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A red-tailed hawk-based optimization model for undertaking energy-saving design of residential buildings

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A B S T R A C T

Energy-saving design is becoming a trending topic and top-priority over the past decades due to high energy costs, limited available resources and growing urban development. Buildings are alluded to as the major contributors of energy consumption and environmental emissions across the globe. This calls for the development of precise forecasting models of energy consumption and carbon emissions. Hence, this research paper harnesses the implementation of several contemporary metaheuristics to accurately project heating and cooling energy (HEN and CEN) in residential buildings. In this respect, black widow optimization, dandelion optimization, dingo optimization, sparrow search, and red-tailed hawk optimization are among the studied metaheuristics in this research study. The prediction accuracies of the developed models are assessed stepping on the measures of i) relative absolute error (RAE), ii) mean absolute error (MAE), iii) mean absolute percentage error (MAPE), iv) root mean squared error (RMSE) and v) Nash-Sutcliffe efficiency (NSE). It is shown that the developed red-tailed hawk optimization-based model succeeded in accomplishing the most precise results of HEN and CEN. In this context, it predicted HEN with RAE (0.201), MAE (1.838), MAPE (7.626%), RMSE (2.826), and NSE (0.921). Besides, it anticipated CEN with RAE (0.234), MAE (2.009), MAPE (7.519%), RMSE (3.246), and NSE (0.883). It can be argued that this research study could benefit architects and designers in creating more energy-efficient buildings at an early stage.

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1. Introduction

The building construction industry accounts for 35% of the total electricity consumption and 38% of the embodied carbon dioxide emissions around the globe (Pachauri & Ahn, 2023). With that in mind, it can be argued that highly energy-efficient buildings are indispensable to advance sustainable development and enhance the quality of people's lives (Aguilar et al., 2021; Le et al., 2023). In turn, accurate prediction of heating and cooling loads of these buildings is crucial to maintain energy savings and enhance indoor thermal comfort (Niza et al., 2022; Um-e-Habiba et al., 2024). In the recent years, several energy simulation software programs were exploited in the research body of work such as TRNSYS, Energy Plus, eQuest, DOE-2, ECOTECT and ESP-r (Ding et al., 2020; Sezer et al., 2023). However, these programs are over-parameterized and time-consuming (Herbinger et al., 2023; Runge & Zmeureanu, 2019).

Over the past two decades, substantial numbers of data-driven models have been reported to predict energy performance of different types of buildings (Abdelkader et al., 2022). Some research efforts dealt with energy profiles of residential buildings. (Seo et al., 2022) applied artificial neural networks (ANN), support vector regression (SVR) and multiple linear regression (MLR) to simulate the heating energy demand of old households. The authors evinced that energy demand can be determined by knowing only heating area and year of construction only. It was concluded that ANN and SVR were the highest performing models over MLR. In a second study, (Soufiane & Ahmad Nia, 2023) used ANN as a predictive tool of energy demand of dwelling in arid region. The selected input parameters were glazing type, natural ventilation schedule,

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window to wall ratio, type of external walls, among others. They demonstrated that thirteen hidden neurons and tangent activation function produced the most accurate simulation results.

(Olu-Ajayi et al., 2022) compared the accuracies of the following models in the prediction of annual energy consumption, namely random forest (RF), decision tree, ANN, MLR, deep neural network, SVR, stacking, K-nearest neighbors (KNN) and gradient boosting. The chosen input features involved number of habitable rooms, monthly average wind speed, monthly average temperature, glazed area, energy efficiencies of walls, windows, roof and lighting, etc. DNN was found to be the most accurate model while decision tree was identified as the fastest prediction model. (Lee et al., 2021) developed a DNN-based model for the prediction of heating energy stepping on some factors like building orientation, air changes per hour, type of boiler, window area, door area, floor area, roof area, wall area besides their U-values. They illustrated that the most efficient DNN was composed of five hidden layers and twenty to hidden neurons.

Other studies were concerned with energy performance of office buildings. (Momeni et al., 2024)implemented ANN to project energy consumption of ten office buildings according to their thermal characteristics. The input variables comprised areas of windows and doors, their heat transfer coefficient, external wall area, its heat transfer coefficient, roof area and its hear transfer coefficient. Their model obtained higher accuracies with correlation coefficients of 0.99 and 0.83 for the validation and testing subsets, respectively. In another study, (Roodkoly et al., 2024) looked into the performances of different architectures of machine learning (ML) models such as KNN, RF, support vector machine (SVM) and ANN. The input variables of ML models included orientation of walls with windows, window to wall ratio, type of HVAC system, and U-values of roof, windows, floors and external walls. The output variables included percentage of comfort hours, CO_2 emissions and energy consumption (primary, gas and electricity). It was suggested that ANN was the best performing ML model followed by RF with a slight margin while KNN showed the least predictive results.

