals. As long as the iterations continue, the best solution is kept until a better one is discovered.

The combination process consists of several steps as described below and in the flowchart of Fig. 2.

1 Data: exposing the training data to the primary ANN,
2 ANN adjustment: finding the optimum ANN skeleton and translating the model into mathematical form wherein the weights and biases are variables,
3 Optimization: yielding the ANN equations to the intended MA as its problem function, followed by specifying the MA's parameter (e.g., population size), and running the model,
4 Cost function calculation: calculating a cost function (RMSE here) in each iteration,
5 Condition check: checking if the maximum number of iterations has reached:

No: running the next iteration (repeat Step 3).
Yes: Saving the solution,
Note that, this study conducted a sensitivity analysis for finding the most proper MA's population size.

Fig. 3 shows the chosen ANN topology, which is a three-layered MLP for this study. This configuration is composed of two parts: (a) the compulsory size of the input and output layers, owing to the fixed number of engaged parameters, and (b) the arbitrary size of the hidden layer. The network receives 8 inputs, and after calculations, it releases two outputs, therefore, 8 input neurons and two output neurons are assigned. In the middle layer, the number of neurons can vary until a desirable prediction is achieved. In this work, 10 hidden neurons are opted after observing the accuracy variation by changing this number (trial-and-error). The ANN is introduced hereafter with the name ANN(8, 10, 2). As per Fig. 3, this network consists of $8 \times 10 = 80$ wt between the input and hidden layers, 10 biases belonging to the hidden layer, $10 \times 2 = 20$ wt between the hidden and output layers, and 2 biases belonging to the output layer. It is worth noting that, with the same trial-and-error effort, the activation functions for the output and hidden layers of this ANN are chosen to be Purelin and Tansig, respectively [94].

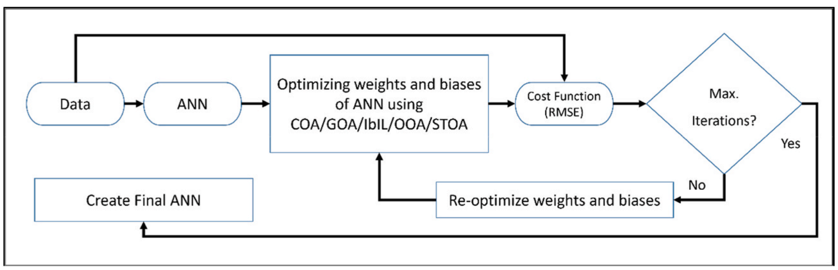


Fig. 2. Flowchart of optimizing ANN using MAs.

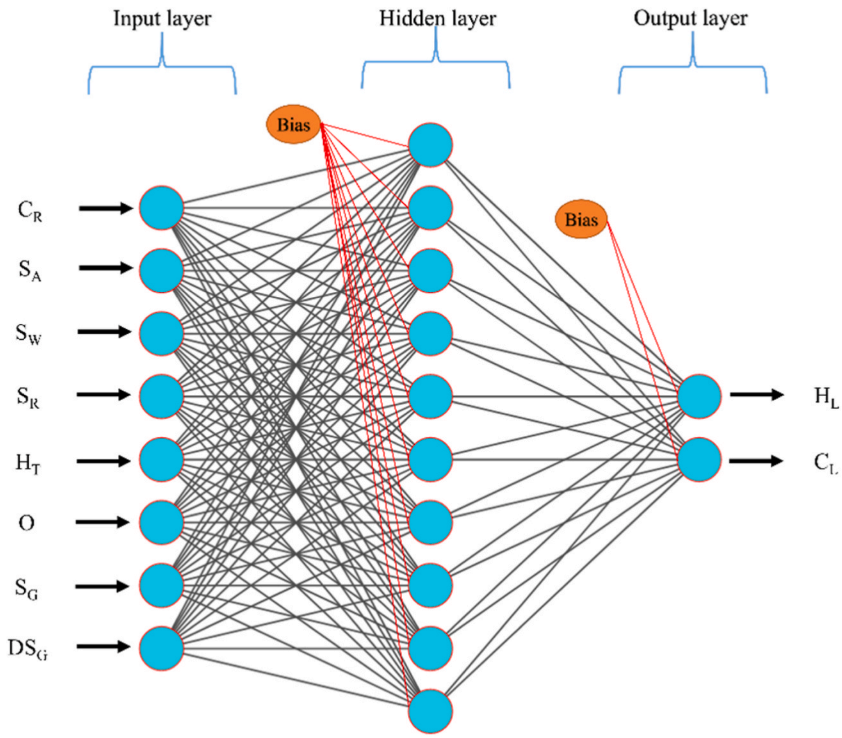


Fig. 3. Schematic view of the ANN(8, 10, 2) and involved parameters.

2.4. Accuracy assessment criteria

The accuracy assessment method of this study is composed of three statistical indicators as follows:

(a) Absolute indicator: two well-known error indicators called RMSE and mean absolute error (MAE) calculate the error as is expressed in Equations (1) and (2), respectively.

$$RMSE = \sqrt{\frac{1}{K}\sum_{i=1}^{K}\left[\left(L_{i_{\exp}} - L_{i_{sim}}\right)\right]^2}, \tag{1}$$

$$MAE = \frac{1}{K}\sum_{i=1}^{K}\left|L_{i_{\exp}} - L_{i_{sim}}\right| \tag{2}$$

where $L_{i_{exp}}$ and $L_{i_{sim}}$ represent the expected and simulated thermal loads (C_L and H_L) and the number of evaluated couples is signified by K.

(b) Relative indicators: The MAPE gives the relative error in percentage, and percentage-PCC (PPCC) gives the correlation quantifying the agreement between the prediction and expectation. Equations (3) and (4) formulate the MAPE and PPCC criteria. Moreover, Nash–Sutcliffe efficiency (NSE) coefficient is expressed by Equation (5).

$$MAPE = \frac{1}{K}\sum_{i=1}^{K}\left|\frac{L_{i_{\exp}} - L_{i_{sim}}}{L_{i_{\exp}}}\right| \times 100, \tag{3}$$

$$PPCC = \frac{\sum_{i=1}^{K}\left(L_{i_{sim}} - \overline{L}_{sim}\right)\left(L_{i_{\exp}} - \overline{L}_{\exp}\right)}{\sqrt{\sum_{i=1}^{K}\left(L_{i_{sim}} - \overline{L}_{sim}\right)^2}\sqrt{\sum_{i=1}^{K}\left(L_{i_{\exp}} - \overline{L}_{\exp}\right)^2}} \times 100, \tag{4}$$

$$NSE = 1 - \frac{\sum_{i=1}^{K}\left(L_{i_{\exp}} - L_{i_{sim}}\right)^2}{\sum_{i=1}^{K}\left(L_{i_{\exp}} - \overline{L}_{\exp}\right)^2} \tag{5}$$

3. Results and discussion

3.1. Optimization results and training

Following the explanations in Section 2.3, the optimization results are illustrated in this part. This task is carried out by creating optimization diagrams of all models for a number of viable population sizes (from 100 to 500 with 100 intervals). Each algorithm is run for 1000 iterations and the cost function of training is saved as the iterations proceed. Since the network has two outputs, the cost function is the RMSE averaged for the C_L and H_L as per Equation (6). Note that, the RMSE represents an error; hence, the lower it comes, the better [65,68].