A third branch of studies addressed energy consumption of educational buildings. (Faiq et al., 2023) proposed a long short-term memory-based model for forecasting daily day ahead energy consumption. They determined eight variables as input data which were wind velocity, temperature, relative humidity, rainfall duration and amount, and types of day and lockdown. The reported model attained lower values of RMSE and MAE than SVR and Gaussian process regression. Furthermore, types of day and lockdown were identified as the most important features according to Shapley additive explanation technique. (Alshibani, 2020) tested different architectures of ANN models for anticipating energy consumption of public school buildings. The authors defined some input parameters such as number of floors, number of students, age of building, number of staff, total roof area, total air-conditioned area, etc. It was pointed out the best ANN architecture was composed of hyperbolic tangent function alongside one hidden layer with three hidden neurons. It was also illustrated that high correlation levels were present between air-conditioned area and number of classrooms as well as between air-conditioned area and number of students.

A fourth multitude of studies were designed for the prediction of energy consumption of commercial buildings. (Ye & Kim, 2018) merged back propagation artificial neural network and Levenberg–Marquardt algorithm for electricity projection of Chinese shopping malls. The researchers used input features of working day, humidity, temperature, wind, and other weather traits. Their model scored lower root mean squared error and mean relative error (4.28%) than the traditional back propagation neural network (659.4). Another research endeavor was carried out by (Kim et al., 2019) to anticipate electricity consumption using Bayesian regularization neural networks. It was shown that the working day has a high influence on electricity consumption while wind speed exhibited a notable low impact. A third research effort was undertaken by (Chae et al., 2016) to simulate sub-hourly electricity consumption. In their work, they adopted an artificial neural network accompanied with Bayesian regularization to deliver day-ahead predictions of 15-minute resolution. In addition, they implemented random forest with bootstrapping to eliminate less important input features. It was manifested that time interval, relative humidity and day type sustain high implication on electricity usage.

2. Research methodology

This study evaluates the performance of red-tailed hawk (RTH) optimizers for predicting HEN and CEN in residential buildings. In particular, RTH is coupled with Elman recurrent neural network (ERNN) for optimizing its parameters and hyperparameters. RTH has been successfully implemented to solve various engineering problems in several fields of applications. Among them, there are: determination of the optimal capacities and positions of fast charging stations (Alshareef & Fathy, 2024), natural language processing (Alshahrani et al., 2023), identification of maximum power points of photovoltaic systems (Almousa et al., 2024), retrieval of parameters of lithium-ion batteries (Almutair et al., 2024), and endorsement the security of smart houses (Alruwaili et al., 2024). Experimental studies also indicated that RTH outperformed a set of highly acclaimed metaheuristics harris-hawks optimizer, gorilla troops optimizer, spider wasp optimizer, grey wolf optimizer, salp swarm optimizer and whale optimizer (Almousa et al., 2024; Almutair et al., 2024; Alshareef & Fathy, 2024; Ferahtia et al., 2023). It is also reported that RTH is characterized by its high exploration abilities, faster convergence rate, and its potential to forgo entangled local points (Alshareef & Fathy, 2024; Ferahtia et al., 2023). This research paper adopts the energy efficiency dataset created by (Tsanas & Xifara, 2012). In it, ECOTECT software was used to analyze energy

performance for several permutations of twelve different building shapes. Eight input features were used to anticipate HEN and CEN which were: i) glazing area distribution, ii) glazing area, iii) wall area, iv) roof area, v) orientation, vi) overall height, vii) surface area, and viii) relative compactness. The developed RTH-based model is tested against a recent generation of meta-heuristics encompassing black widow optimization algorithm (BWOA) (Hayyolalam & Pourhaji Kazem, 2020), dandelion optimization (DO) (Zhao et al., 2022), dingo optimization (DOA) (Bairwa et al., 2021), and sparrow search algorithm (SSA) (Xue & Shen, 2020). BWOA is a population-based algorithm that simulates the unique mating behavior of black widow spiders while DO is a nature-inspired algorithm that was derived from the seed propagation of dandelion plants. DOA draws inspiration from the foraging behavior of dingos while SSA is a swarm intelligence algorithm that emulates the hunting behavior of sparrows. A detailed explanation of RTH is found in section 3.

The performance abilities of the developed RTH-based model are tested using statistical evaluation criteria (RAE, MAE, MAPE, RMSE, and NSE) and regression plots in addition to box plots. Box plots render concise visualization of the distributions and spread of the predictions of machine learning models (minimum, maximum, median, 25th percentile, and 75th percentile) (Das & Nanduri, 2018; Elmousalami et al., 2024). As for regression plots, they measure the models' accuracy and embody how much the model's outputs are close to the actual targets (Kellouche et al., 2024; Wang et al., 2024). Furthermore, reliability analysis is carried out to measure the overall consistency of the metaheuristic-based models (Raheja et al., 2022; Seyedian et al., 2022). In essence, relative absolute error is predicated as a percentage and then compared against a predefined threshold (usually 20%). The reliability factor of a certain data instance is set to 1 if the relative absolute error is less than the threshold, and in turn, the overall reliability of a designated model is determined as the average of the reliability factors of data instances. The predictive abilities of the investigated models are then experimented capitalizing on the objective function criterion (OBJ) that houses the two statistical parameters of mean absolute error and determination coefficient for the training and testing datasets (Ahmad et al., 2024; Najafzadeh & Ghaemi, 2019). The developed discrepancy ratio (DDR) is another quantitative indicator that is applied herein to give detailed information pertaining to the distribution of errors (Noori et al., 2010; Samadi et al., 2020). If the DDR value is zero, then the forecasted value is equivalent to the observed value. However, if the DDR value is more than one, thus the forecasted value is overestimated and it is underestimated if the DDR value is less than one.