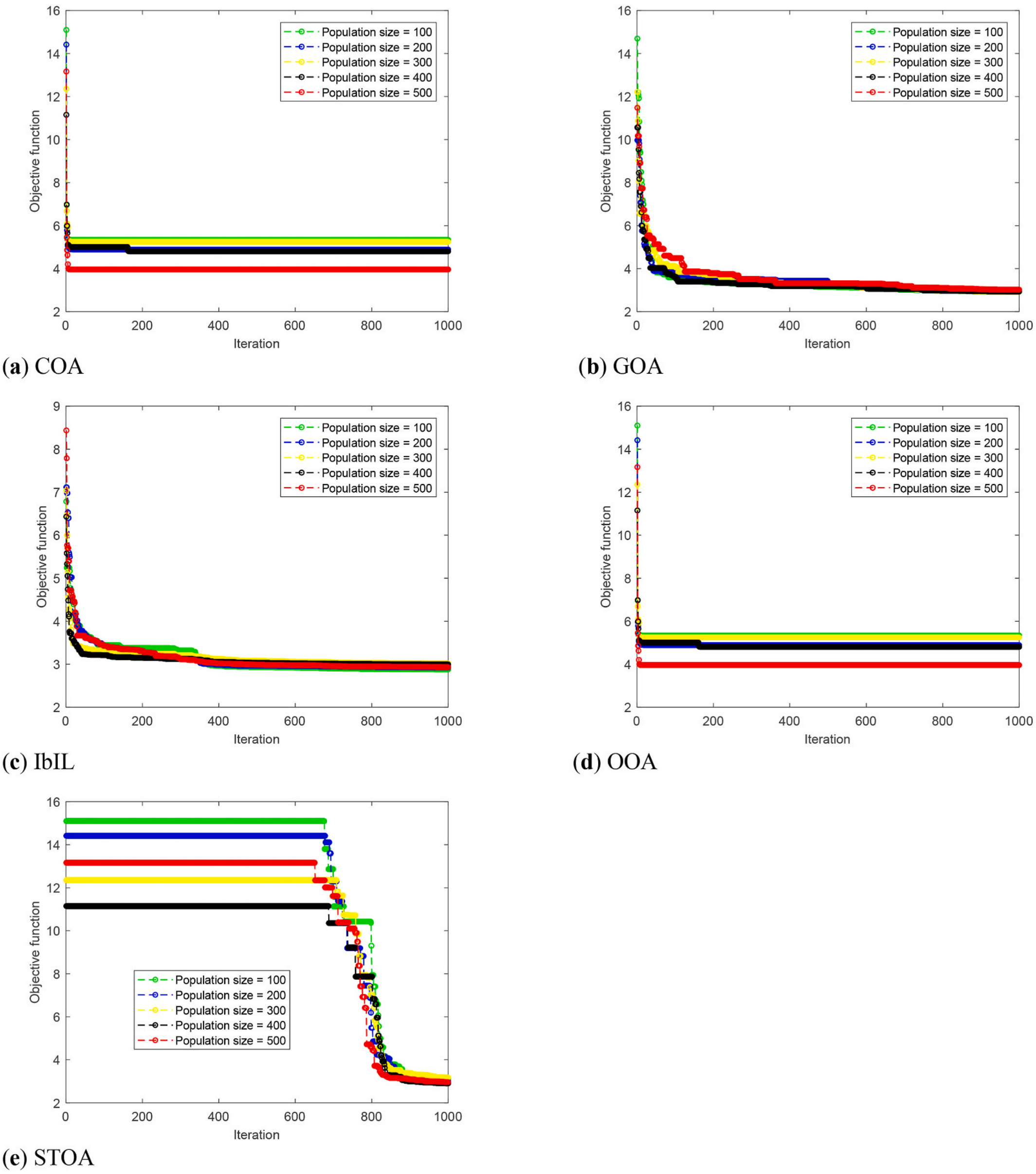


Fig. 4. Cost function (i.e., objective function) reduction procedure by coupled ANN-metaheuristic algorithms.

$$\text{Cost function} = \frac{RMSE_{\mathrm{CL}} + RMSE_{\mathrm{HL}}}{2}, \tag{6}$$

Fig. 4 (a)-(e) show the optimization direction of each algorithm. As is shown, the strategy of each algorithm is different for cost function reduction. The COA and OOA show a higher sensitivity to the population size. As explained above, the values of 500, 100, 100, 500, and 400 are selected as the best population size of COA, GOA, IbIL, OOA, and STOA algorithms, respectively.

3.2. Thermal loads modeling

Each network that was optimized in the previous section produces two values of C_L and H_L for a given building condition. Accordingly, 614 × 2 = 1228 and 154 × 2 = 308 predictions are carried out for the train and test datasets, respectively. Famously, evaluating the accuracy of the first dataset reveals the goodness of learning by the models and the accuracy of the later dataset reveals their generalizability. The training and testing results are statistically evaluated in this section.

3.2.1. Error indicators

For learning the H_L pattern, the COA, GOA, IbIL, OOA, and STOA algorithms reached the RMSEs of 3.6669, 2.7252, 2.6997, 3.2894, and 2.7005, respectively. These values are associated with the MAEs of 2.7732, 1.8953, 1.8836, 2.4383, and 1.8616, MAPEs of 13.3051%, 8.7549%, 8.6040%, 11.7620%, and 8.6305%, and NSEs of 0.8692, 0.9278, 0.9291, 0.8948, and 0.9291. This thermal load was predicted for unseen building circumstances with the RMSEs of 3.6801, 2.4417, 2.5588, 3.0210, and 2.4445, along with the MAEs of 2.6817, 1.6329, 1.7198, 2.1598, and 1.5989, MAPEs of 12.9445%, 7.4850%, 7.8458%, 10.4248%, and 7.2942%, and NSEs of 0.0.8606, 0.9386, 0.9326, 0.9061, and 0.9385.

As far as the C_L is concerned, the error of the learning process was demonstrated with the RMSEs of 4.2327, 3.1149, 3.0491, 3.7238, and 3.0913 associated with the MAEs of 3.3783, 2.1836, 2.1200, 2.7723, and 2.1996, MAPEs of 15.6894%, 8.7006%, 8.4540%, 11.3833%, and 8.7642%, and NSEs of 0.8032, 0.8934, 0.8979, 0.8477, and 0.8950. Then, the models could predict it with RMSEs of 4.50, 2.80, 2.83, 3.70, and 2.82, MAEs of 3.5627, 1.8480, 1.8629, 2.6309, and 1.8955, MAPEs of 16.5058%, 6.9772%, 7.0489%, 10.4430%, and 7.2409%, and NSEs of 0.7690, 0.9105, 0.9084, 0.8433, and 0.9091.

From the above assessment, train results demonstrate that the behavior of both C_L and H_L has been clearly analyzed and understood

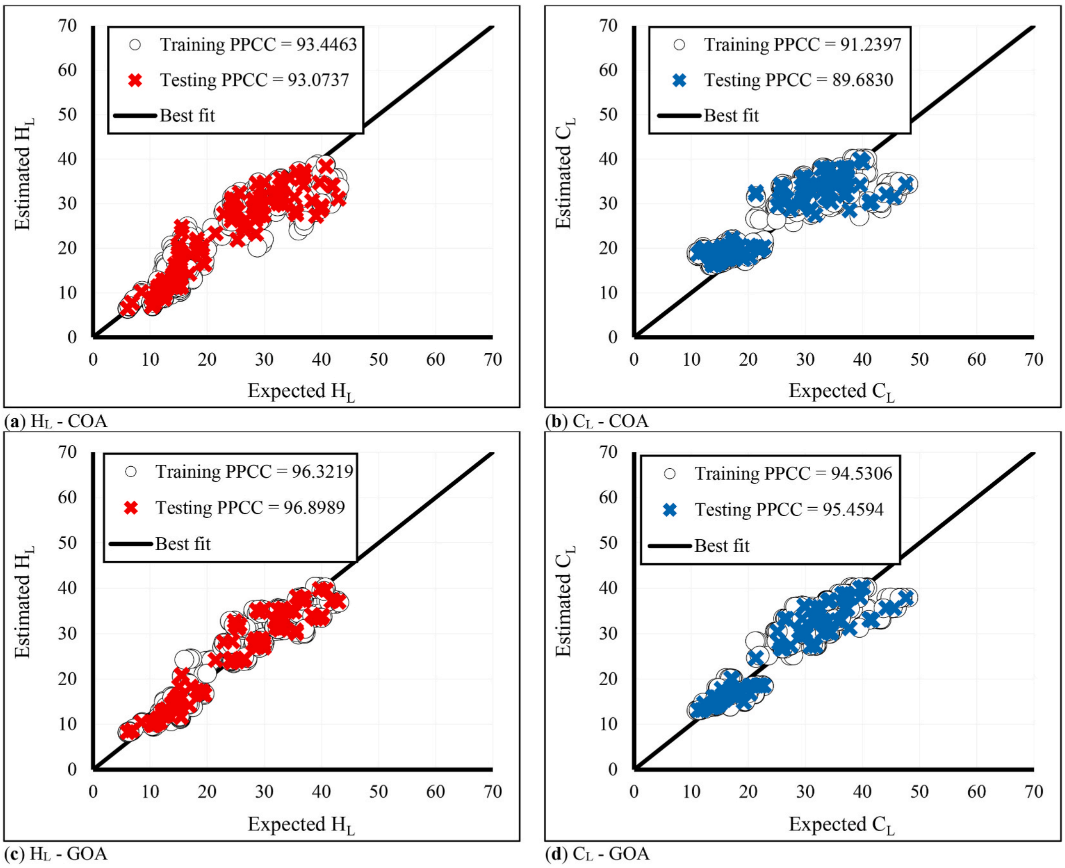
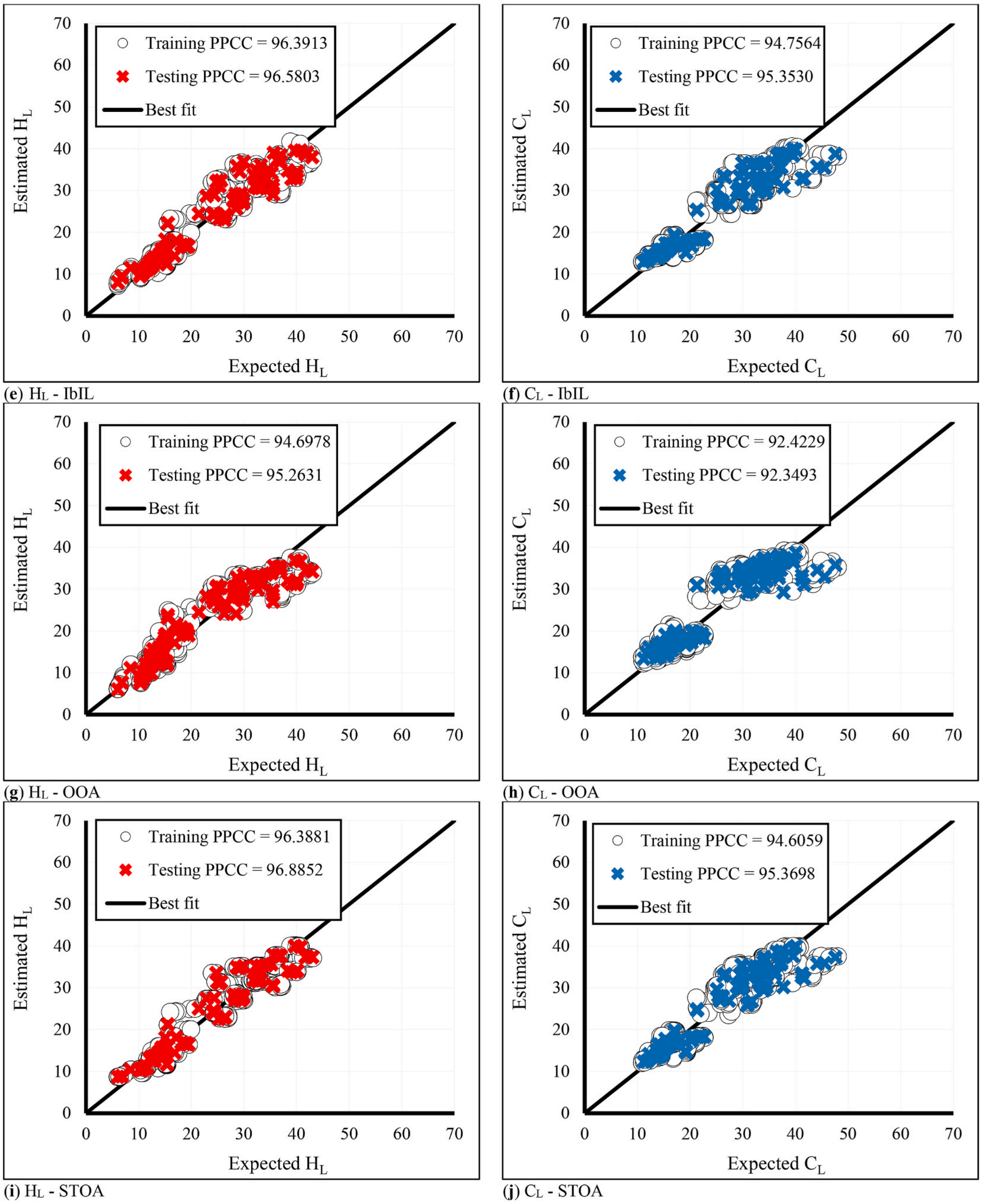


Fig. 5. Train and test correlation results of the H_L and C_L.



(e) H_L - IbIL **(f)** C_L - IbIL
(g) H_L - OOA **(h)** C_L - OOA
(i) H_L - STOA **(j)** C_L - STOA

Fig. 5. (*continued*).

by all models. Likewise, test results indicate that all models have enough reliability for extrapolating these patterns. However, the variations in the obtained values suggest some distinctions in their performance. Hence, a comparative ranking is performed in the following sections.

3.2.2. Correlation indicator

After error evaluations, the correlation reveals the agreement level between the reality and models' products. The results of this section are also graphically shown in Fig. 5 (a)–(j). Each sub-figure contains both train and test results of either C_L or H_L.

A general view of the above charts demonstrates a great agreement between the expected thermal loads and the models' predictions. However, this agreement is more obvious for the results.

For learning the H_L pattern, the COA, GOA, IbIL, OOA, and STOA algorithms reached the PPCCs of 93.4461%, 96.3219%, 96.3913%, 94.6978%, and 96.3881%, respectively. This thermal load was predicted for unseen building circumstances with the PPCCs of 93.0737%, 96.8989%, 96.5803%, 95.2631%, and 96.8852%.

As far as the C_L is concerned, the fitness of the learning process was demonstrated with the PPCCs of 91.2397%, 94.5306%, 94.7564%, 92.4229%, and 94.6059%. Then, the models could predict it with the PPCCs of 89.6830%, 95.4594%, 95.3530%, 92.3493%, and 95.3698%.

3.3. Ranking and discussion

From the previous section, it was inferred that all presented models are potentially able to learn and predict the thermal load patterns of a residential building under various assumptions. However, the used accuracy criteria reflected different levels of accuracy for each model and each predicted parameter. In this part, a detailed ranking is performed among the models to show which ones are more suitable for each task. Table 3 collects all calculated accuracy criteria.

Moreover, Fig. 6 (a)-(j) illustrate the obtained accuracy indicators (RMSE, MAE, MAPE, PPCC, and NSE) in the form of bar charts along with the relevant values. A ranking system is also developed to quantitatively compare the used models. In this regard, for each accuracy criterion, each model receives a score from 1 to 5. The higher the accuracy, the higher the assigned score. For instance, in Fig. 6 (b) – testing phase – the GOA receives 5, while COA receives 1. In the end, the sum of these scores gives the total score (TS) as illustrated in Fig. 6 (k) and (l).

For learning the H_L pattern, the IbIL algorithm attained the lowest RMSE and MAPE, and the largest PPCC and NSE, followed by the STOA and GOA. In the test phase, however, the STOA and GOA surpassed IbIL. Overall, based on the slight differences in the train and test accuracies, the STOA emerges as the most accurate model, followed by the IbIL and GOA. The same ranking is obtained for learning the C_L pattern, i.e., the IbIL algorithm attained the highest correlation and smallest errors, followed by the STOA and GOA. In the test phase, however, the GOA and STOA surpassed IbIL. Overall, based on the slight differences in the train and test accuracies, the IbIL and GOA gained the first rank jointly, and the STOA emerged as the second accurate model. To sum up, based on Fig. 6 (k) and (l), the final TSs (training TS + testing TS) are as follows:

- for the STOA: 21 + 22 = 43 in H_L prediction and 18 + 18 = 36 in C_L prediction,
- for the OOA: 10 + 10 = 20 in H_L prediction and 10 + 10 = 20 in C_L prediction,
- for the IbIL: 24 + 15 = 39 in H_L prediction and 25 + 17 = 42 in C_L prediction,
- for the GOA: 15 + 23 = 38 in H_L prediction and 17 + 25 = 42 in C_L prediction,
- for the COA: 5 + 5 = 10 in H_L prediction and 5 + 5 = 10 in C_L prediction,

Hence, the GOA, STOA, and IbIL are considered the outstanding models of this study. They are accordingly recommended for practical analysis of residential buildings in terms of the required thermal loads.