Furthermore, feature engineering is implemented to determine the most important design variables that sustain the highest influence on energy demand in residential buildings. The used feature selection algorithms comprise neighborhood component analysis (Kumar Agrawal & Chakraborty, 2023), ReliefF (Lou et al., 2024), regression tree (R_TR) (Breiman et al., 1984), boosted regression trees (BOOST_TR) (Zhang et al., 2023), and bagged regression trees (BAG_TR) (Elshaboury et al., 2024). Mean reciprocal rank is applied to gather and sort the rankings retrieved from the applied feature selection algorithms (Toochaei & Moeini, 2023).

3. Red-Tailed HAWK optimization

Red-tailed hawk algorithm is a recent bio-inspired metaheuristic that emulates the hunting actions of red-tailed hawks (Ferahtia et al., 2023). The hunting activities comprise three main stages of i) high soaring, ii) low soaring and iii) stooping and swooping. In the high soaring stage, red-tailed hawks soar high in the sky aiming to locate a better place of food availability. The mathematical expression of this stage is shown in Eq. (1).

$$\mathrm{X(t)} = \mathrm{X_{best}} + \left(\mathrm{X_{mean}} + \mathrm{X(t-1)}\right) \times \mathrm{Levy(dim)} \times \mathrm{TF(t)} \tag{1}$$

where;

$\mathrm{X(t)}$ denotes the position of red-tailed hawk at the t-th iteration. $\mathrm{X_{best}}$ is the best attained position so far. $\mathrm{X_{mean}}$ is the mean of the positions of red-tailed hawks. Levy stands for the flight distribution function of levy and it can be determined using Eq. (2) and Eq. (3). $\mathrm{TF(t)}$ signifies the transition factor distribution and it can be computed using Eq. (4).

$$\mathrm{Levy(dim)} = \mathrm{s}\frac{\mu.\sigma}{|\nu|^{\beta-1}} \tag{2}$$

$$\sigma = \left(\frac{\Gamma(1+\beta).\sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(1+\frac{\beta}{2}\right).\beta.2^{\left(1-\frac{\beta}{2}\right)}}\right) \tag{3}$$

$$\mathrm{TF(t)} = 1 + \sin\left(2.5 + \frac{\mathrm{t}}{\mathrm{T_{max}}}\right) \tag{4}$$

where S and β are constants that are usually taken as 0.01 and 1.5, respectively. dim is the dimension of the optimization problem. ν is a randomly generated number between 0 and 1. Γ stands for the gamma function. T_{max} is the maximum number of iterations. In the low soaring stage, red-tailed hawks encircle the prey by navigating lower to the ground surface in a spiral pattern. This stage can be mathematically modelled using Eq. (5) and Eq. (6).

$$X(t) = X_{best} + \big(x(t) + y(t)\big).StepSize(t) \tag{5}$$

$$StepSize(t) = X(t) - X_{mean} \tag{6}$$

where;

x(t) and y(t) are the direction coordinates and they can be expressed as per Eq. (7).

$$\begin{cases} x(t) = R(t).\sin(\theta(t)) \\ y(t) = R(t).\cos(\theta(t)) \end{cases} \begin{cases} R(t) = R_0.(r - \frac{t}{t_{max}}).rand \\ \theta(t) = A.(r - \frac{t}{T_{max}}).rand \end{cases} \begin{cases} x(t) = \frac{x(t)}{\max |x(t)|} \\ y(t) = \frac{y(t)}{\max |y(t)|} \end{cases} \tag{7}$$

where R_0 is the primary radius value within the range [0.5, 3] and A is the angle gain within the range [5, 15]. rand is a randomly generated number between 0 and 1. r is the control gain within the interval [1, 2]. The aforementioned parameters aid red-tailed hawk to fly around the prey in spiral line. In the third stage, red-tailed hawks abruptly stoop and attack their prey from the optimal position obtained in the low soaring stage. This stage is modeled using Eqs. (8-10).

$$X(t) = \alpha(t).X_{best} + x(t).StepSize1(t) + y(t).StepSize2(t) \tag{8}$$

$$StepSize1(t) = X(t) - TF(t).X_{mean} \tag{9}$$

$$StepSize2(t) = G(t).X(t) - TF(t).X_{best} \tag{10}$$

$$\alpha(t) = \sin^2(2.5 - \frac{t}{T_{max}}) \tag{11}$$

$$G(t) = 2.(1 - \frac{t}{T_{max}}) \tag{12}$$

where α is the hawk's acceleration that boosts the convergence rate and G signifies the gravity effect that minimizes the exploitation diversity when the reed-tailed hawk is approaching its prey.

4. Performance measurement

The developed red-tailed hawk-based model is validated using five evaluation indices (Coffie & Cudjoe, 2023; Uncuoglu et al., 2022; Yang et al., 2024) of 1) RAE, 2) MAE, 3) MAPE, 4) RMSE and 5) NSE. These indicators are used to examine the conformity between the predicted and actual HEN and CEN (see Equations (13)-(16)). In this regard, the most preferred models are the ones linked with the lowest RAE, MAE and MAPE besides the highest NSE.

$$RAE = \frac{\sum_{j=1}^{r}\big(EN_j - EN_A_j\big)}{\sum_{j=1}^{r}\big(EN_A_j - EN_A^-\big)} \tag{13}$$

$$MAE = \frac{\sum_{j=1}^{r}\big(EN_j - EN_A_j\big)}{r} \tag{14}$$

$$\mathrm{MAPE} = \frac{100}{\mathrm{r}} \times \sum_{\mathrm{j}=1}^{\mathrm{r}} \frac{|\mathrm{EN}_\mathrm{j} - \mathrm{EN_A}_\mathrm{j}|}{\mathrm{EN_A}_\mathrm{j}} \tag{15}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{\mathrm{j}=1}^{\mathrm{r}} \left(\mathrm{EN}_\mathrm{j} - \mathrm{EN_A}_\mathrm{j}\right)^2}{\mathrm{r}}} \tag{16}$$

$$\mathrm{NSE} = 1 - \frac{\sum_{\mathrm{j}=1}^{\mathrm{r}} \left(\mathrm{EN}_\mathrm{j} - \mathrm{EN_A}_\mathrm{j}\right)^2}{\sum_{\mathrm{j}=1}^{\mathrm{r}} \left(\mathrm{EN_A}_\mathrm{j} - \mathrm{EN_A}^{-}\right)^2} \tag{17}$$

where EN_j and $\mathrm{EN_A}_\mathrm{j}$ refer to the predicted and actual HEN/CEN of the $\mathrm{j}-\mathrm{th}$ sample. $\mathrm{EN_A}^{-}$ is the mean of the actual HEN/CEN.

5. Model implementation

The used dataset is composed of 768 observations and each case is linked with eight independent variables that affect the real-valued responses of HEN and CEN. Among these data samples, 615 samples (80% of the dataset) were identified to train the artificial intelligence models while the remaining 20% (i.e., 153 observations) was used to assess the predictive efficiencies of these models. The descriptive statistics of the input and output variables are outlined in Table 1. The utilized indicators of statistical analysis include minimum, maximum, average, median, standard deviation, mode, skewness, sample variance, standard error, range, kurtosis, coefficient of variation, and number of possible scenarios. For the purpose of guaranteeing fair comparisons of metaheuristics, the basic tuning parameters of number of search agents and number of possible iterations are set to 50 and 250, respectively. In the SSA, the population size of producers constitutes 20% of the entire population size. In the BWOA, the rate of mutation, rate of cannibalism, and rate of procreating are assumed 0.4, 0.44 and 0.6, respectively.

Table 1
Statistical analysis of the used energy efficiency dataset

Descriptive statistic	Glazing area distribution	Glazing area	Wall area	Roof area	Orientation	Overall height	Surface area	Relative compactness
Minimum	0.00	0.00	245.00	110.25	2.00	3.50	514.50	0.62
Maximum	5.00	0.40	416.50	220.50	5.00	7.00	808.50	0.98
Average	2.81	0.23	318.50	176.60	3.50	5.25	671.71	0.76
Median	3.00	0.25	318.50	183.75	3.50	5.25	673.75	0.75
Standard deviation	1.55	0.13	43.60	45.14	1.12	1.75	88.03	0.11
Mode	1	0.1	294	220.5	2	7	514.5	0.98
Skewness	-0.09	-0.06	0.53	-0.16	0.00	0.00	-0.13	0.50
Sample variance	2.41	0.02	1903.27	2039.96	1.25	3.07	7759.16	0.01
Standard error	0.06	0.00	1.57	1.63	0.04	0.06	3.18	0.00
Range	5.00	0.40	171.50	110.25	3.00	3.50	294.00	0.36
Kurtosis	-1.15	-1.33	0.12	-1.78	-1.36	-2.01	-1.06	-0.71
Coefficient of variation	55.11%	56.80%	13.69%	25.56%	31.94%	33.33%	13.11%	13.83%
Number of possible scenarios	6	4	7	4	2.00	2	12	12