This study provided capable predictive frameworks by establishing an optimal relationship between the building conditions (i.e., eight conditioning parameters of C_R, S_A, S_W, S_R, H_T, O, S_G, and DS_G) and H_L-C_L simultaneously. Referring to Fig. 3, the used network consists of 112 wt and biases which were optimized by the MAs in each iteration. Hence, this work proved that MA-enabled methodologies can handle heavy calculations. The main contribution of the used MAs lies in optimizing the weights and biases that are responsible for establishing a non-linear model for predicting the H_L-C_L based on the building conditions. Considering 5 used MAs, each ran with 5 population sizes by 1000 iterations, the solutions provided in this research are deemed optimized after these extensive trial-and-error efforts. Hereupon, this work can shed light in the way of proper selection of MAs, as well as, being a nice benchmark for future research in the field of EPB analysis. Concerning real-world applications, the proposed models can be applied to:

- Optimizing the design of energy-efficient buildings and occupant comfort,
- Optimizing the design of energy systems such as HVAC,
- Forecasting thermal energy consumption,
- Improving the automation of smart buildings and maintenance planning,
- Long-Term urban planning and policy making.

Table 3
Collected accuracy indices for the performed predictions.

Phase		Train					Test				
Model		COA	GOA	IbIL	OOA	STOA	COA	GOA	IbIL	OOA	STOA
H_L	RMSE	3.6669	2.7252	2.6997	3.2894	2.7005	3.6801	2.4417	2.5588	3.0210	2.4445
	MAE	2.7732	1.8953	1.8836	2.4383	1.8616	2.6817	1.6329	1.7198	2.1598	1.5989
	MAPE	13.3051	8.7549	8.6040	11.7620	8.6305	12.9445	7.4850	7.8458	10.4248	7.2942
	PPCC	93.4463	96.3219	96.3913	94.6978	96.3881	93.0737	96.8989	96.5803	95.2631	96.8852
	NSE	0.8692	0.9278	0.9291	0.8948	0.9291	0.8606	0.9386	0.9326	0.9061	0.9385
C_L	RMSE	4.2327	3.1149	3.0491	3.7238	3.0913	4.5029	2.8031	2.8357	3.7088	2.8245
	MAE	3.3783	2.1836	2.1200	2.7723	2.1996	3.5627	1.8480	1.8629	2.6309	1.8955
	MAPE	15.6894	8.7006	8.4540	11.3833	8.7642	16.5058	6.9772	7.0489	10.4430	7.2409
	PPCC	91.2397	94.5306	94.7564	92.4229	94.6059	89.6830	95.4594	95.3530	92.3493	95.3698
	NSE	0.8032	0.8934	0.8979	0.8477	0.8950	0.7690	0.9105	0.9084	0.8433	0.9091

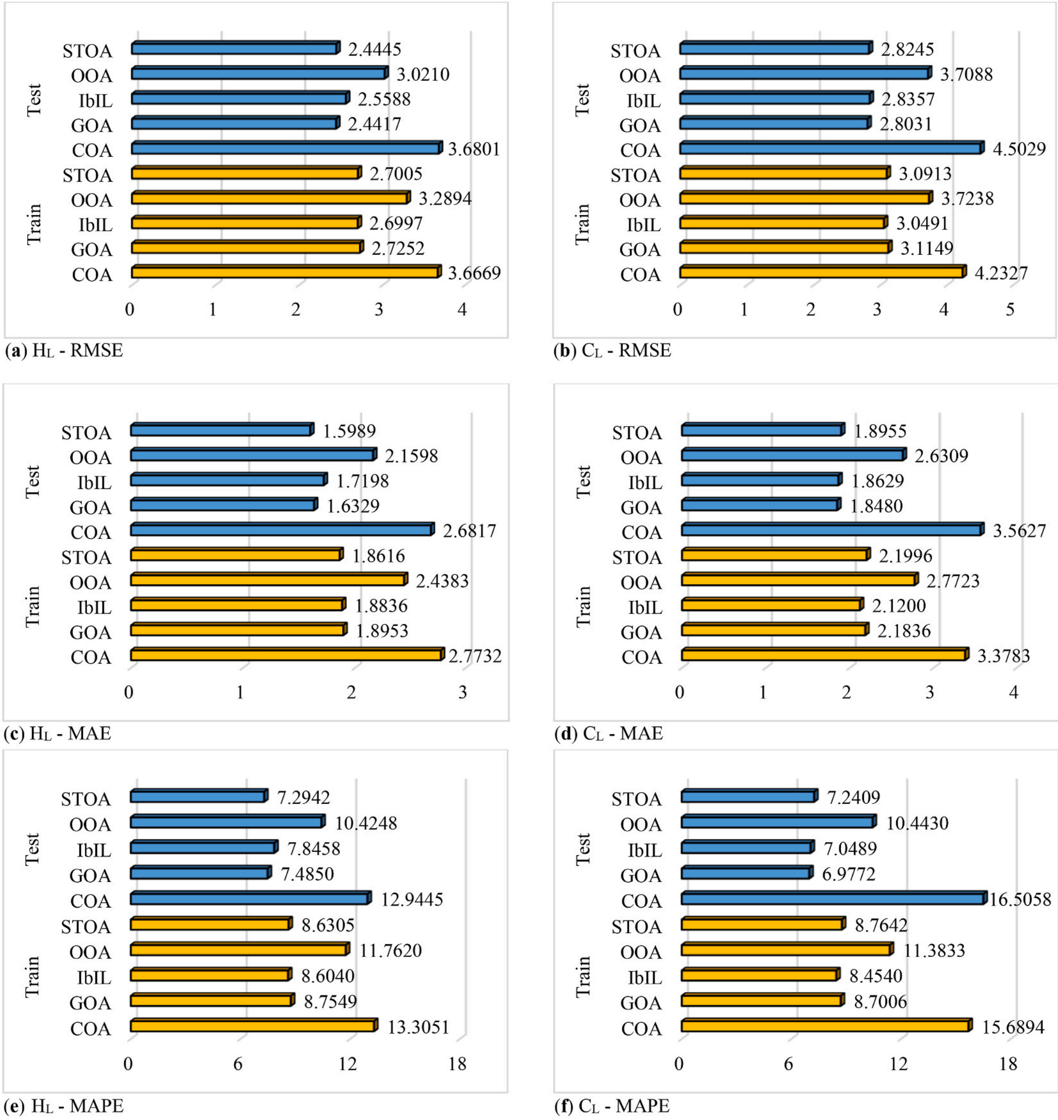
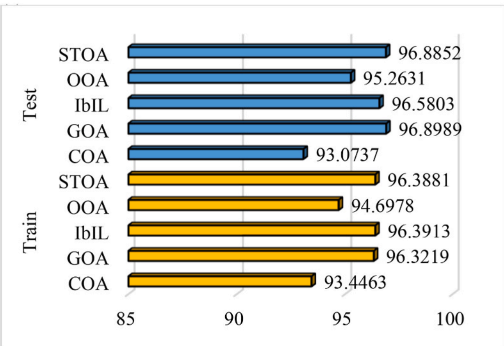


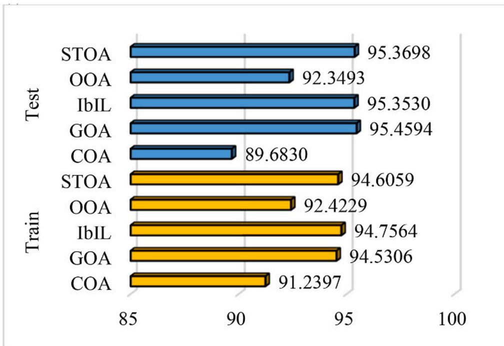
Fig. 6. Obtained accuracy criteria and their comparison in the prediction of H_L and C_L.

As an example of optimal building design, Fig. 7 (a) and (b) show sensitivity of the H_L and C_L to the increment of C_R (varying from 0.62 to 0.98). Having the prediction results in these charts, it can be seen that all models have captured a strong understanding from these behaviors, and they can predict it with high accuracy.