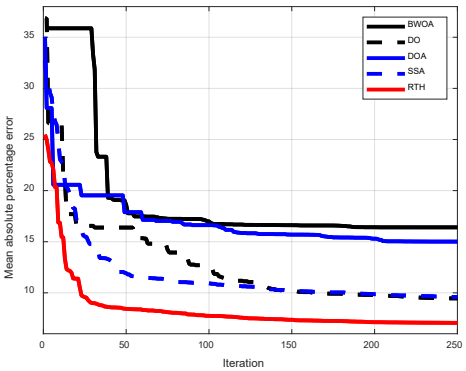

Fig. 1. Convergence curves of the hybrid ERNN models for predicting HEN

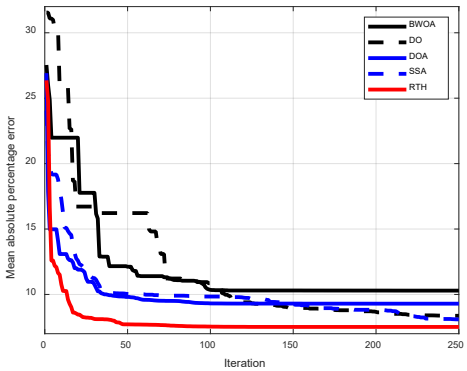

Fig. 2. Convergence curves of the hybrid ERNN models for predicting CEN

Fig. 1 shows the convergence curves of the HEN prediction models in terms of MAPE. It is noticed that ERNN-RTH has the best convergence followed by ERNN-SSA, ERNN-DO, ERNN-DOA while ERNN-BWOA has the worst convergence. The error convergence curves of the CEN prediction models are depicted in Fig. 2. The convergence paths confirm that ERNN-RTH (7.52%) has the lowest training MAPE followed by ERNN-SSA (MAPE=8.1%), ERNN-DO (MAPE=8.37%), ERNN-DOA (MAPE=9.29%), and finally ERNN-BWOA (MAPE=10.29%). Fig. 3 and Fig. 4 display visual representations of the actual and predicted HEN using the models of ERNN-RTH and ERNN-BWOA, respectively. As can be seen, they corroborate the superior performance of ERNN-RTH such that the predicted values of HEN are close to the actual ones. On the other hand, ERNN-BWOA produced predictions of HEN from the actual observations. Figures 5 and 6 depict graphical distributions of the observed and anticipated CEN using ERNN-RTH and ERNN-BWOA, respectively. It can be noted that minor differences are given between the actual and predicted CEN using ERNN-RTH. Conversely, significant variations are exhibited between the actual and forecasted CEN using ERNN-BWOA.

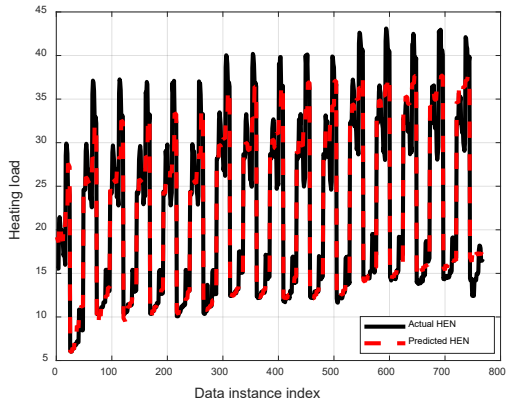

Fig. 3. Visual representation of the actual and predicted HEN using ERNN-RTH

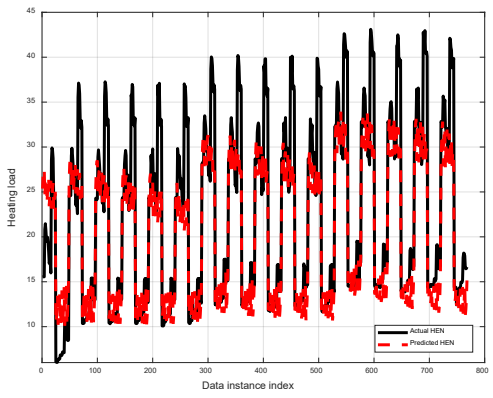

Fig. 4. Visual representation of the actual and predicted HEN using ERNN-BWOA

Table 2 displays statistical assessments of the prediction models of HEN. It can be noticed that the developed ERNN-RTH model is superior over other predictive tools. In this context, it achieved the lowest values of MAPE (7.63%), RMSE (2.83), MAE (1.84), and RAE (0.2) besides the highest value of NSE (0.92). The prediction analysis also elucidates that ERNN-DO provided acceptable results with MAPE, RMSE, MAE, RAE, and NSE of 9.39%, 2.95, 2.08, 0.23, and 0.91, respectively. On the other hand, ENN-BWOA provided the highest error estimates of HEN with MAPE, RMSE, MAE, RAE, and NSE of 16%, 5.09, 3.61, 0.39, and 0.75, respectively. Table 3 reports a comparison between the prediction models of CEN. The outcome exemplified that ENN-RTH performs better than the remainder of the models. In this respect, it obtained MAPE, RMSE, MAE, RAE, and NSE of 7.52%, 3.25, 2.01, 0.23, and 0.88, respectively. On the contrary, ERNN-BWOA attained the highest error values with MAPE, RMSE, MAE, RAE, and NSE of 9.94%, 4.21, 2.72, 0.32, and 0.8, respectively.