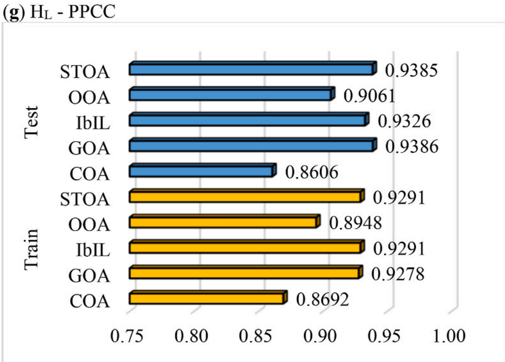
The solutions discovered in this study by three outstanding algorithms (i.e., GOA, STOA, and IbIL) is more accurate than many previous solutions in earlier studies. Table 4 presents some examples of the previously used algorithms. In this table, the testing RMSE and MAE of the GOA, STOA, and IbIL are compared to various metaheuristic algorithms, namely genetic algorithm (GA) [95], imperialist competitive algorithm (ICA) [96], wind-driven optimization (WDO) [97], whale optimization algorithm (WOA) [98], spotted hyena optimization (SHO) [99], salp swarm algorithm (SSA) [100], grasshopper optimization algorithm (GOA2) [101], artificial bee colony (ABC) [102], particle swarm optimization (PSO) [103], firefly algorithm (FA) [104], optics-inspired optimization (OIO) [105], shuffled complex evolution (SCE) [106], teaching–learning-based optimization (TLBO) [107], political optimizer (PO) [108], heap-based optimizer (HBO) [109], Henry gas solubility optimization (HGSO) [110], cuttle-fish optimization algorithm (CFOA) [111], backtracking search optimization algorithm (BSA) [112], chimp optimization algorithm (ChOA) [113], satin bowerbird optimization (SBO) [114], future search algorithm (FSA) [115], symbiotic organism search (SOS) [116], ant colony optimization (ACO) [117], Harris hawks optimization (HHO) [118], and elephant herding optimization (EHO) [119]. As per Tables 4 and it can be seen that both testing RMSE and testing MAE of the elite models in this study are (in most cases considerably) lower than the mentioned algorithms. Hence, it can be deduced that the suggested models can enhance the EPB analysis.



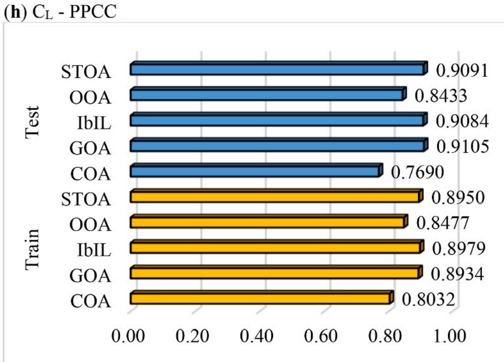
(g) H_L - PPCC



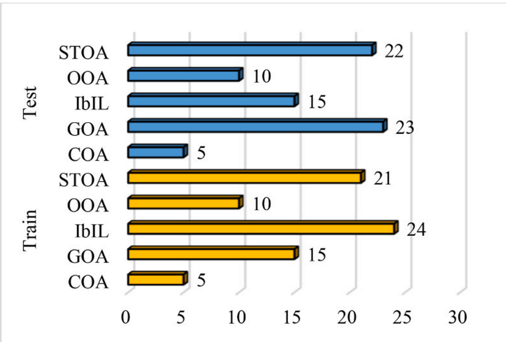
(h) C_L - PPCC



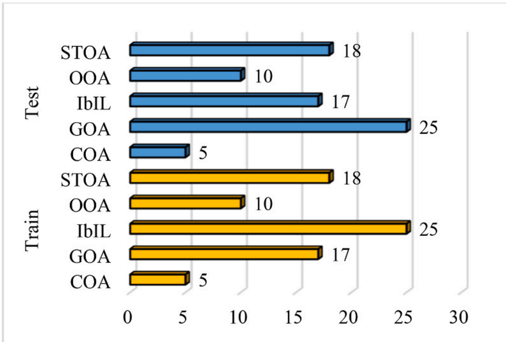
(i) H_L - NSE



(j) C_L - NSE

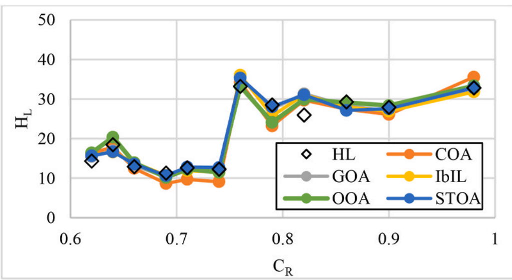


(k) H_L - TS

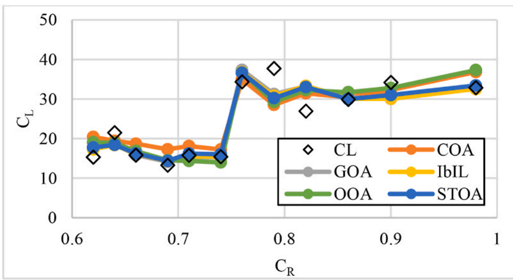


(l) C_L - TS

Fig. 6. (*continued*).



(a) H_L



(b) C_L

Fig. 7. The behavior of actual and predicted H_L and C_L vs. the increment of C_R.

Regarding the limitations of this study, the used dataset and applied methodology can be argued. First, the MAs used in this study were applied to ANN solely, while several other machine learning models e.g., the ANFIS, SVM, and long short-term memory (LSTM) networks can be regarded as well. Moreover, updating the used MAs with the most recent algorithms is of great interest for conducting

Table 4
Comparison of the testing RMSE and MAE calculated in this study with previous literature.

H_L				C_L			
Study	Model	Error criterion		Study	Model	Error criterion	
		RMSE	MAE			RMSE	MAE
[120]	FA	2.5456	1.7979	[120]	FA	2.5456	1.7979
	OIO	2.7099	1.9278		OIO	2.7099	1.9278
[121]	ABC	2.6159	1.9111	[121]	ABC	3.1728	2.1760
	PSO	2.5693	1.863		PSO	3.1222	2.1360
[34]	GA	2.8878	2.0622	[34]	GA	2.8598	2.0982
	ICA	2.7819	2.0089		ICA	2.7995	2.1054
[33]	WDO	2.8312	1.9863	[33]	WDO	3.1945	2.2424
	WOA	2.9213	2.1921		WOA	3.3581	2.5390
	SHO	4.1501	3.1092		SHO	6.0445	4.5930
	SSA	2.7527	1.9178		SSA	3.1471	2.1830
[122]	GOA2	2.4459	1.7373	[123]	ACO	3.3561	2.6011
[68]	PO	2.463	1.775		HHO	3.1925	2.3265
	HBO	3.119	2.395		EHO	3.0464	2.1284
	HGSO	3.054	2.234	[124]	GOA2	2.7628	1.8951
	CFOA	3.358	2.559		FA	2.9411	2.0265
[125]	BSA	2.6447	1.9083	[66]	FSA	3.4552	2.5221
					SOS	2.5983	1.8204
					ChOA	3.2729	2.3262
					SBO	3.0312	2.0761
This study	GOA	2.4417	1.6329	This study	GOA	2.4417	1.6329
	IbIL	2.5588	1.7198		IbIL	2.5588	1.7198
	STOA	2.4445	1.5989		STOA	2.4445	1.5989

comparative studies. In the meanwhile, the models are recommended to be tested with external datasets (along with the used UCI Repository dataset [79]) in order to improve their generalizability. For this purpose, the dataset provided by Chegari, Tabaa [126] can be regarded in future applications. This dataset takes the annual thermal energy demand as the output, being a function of H_L, C_L, and building's area.

Based on the importance assessment carried out via the random forest model in the previous studies, a dimensionality reduction can be considered for this dataset. Zheng, Lyu [127] used the same dataset and investigated the importance of the inputs in C_L prediction. According to the results (Fig. 4 of the cited paper), the S_G emerged as the most important input followed by C_R, while S_W, H_T, and O were the least important inputs. As for the H_L prediction, Wu, Foong [125] did the same analysis (Fig. 2 of the cited paper) and observed similar results. The S_G emerged as the most important input followed by C_R, while S_W, H_T, and O were the least important inputs. These results can reflect a potential idea for future utilization of this dataset to see whether the accuracy of prediction changes by removing the less important inputs.

4. Conclusions

Several metaheuristic-based solutions were suggested and tested for solving the problem of thermal load estimation in buildings. Five ANN(8, 10, 2) models were created and optimized in incorporation with these metaheuristic algorithms: coati optimization algorithm (COA), gazelle optimization algorithm (GOA), incomprehensible but intelligible-in-time logics (IbIL), osprey optimization algorithm (OOA), and sooty tern optimization algorithm (STOA). Each ensemble model aimed at predicting the heating and cooling loads of a residential building. These algorithms are all novel optimizers that have not been previously regarded for this purpose. Hence, a score-based statistical comparison was performed to determine the outstanding ones. It was observed that.

- Trial-and-error efforts determined the best population size of 500, 100, 100, 500, and 400 for the COA, GOA, IbIL, OOA, and STOA algorithms, respectively.
- Referring to the obtained PPCCs >89%, all five techniques are capable of a fine prediction of thermal loads.
- Based on the final TSs of 43, 20, 39, 38, and 10 in HL prediction and 36, 20, 42, 42, and 10 in CL prediction for the STOA, OOA, IbIL, GOA, and COA, respectively, the GOA, IbIL, and STOA were found to be more promising than the COA and OOA. Therefore, the suitability of these algorithms was the pivotal finding of this research. Moreover, these three algorithms were more accurate than a loarge number of metaheuristic algorithms used in earlier studies.
- The hybrids of ANN with GOA, IbIL, and STOA algorithms are recommended for practical usage by energy and building engineers to optimize the necessary thermal loads with reference to the buildings' characteristics. A viable application in this sense can be optimizing the performance of the HVAC systems.
- Notwithstanding these findings, there were a few limitations which can be potential ideas for future studies. For instance, regarding data, this study used only one dataset and applying an external dataset would add to the generalizability of the models. Moreover, investigating the effect of feature selection (dimension reduction) can be another research line. About methodology, future studies

are recommended to compare the used algorithms with newer generations of metaheuristic algorithms to update the solution and detect the most accurate model.

Data availability

All data analyzed during this study was (can be) freely downloaded from UCI Repository [79] based on a study by Tsanas and Xifara [67]. Also, the code of the used algorithms is available upon reasonable request from the author.

CRediT authorship contribution statement

Guoqing Guo: Investigation. **Peng Liu:** Investigation. **Yuchen Zheng:** Investigation.

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.

References

[1] S. Lu, et al., Adaptive control of time delay teleoperation system with uncertain dynamics, Frontiers in Neurorobotics 16 (2022) 928863.
[2] W. Zhang, et al., Experimental study of a composite beam externally bonded with a carbon fiber-reinforced plastic plate, Journal of Building Engineering 71 (2023) 106522.
[3] T. Li, et al., You are how you use apps: user profiling based on spatiotemporal app usage behavior, ACM Transactions on Intelligent Systems and Technology 14 (4) (2023) 1–21. Article No.: 71.
[4] L. Sun, et al., The rheological performance of shear-thickening fluids based on carbon fiber and silica nanocomposite, Physics of Fluids 35 (3) (2023).
[5] Y. Himeur, et al., Next-generation energy systems for sustainable smart cities: roles of transfer learning, Sustainable Cities and Society (2022) 104059.
[6] M. Ma, et al., Comparative analysis on international construction and demolition waste management policies and laws for policy makers in China, Journal of Civil Engineering and Management 29 (2) (2023), 107–130-107–130.
[7] H. Huang, et al., Property assessment of high-performance concrete containing three types of fibers, International Journal of Concrete Structures and Materials 15 (1) (2021) 1–17.
[8] X. Liu, et al., Monitoring house vacancy dynamics in the pearl river delta region: a method based on NPP-viirs night-time light remote sensing images, Land 12 (4) (2023) 831.
[9] Q. Fu, et al., ED-DQN: An event-driven deep reinforcement learning control method for multi-zone residential buildings, Building and Environment (2023) 110546.
[10] Z. Wang, et al., Thermal evolution of chemical structure and mechanism of oil sands bitumen, Energy 244 (2022) 123190.
[11] Z. Liu, et al., Risk assessment and alleviation of regional integrated energy system considering cross-system failures, Applied Energy 350 (2023) 121714.
[12] X. Li, et al., Race to environmental sustainability: can structural change, economic expansion and natural resource consumption effect environmental sustainability? A novel dynamic ARDL simulations approach, Resources Policy 86 (2023) 104044.
[13] R. Zhao, et al., A practical simulation of carbon sink calculation for urban buildings: a case study of Zhengzhou in China, Sustainable Cities and Society 99 (2023) 104980.
[14] M. Santamouris, Innovating to zero the building sector in Europe: minimising the energy consumption, eradication of the energy poverty and mitigating the local climate change, Solar Energy 128 (2016) 61–94.
[15] A. Colmenar-Santos, et al., Solutions to reduce energy consumption in the management of large buildings, Energy and Buildings 56 (2013) 66–77.
[16] A.S. Shah, et al., A review on energy consumption optimization techniques in IoT based smart building environments, Information 10 (3) (2019) 108.
[17] A.G. Kwok, N.B. Rajkovich, Addressing climate change in comfort standards, Building and environment 45 (1) (2010) 18–22.
[18] R. Yao, B. Li, K. Steemers, Energy policy and standard for built environment in China, Renewable Energy 30 (13) (2005) 1973–1988.
[19] A. Handbook, HVAC Systems and Equipment, vol. 39, 1996 chapter.
[20] A. Afram, F. Janabi-Sharifi, Review of modeling methods for HVAC systems, Applied thermal engineering 67 (1–2) (2014) 507–519.
[21] N. Hossein Motlagh, et al., Internet of things (IoT) and the energy sector, Energies 13 (2) (2020) 494.
[22] K. Li, et al., Dynamic energy efficient task offloading and resource allocation for noma-enabled iot in smart buildings and environment, Building and Environment 226 (2022) 109513.
[23] H. Jiang, et al., An energy-efficient framework for internet of things underlaying heterogeneous small cell networks, IEEE Transactions on Mobile Computing 21 (1) (2020) 31–43.
[24] W. Gao, et al., Comprehensive preference learning and feature validity for designing energy-efficient residential buildings using machine learning paradigms, Applied Soft Computing 84 (2019) 105748.
[25] L. Pérez-Lombard, et al., A review of HVAC systems requirements in building energy regulations, Energy and buildings 43 (2–3) (2011) 255–268.
[26] L. Pérez-Lombard, J. Ortiz, C. Pout, A review on buildings energy consumption information, Energy and buildings 40 (3) (2008) 394–398.
[27] K. Amasyali, N.M. El-Gohary, A review of data-driven building energy consumption prediction studies, Renewable and Sustainable Energy Reviews 81 (2018) 1192–1205.
[28] K. Li, et al., A state of the art review on the prediction of building energy consumption using data-driven technique and evolutionary algorithms, Building Services Engineering Research and Technology 41 (1) (2020) 108–127.
[29] H.-x. Zhao, F. Magoulès, A review on the prediction of building energy consumption, Renewable and Sustainable Energy Reviews 16 (6) (2012) 3586–3592.
[30] D.A. York, C.C. Cappiello, K.H. Olson, DOE-2 Reference Manual: Version 2.1 C, Los Alamos National Laboratory, Solar Energy Group, 1984.
[31] D.B. Crawley, et al., EnergyPlus: creating a new-generation building energy simulation program, Energy and buildings 33 (4) (2001) 319–331.
[32] D. Yan, et al., DeST—an integrated building simulation toolkit Part I: fundamentals, in: Building Simulation, Springer, 2008.
[33] Z. Guo, et al., Optimal modification of heating, ventilation, and air conditioning system performances in residential buildings using the integration of metaheuristic optimization and neural computing, Energy and Buildings 214 (2020) 109866.
[34] D. Tien Bui, et al., Predicting heating and cooling loads in energy-efficient buildings using two hybrid intelligent models, Applied Sciences 9 (17) (2019) 3543.
[35] P.P. Kasaraneni, et al., Analytical enumeration of redundant data anomalies in energy consumption readings of smart buildings with a case study of darmstadt smart city in Germany, Sustainability 14 (17) (2022) 10842.
[36] Y. Ahn, B.S. Kim, Prediction of building power consumption using transfer learning-based reference building and simulation dataset, Energy and Buildings 258 (2022) 111717.
[37] A. Capozzoli, et al., Automated load pattern learning and anomaly detection for enhancing energy management in smart buildings, Energy 157 (2018) 336–352.