Table 1
Performance Indicators of the machine learning models for predicting HEN

Model	MAPE	RMSE	MAE	RAE	NSE
ERNN-BWOA	16.00%	5.09	3.61	0.39	0.75
ERNN-DO	9.39%	2.95	2.08	0.23	0.91
ERNN-DOA	15.04%	4.48	3.18	0.35	0.8
ERNN-SSA	10.44%	3.18	2.17	0.24	0.9
ERNN-RTH	7.63%	2.83	1.84	0.2	0.92

The values of OBJ criterion, reliability, and DDR of the heating energy prediction models are depicted in Table 4. It is evident that the developed ERNN-RTH has the lowest value of OBJ criterion (2.13) and the highest value of reliability (88.93%). In addition, its DDR value (0.003) is the closest to zero. This demonstrates that ERNN-RTH is the most qualified model to anticipate HEN of residential buildings. It is also manifested that ERNN-DO is the second most reliable model (87.1%) in comparison to other models meanwhile it scored the second lowest OBJ criterion (2.33) and proper DDR value (-0.004). Additionally, the predictive abilities of ENN-BWOA is the least reliable (68.36%) in forecasting HEN. Moreover, it attained the highest value of OBJ criterion (4.51) and it underestimated the observed HEN (DDR=-0.042). The values of OBJ criterion, reliability and DDR of the cooling energy prediction models are illustrated in Table 2. The developed ERNN-RTH accomplished the best values of OBJ criterion (2.24), reliability (89.19%) and DDR (-0.007). With that said, it can be argued that ERNN-RTH is the most suitable prediction model of CEN. It is also observed that ERNN-DOA (89.08%) and ERN-SSA (89.06%) are the second and third highest reliable models. Besides, it is noted that ERNN-BWOA highly underestimated CEN (DDR=-0.031) simultaneously, it had the lowest value of reliability (86.07%) and highest value of OBJ (3.18). This implicates the inability of ERNN-BWOA to project CEN of residential buildings.

Table 2
Performance Indicators of the machine learning models for predicting CEN

Model	MAPE	RMSE	MAE	RAE	NSE
ERNN-BWOA	9.94%	4.21	2.72	0.32	0.8
ERNN-DO	8.28%	3.33	2.2	0.26	0.87
ERNN-DOA	9.23%	3.7	2.48	0.29	0.85
ERNN-SSA	8.09%	3.49	2.26	0.26	0.87
ERNN-RTH	7.52%	3.25	2.01	0.23	0.88

Table 3
Performance results of OBJ criterion, reliability, and DDR of heating energy prediction models

Model	OBJ	Reliability	Average DDR
ERNN-BWOA	4.51	68.36%	-0.042
ERNN-DO	2.33	87.1%	-0.004
ERNN-DOA	3.87	75.91%	-0.03
ERNN-SSA	2.57	84.38%	0.022
ERNN-RTH	2.13	88.93%	0.003

Table 4
Performance results of OBJ criterion, reliability, and DDR of cooling energy prediction models

Model	OBJ	Reliability	Average DDR
ERNN-BWOA	3.18	86.07%	-0.031
ERNN-DO	2.49	86.85%	-0.017
ERNN-DOA	2.83	89.08%	-0.017
ERNN-SSA	2.6	89.06%	-0.026
ERNN-RTH	2.24	89.19%	-0.007

Fig. 7 and Fig. 8 represent the regression diagrams of ERNN-RTH and ERNN-BWOA (HEN prediction). It is indicated that the determination coefficients (R^2) of ERNN-RTH and ERNN-BWOA are 92.3% and 79.7%, respectively. Therefore, ERNN-RTH is more feasible in predicting HEN of residential buildings. Fig. 9 and Fig. 10 illustrate the regression plots of ERNN-RTH and ERNN-BWOA (CEN prediction). The regression analysis shows a satisfactory level of agreement between the ERNN-RTH and the actual observations. However, inaccurate predictions are experienced in the ERNN-BWOA.

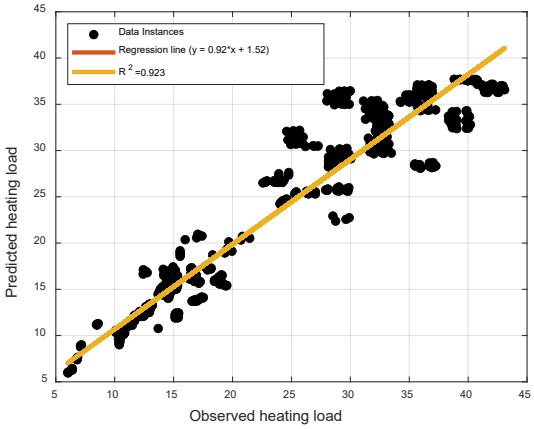

Fig. 5. Regression plot of ERNN-RTH (HEN prediction)

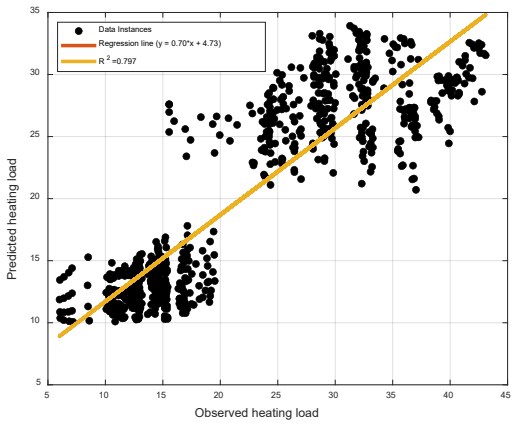

Fig. 6. Regression plot of ERNN-BWOA (HEN prediction)

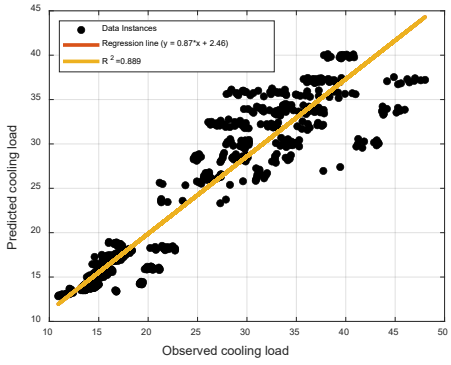

Fig. 7. Regression plot of ERNN-RTH (CEN prediction)

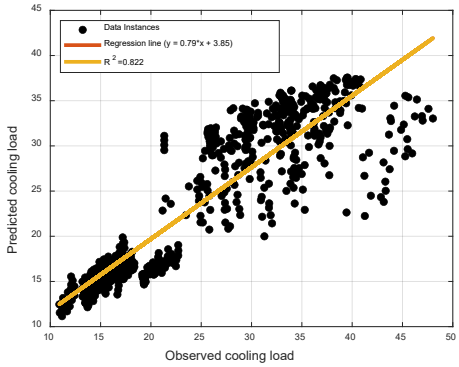

Fig. 8. Regression plot of ERNN-BWOA (CEN prediction)

Target diagrams display the performances of HEN and CEN (see Fig. 9 and Fig. 10) by plotting the values of normalized bias (y-axis) and unbiased root mean squared difference (x-axis). With that said, the most efficacious model is the nearest one to the circle's center. With regards to HEN prediction, it can be observed that ERNN-RTH (urmsd=2.807, bias=0.3228), ERNN-DO (urmsd=2.9186, bias=0.3986), and ERNN-SSA (urmsd=3.1741, bias=0.1703) are the closest modes to the reference point while ERNN-BWOA (urmsd=4.6817, bias=2.0004) is the remotest one. As for cooling loads, it is propounded that ERNN-RTH (urmsd=3.1687, bias=0.706) is the best prediction model followed by ERNN-DO (urmsd=3.2456, bias=0.7362) while ERNN-BOWA (urmsd=4.0252, bias=1.2504) is the farthest model to the reference point.

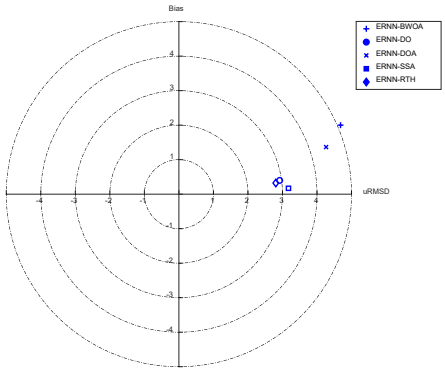

Fig. 9. Target diagram of HEN prediction models

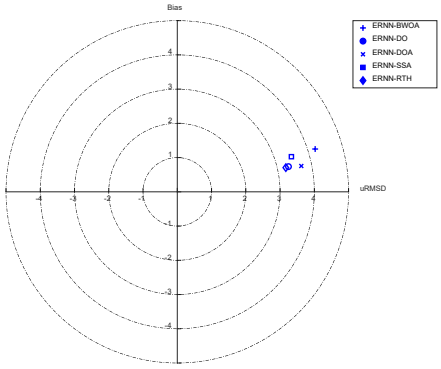

Fig. 10. Target diagram of CEN prediction models

The actual and predicted distributions of HEN are shown in Fig. 11. A clear resemblance is shown between the actual and predicted HEN by ERNN-RTH. However, ERNN-BWOA and ERNN-DOA give far distributions from the actual HEN. Box Plots of the observed and forecasted CEN are visualized in Fig. 12. It is understood that the boxes of ERR-RTH and ERNN-DOA are quite similar to the actual ones. Nonetheless, the box of ERNN-SSA is comparatively distinctive from the actual distribution.