[38] Y. Himeur, et al., AI-big data analytics for building automation and management systems: a survey, actual challenges and future perspectives, Artificial Intelligence Review 56 (6) (2023) 4929–5021.
[39] L. Lei, et al., A dynamic anomaly detection method of building energy consumption based on data mining technology, Energy 263 (2023) 125575.
[40] Y. Himeur, et al., Artificial intelligence based anomaly detection of energy consumption in buildings: a review, current trends and new perspectives, Applied Energy 287 (2021) 116601.
[41] Y. Himeur, et al., A novel approach for detecting anomalous energy consumption based on micro-moments and deep neural networks, Cognitive Computation 12 (2020) 1381–1401.
[42] A. Copiaco, et al., An innovative deep anomaly detection of building energy consumption using energy time-series images, Engineering Applications of Artificial Intelligence 119 (2023) 105775.
[43] C. Fan, et al., A novel image-based transfer learning framework for cross-domain HVAC fault diagnosis: From multi-source data integration to knowledge sharing strategies, Energy and Buildings 262 (2022) 111995.
[44] A.N. Sayed, Y. Himeur, F. Bensaali, Deep and transfer learning for building occupancy detection: a review and comparative analysis, Engineering Applications of Artificial Intelligence 115 (2022) 105254.
[45] A.N. Sayed, Y. Himeur, F. Bensaali, From time-series to 2d images for building occupancy prediction using deep transfer learning, Engineering Applications of Artificial Intelligence 119 (2023) 105786.
[46] E. Karakolis, et al., An end-to-end approach for scalable real time Anomaly detection in smart buildings, in: 2022 13th International Conference on Information, Intelligence, Systems & Applications (IISA), IEEE, 2022.
[47] S. Ardabili, et al., Systematic review of deep learning and machine learning for building energy, Frontiers in Energy Research 10 (2022) 254.
[48] M. Khalil, et al., Machine Learning, Deep Learning and Statistical Analysis for forecasting building energy consumption—a systematic review, Engineering Applications of Artificial Intelligence 115 (2022) 105287.
[49] S. Zhang, et al., Deep transfer learning for city-scale cellular traffic generation through urban knowledge graph, in: Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, 2023.
[50] W. Zheng, et al., A deep fusion matching network semantic reasoning model, Applied Sciences 12 (7) (2022) 3416.
[51] I. Karijadi, S.-Y. Chou, A hybrid RF-LSTM based on CEEMDAN for improving the accuracy of building energy consumption prediction, Energy and Buildings 259 (2022) 111908.
[52] R. Olu-Ajayi, et al., Building energy consumption prediction for residential buildings using deep learning and other machine learning techniques, Journal of Building Engineering 45 (2022) 103406.
[53] H. Khajavi, A. Rastgoo, Improving the prediction of heating energy consumed at residential buildings using a combination of support vector regression and meta-heuristic algorithms, Energy 272 (2023) 127069.
[54] A.S. Jihad, M. Tahiri, Forecasting the heating and cooling load of residential buildings by using a learning algorithm “gradient descent”, Morocco, Case studies in thermal engineering 12 (2018) 85–93.
[55] A. Moradzadeh, et al., Performance evaluation of two machine learning techniques in heating and cooling loads forecasting of residential buildings, Applied Sciences 10 (11) (2020) 3829.
[56] S.S. Roy, et al., Forecasting heating and cooling loads of buildings: a comparative performance analysis, Journal of Ambient Intelligence and Humanized Computing 11 (2020) 1253–1264.
[57] À. Nebot, F. Mugica, Energy performance forecasting of residential buildings using fuzzy approaches, Applied Sciences 10 (2) (2020) 720.
[58] M. Gong, et al., Gradient boosting machine for predicting return temperature of district heating system: a case study for residential buildings in Tianjin, Journal of Building Engineering 27 (2020) 100950.
[59] Z. Chen, et al., Interpretable machine learning for building energy management: a state-of-the-art review, Advances in Applied Energy (2023) 100123.
[60] T. Peirelinck, et al., Transfer learning in demand response: a review of algorithms for data-efficient modelling and control, Energy and AI 7 (2022) 100126.
[61] M. Peña, et al., Decision support system to classify and optimize the energy efficiency in smart buildings: a data analytics approach, Sensors 22 (4) (2022) 1380.
[62] H. Moayedi, et al., Modification of landslide susceptibility mapping using optimized PSO-ANN technique, Engineering with Computers 35 (3) (2019) 967–984.
[63] A.M. Fallah, et al., Novel neural network optimized by electrostatic discharge algorithm for modification of buildings energy performance, Sustainability 15 (4) (2023) 2884.
[64] C. Lin, Y. Lin, A metaheuristic Hybrid of double-target multi-layer Perceptron for energy performance Analysis in residential buildings, Buildings 13 (4) (2023) 1086.
[65] H.A. Alkhazaleh, et al., Prediction of thermal energy demand using fuzzy-based models synthesized with metaheuristic algorithms, Sustainability 14 (21) (2022) 14385.
[66] N. Jahanafroozi, et al., New heuristic methods for sustainable energy performance analysis of HVAC systems, Sustainability 14 (21) (2022) 14446.
[67] A. Tsanas, A. Xifara, Accurate quantitative estimation of energy performance of residential buildings using statistical machine learning tools, Energy and Buildings 49 (2012) 560–567.
[68] F. Nejati, et al., Machine learning method based on symbiotic organism search algorithm for thermal load prediction in buildings, Buildings 13 (3) (2023) 727.
[69] Y. Gong, E.S. Zoltán, J. Gyergyák, A neural network Trained by multi-tracker optimization algorithm Applied to energy performance Estimation of residential buildings, Buildings 13 (5) (2023) 1167.
[70] Y. Peng, Y. Chen, Integrative soft computing approaches for optimizing thermal energy performance in residential buildings, Plos one 18 (9) (2023) e0290719.
[71] C. Lin, J. Wang, Metaheuristic-designed systems for simultaneous simulation of thermal loads of building, Smart Structures and Systems 29 (5) (2022) 677–691.
[72] L.T. Le, et al., A comparative study of PSO-ANN, GA-ANN, ICA-ANN, and ABC-ANN in estimating the heating load of buildings' energy efficiency for smart city planning, Applied Sciences 9 (13) (2019) 2630.
[73] H. Moayedi, H. Nguyen, L. Kok Foong, Nonlinear evolutionary swarm intelligence of grasshopper optimization algorithm and gray wolf optimization for weight adjustment of neural network, Engineering with Computers 37 (2021) 1265–1275.
[74] M. Dehghani, et al., Coati Optimization Algorithm: a new bio-inspired metaheuristic algorithm for solving optimization problems, Knowledge-Based Systems 259 (2023) 110011.
[75] J.O. Agushaka, A.E. Ezugwu, L. Abualigah, Gazelle Optimization Algorithm: a novel nature-inspired metaheuristic optimizer, Neural Computing and Applications 35 (5) (2023) 4099–4131.
[76] M. Mirrashid, H. Naderpour, Incomprehensible but Intelligible-in-time logics: theory and optimization algorithm, Knowledge-Based Systems (2023) 110305.
[77] Trojovský, P. and M. Dehghani, Osprey Optimization Algorithm: a new bio-inspired metaheuristic algorithm for solving engineering optimization problems. Frontiers in Mechanical Engineering. 8: p. 136.
[78] G. Dhiman, A. Kaur, STOA: a bio-inspired based optimization algorithm for industrial engineering problems, Engineering Applications of Artificial Intelligence 82 (2019) 148–174.
[79] http://archive.ics.uci.edu/dataset/242/energy+efficiency.
[80] S.S. Sammen, et al., Binary coati optimization algorithm-multi-kernel least square support vector machine-extreme learning machine model (BCOA-MKLSSVM-ELM): a new hybrid machine learning model for predicting reservoir water level, Water 15 (8) (2023) 1593.
[81] H.Y. Ahmed, et al., A multi-objective planning Strategy for electric vehicle charging Stations towards low carbon-oriented modern power systems, Sustainability 15 (3) (2023) 2819.
[82] E.H. Houssein, et al., Boosted sooty tern optimization algorithm for global optimization and feature selection, Expert Systems with Applications 213 (2023) 119015.