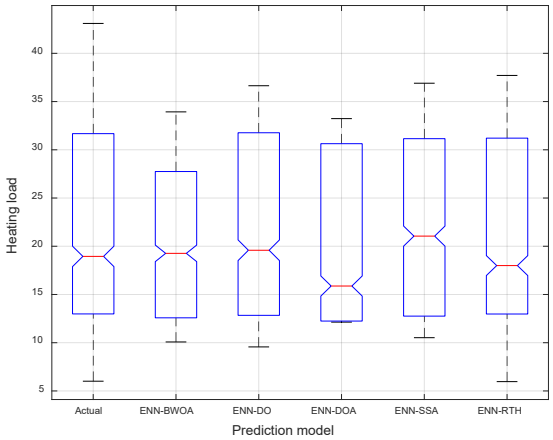

Fig. 11. Box plots of the actual and predicted HEN using hybrid ERNN models

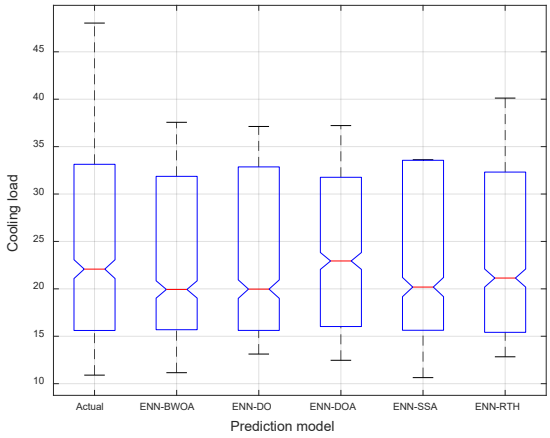

Fig. 12. Box plots of the actual and predicted CEN using hybrid ERNN models

Fig. 13 enumerates the importance ranks of different features on heating energy consumption. As can be seen, the glazing area is the most important building characteristic according to three feature selection algorithms, i.e., ReliefF, NCA and BAG_TR. In addition to that, relative compactness and roof area are found to be the most influential factors according to R_TR and BOOST_TR, respectively. Nonetheless, orientation is the least influential factor as indicated by NCA and R_TR, respectively. Fig. 14 sorts the influence of building characteristics on cooling energy consumption. It is shown that glazing areas have the highest impact on cooling energy consumption, stepping on ReliefF, NCA and BAG_TR. Moreover, R_TR and BOOST_TR identified surface area as the most impactful building characteristic on CEN. On the other hand, orientation exhibited the least influence from the perspectives of R_TR and BAG_TR. The final rankings of building characteristics are shown in Table 6. Glazing area is identified as the most contributing factor on both HEN and CEN which conforms with the findings deduced from (Tsanas & Xifara, 2012) and (Nebot & Mugica, 2020). Moreover, it is suggested that orientation and overall height sustain the lowest impacts on heating and cooling profiles, respectively. Similar conclusions were reached by (Ribeiro et al., 2020) who utilized random forest and differential evolution for carrying out feature selection.

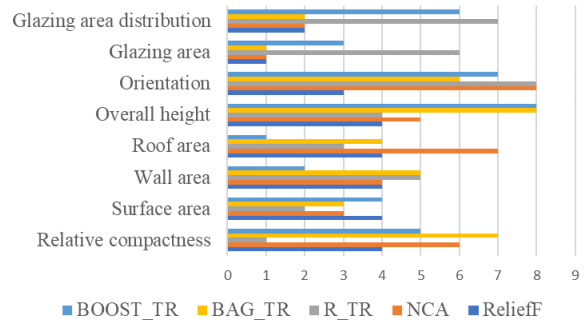

Fig. 13. Ranking the influence of building features on heating loads

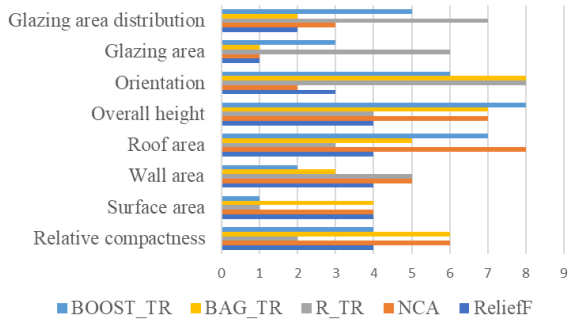

Fig. 14. Ranking the influence of building features on cooling loads

Table 5
Final rankings of building characteristics

Feature	Mean reciprocal rank (HEN)	Final rank (HEN)	Mean reciprocal rank (CEN)	Final rank (CEN)
Relative compactness	1.76	4	1.33	5
Surface area	1.67	5	2.75	2
Wall area	1.4	6	1.48	4
Roof area	1.98	2	1.05	7
Overall height	0.95	7	0.91	8
Orientation	0.89	8	1.25	6
Glazing area	3.5	1	3.5	1
Glazing area distribution	1.81	3	1.68	3

6. Conclusion

Energy performance modeling received substantial worldwide recognition in the recent two decades. Hitherto, this study paper resolves the intense issue of energy consumption by suggesting a red-tailed hawk-based solution for estimating heating and cooling patterns in residential buildings. Other various optimizers were considered such as DO, DOA, BWOA, and SSA, and the indicators of RAE, MAE, MAPE, RMSE, NSE, OBJ criterion, reliability, and average DDR were applied to evaluate the predictive performances of the applied machine learning models. Notably, the developed RNN-RTH model offered superior accuracies followed by ERNN-DO in predicting HEN and CEN in residential buildings. On the other hand, ERNN-BWOA produced the highest prediction error of HEN and CEN. It was revealed that the developed ERNN-RTH managed to improve the prediction accuracies of HEN of ERNN-BOWA, ERNN-DO, ERNN-DOA, and ERNN-SSA by 51.16%, 10.63%, 43.9% and 25.26%, respectively. In relation with CEN, the developed ERNN-RTH reduced the prediction error of ERNN-BOWA, ERNN-DO, ERNN-DOA, and ERNN-SSA by 29.38%, 14.87%, 20.56%, and 18.35%, respectively. In the light of all the results, it can be argued that the developed ERNN-RTH can stand as a promising tool in forecasting HEN and CEN in residential buildings, thereby endorsing efficient energy planning, design and conservation.

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