[83] J. He, et al., Enhanced sooty tern optimization algorithm using multiple search guidance strategies and multiple position update modes for solving optimization problems, Applied Intelligence 53 (6) (2023) 6763–6799.
[84] E.H. Houssein, et al., Dynamic coati optimization algorithm for biomedical classification tasks, Computers in Biology and Medicine 164 (2023) 107237.
[85] E. Baş, G. Yildizdan, Enhanced coati optimization algorithm for big data optimization problem, Neural Processing Letters (2023) 1–69.
[86] L. Abualigah, A. Diabat, R.A. Zitar, Orthogonal learning Rosenbrock's direct rotation with the gazelle optimization algorithm for global optimization, Mathematics 10 (23) (2022) 4509.
[87] D. Izci, S. Ekinci, Fractional order controller design via gazelle optimizer for efficient speed regulation of micromotors. e-Prime-Advances in Electrical Engineering, Electronics and Energy 6 (2023) 100295.
[88] F.A. Samoon, I. Hussain, S.J. Iqbal, ILA optimisation based Control for enhancing DC link Voltage with Seamless and adaptive VSC Control in a PV-BES based AC microgrid, Energies 16 (21) (2023) 7309.
[89] A.A. Ismaeel, et al., Performance of osprey optimization algorithm for solving economic load dispatch problem, Mathematics 11 (19) (2023) 4107.
[90] Y. Zhang, P. Liu, Research on reactive power optimization based on hybrid osprey optimization algorithm, Energies 16 (20) (2023) 7101.
[91] E.H. Houssein, et al., Boosted sooty tern optimization algorithm for global optimization and feature selection, Expert Systems with Applications 213 (2023) 119015.
[92] M.A. Saleem, et al., Sooty tern optimization algorithm-based deep learning model for diagnosing NSCLC tumours, Sensors 23 (4) (2023) 2147.
[93] M. Mehrabi, M. Scaioni, M. Previtali, Forecasting air quality in kiev during 2022 military conflict using sentinel 5P and optimized machine learning, IEEE Transactions on Geoscience and Remote Sensing 61 (2023), https://doi.org/10.1109/TGRS.2023.3292006.
[94] M. Mehrabi, Landslide susceptibility zonation using statistical and machine learning approaches in Northern Lecco, Italy, Natural Hazards (2021) 1–37.
[95] J.H. Holland, Genetic algorithms, Scientific american 267 (1) (1992) 66–73.
[96] E. Atashpaz-Gargari, C. Lucas, Imperialist competitive algorithm: an algorithm for optimization inspired by imperialistic competition, in: 2007 IEEE Congress on Evolutionary Computation, Ieee, 2007.
[97] Z. Bayraktar, M. Komurcu, D.H. Werner, Wind Driven Optimization (WDO): a novel nature-inspired optimization algorithm and its application to electromagnetics, in: 2010 IEEE Antennas and Propagation Society International Symposium, IEEE, 2010.
[98] S. Mirjalili, A. Lewis, The whale optimization algorithm, Advances in engineering software 95 (2016) 51–67.
[99] G. Dhiman, V. Kumar, Multi-objective spotted hyena optimizer: a Multi-objective optimization algorithm for engineering problems, Knowledge-Based Systems 150 (2018) 175–197.
[100] S. Mirjalili, et al., Salp Swarm Algorithm: a bio-inspired optimizer for engineering design problems, Advances in Engineering Software 114 (2017) 163–191.
[101] S. Saremi, S. Mirjalili, A. Lewis, Grasshopper optimisation algorithm: theory and application, Advances in Engineering Software 105 (2017) 30–47.
[102] D. Karaboga, An Idea Based on Honey Bee Swarm for Numerical Optimization, Technical report-tr06, Erciyes university, engineering faculty, computer, 2005.
[103] J. Kennedy, R. Eberhart, Particle swarm optimization, in: Proceedings of ICNN'95-International Conference on Neural Networks, 1995.
[104] X.-S. Yang, Firefly algorithm, Nature-inspired metaheuristic algorithms 20 (2008) 79–90.
[105] A.H. Kashan, A new metaheuristic for optimization: optics inspired optimization (OIO), Computers & Operations Research 55 (2015) 99–125.
[106] Q. Duan, V.K. Gupta, S. Sorooshian, Shuffled complex evolution approach for effective and efficient global minimization, Journal of optimization theory and applications 76 (3) (1993) 501–521.
[107] R.V. Rao, V.J. Savsani, D. Vakharia, Teaching–learning-based optimization: a novel method for constrained mechanical design optimization problems, Computer-Aided Design 43 (3) (2011) 303–315.
[108] Q. Askari, I. Younas, M. Saeed, Political Optimizer: a novel socio-inspired meta-heuristic for global optimization, Knowledge-based systems 195 (2020) 105709.
[109] Q. Askari, M. Saeed, I. Younas, Heap-based optimizer inspired by corporate rank hierarchy for global optimization, Expert Systems with Applications 161 (2020) 113702.
[110] F.A. Hashim, et al., Henry gas solubility optimization: a novel physics-based algorithm, Future Generation Computer Systems 101 (2019) 646–667.
[111] A.S. Eesa, A.M.A. Brifcani, Z. Orman, Cuttlefish algorithm-a novel bio-inspired optimization algorithm, International Journal of Scientific & Engineering Research 4 (9) (2013) 1978–1986.
[112] P. Civicioglu, Backtracking search optimization algorithm for numerical optimization problems, Applied Mathematics and computation 219 (15) (2013) 8121–8144.
[113] M. Khishe, M.R. Mosavi, Chimp optimization algorithm, Expert systems with applications 149 (2020) 113338.
[114] S.H.S. Moosavi, V.K. Bardsiri, Satin bowerbird optimizer: a new optimization algorithm to optimize ANFIS for software development effort estimation, Engineering Applications of Artificial Intelligence 60 (2017) 1–15.
[115] M. Elsisi, Future search algorithm for optimization, Evolutionary Intelligence 12 (1) (2019) 21–31.
[116] M.-Y. Cheng, D. Prayogo, Symbiotic organisms search: a new metaheuristic optimization algorithm, Computers & Structures 139 (2014) 98–112.
[117] A. Colorni, M. Dorigo, V. Maniezzo, Distributed optimization by ant colonies, in: Proceedings of the First European Conference on Artificial Life, 1992. Cambridge, MA.
[118] A.A. Heidari, et al., Harris Hawks optimization: Algorithm and applications, Future Generation Computer Systems 97 (2019) 849–872.
[119] G.-G. Wang, S. Deb, L.d.S. Coelho, Elephant herding optimization, in: 2015 3rd International Symposium on Computational and Business Intelligence (ISCBI), IEEE, 2015.
[120] K. Almutairi, et al., A TLBO-tuned neural Processor for predicting heating Load in residential buildings, Sustainability 14 (10) (2022) 5924.
[121] G. Zhou, et al., Employing artificial bee colony and particle swarm techniques for optimizing a neural network in prediction of heating and cooling loads of residential buildings, Journal of Cleaner Production 254 (2020) 120082. https://doi.org/10.1016/j.jclepro.2020.120082.
[122] H. Moayedi, H. Nguyen, L. Foong, Nonlinear evolutionary swarm intelligence of grasshopper optimization algorithm and gray wolf optimization for weight adjustment of neural network, Engineering with Computers 37 (2019) 1265–1275.
[123] H. Moayedi, M.A. Mu'azu, L.K. Foong, Novel swarm-based approach for predicting the cooling load of residential buildings based on social behavior of elephant herds, Energy and Buildings 206 (2020) 109579.
[124] H. Moayedi, A. Mosavi, Suggesting a stochastic fractal search paradigm in combination with artificial neural network for early prediction of cooling load in residential buildings, Energies 14 (6) (2021) 1649.
[125] D. Wu, L.K. Foong, Z. Lyu, Two neural-metaheuristic techniques based on vortex search and backtracking search algorithms for predicting the heating load of residential buildings, Engineering with Computers (2020) 1–14.
[126] B. Chegari, et al., Multi-objective optimization of building energy performance and indoor thermal comfort by combining artificial neural networks and metaheuristic algorithms, Energy and Buildings 239 (2021) 110839.
[127] S. Zheng, Z. Lyu, L.K. Foong, Early prediction of cooling load in energy-efficient buildings through novel optimizer of shuffled complex evolution, Engineering with Computers (2020) 1–15.