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ARTICLE

Studying the Implementation of State-of the Art Meta-heuristics to Boost Energy Conservation of Residential Buildings

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Abstract

Residential households consume considerable portions of energy use and CO_2 emissions. Accordingly, fast and accurate prediction of magnitudes of heating and cooling demands (HD and CD) are indispensable to facilitate delivering optimum designs of energy-efficient buildings. This research paper investigates and compares nine state-of-the-art bio-inspired meta-heuristics capitalizing on their usefulness in anticipating amounts of HD and CD in residential buildings. These meta-heuristics are coupled with Elman recurrent neural network (ERNN) to build reliable energy prediction models. They involve 1) whale optimization algorithm (WOA), 2) chimp optimization algorithm (CHOA), 3) dragonfly algorithm (DA), 4) multiverse optimization algorithm (MVO), 5) mountaineering team-based optimization algorithm (MTBO), 6) antlion optimization algorithm (MVO), 7) sine–cosine optimization algorithm (SCA), 8) gold rush optimization algorithm (GRO), and 9) dung beetle optimization algorithm (DBO). The accuracies of these models are appraised using various quantitative and visual comparisons. It is concluded that the MVO-based model is the most accurate predictive model of heating demands with MAPE (9.8%), RAE (0.249), IAE (0.102), MAE (2.275) and RRSE (0.333). It is also elucidated that the MTBO-based is the most powerful forecasting model of cooling demands with MAPE (8.56%), RAE (0.26), IAE (0.091), MAE (2.233) and RRSE (0.437). In addition, the DA-based model is the least preferred in the anticipation of HD (MAPE= 15.9%, RAE=0.401, IAE=0.164, MAE=3.665 and RRSE=0.51) and CD (MAPE= 23.17%, RAE=0.691, IAE=0.241, MAE=5.926 and RRSE=1.012). With that said, it is underlined that the reported models can usher sustainable architectural designs that can support energy conservation of residential buildings.

Keywords: Heating and cooling demands; Bio-inspired meta-heuristics; Residential buildings; Elman recurrent neural network; Multiverse optimization; Mountaineering team-based optimization

1. INTRODUCTION

Building sector accounts for approximately 39% of worldwide energy consumption and 38% of global Greenhouse gases [1-3]. Hence, saving energy consumption in buildings is quintessential to address limited energy reserves and pollution of built environment. Prediction of building energy consumption is an acclaimed topic that scholars have widely explored over the past few years. With the soaring advancements in artificial intelligence, more research endeavours are directed towards developing efficient data-driven models to anticipate building energy consumption. Amasyali and El-Gohary [4] created a deep neural network model to forecast buildings' cooling loads using weather pertaining conditions. Among the identified features, there were direct normal radiation, direct normal illuminance, dew point temperature, dry bulb temperature, wind temperature and precipitable water,

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among others. Their model was a three-layered deep neural network that accommodated Bayesian regularization with Levenberg–Marquart backpropagation algorithm. Support vector machines with Gaussian kernel function attained the lowest testing coefficient of variation (8.59%) and determination coefficient (96.36%). In the same vein, Lee et al. [5] delved into finding the optimum architecture of deep neural network in the prediction of heating consumption of old houses. In this context, eleven key input factors were defined such as orientation, region, boiler type, boiler efficiency, heat transmission coefficients of window, door and floor besides others. The optimization of deep neural network architecture was triggered by the determination coefficient, such that the highest prediction accuracies were obtained from five hidden layers and twenty-two hidden neurons.

In another study, Fu et al. [6] merged deep neural network alongside transfer reinforcement learning to ameliorate the prediction capacity of energy consumption models. In it, stack denoising autoencoder was added to map the features of energy consumption and propagate their traits between hidden layers. The output of deep neural network was then fed into deep reinforcement Sarsa algorithm to deliver the prediction task. Their model was able to yield mean absolute error, mean absolute percentage error, mean squared error and root mean squared error of 0.1153, 0.1021, 0.1304 and 0.3216, respectively. In a fourth study, Yang et al. [7] applied deep recurrent networks to anticipate energy consumption of institutional buildings. They analyzed four methods of data imputation, namely spline interpolation, ARIMA (autoregressive integrated moving average) with Kalman filter, exponential moving average and structural model with Kalman filter. It was indicated that the structural model provided the lowest RMSE and regularized deep networks could address overfitting issue sand enhance prediction performance.

Another set of research studies deployed artificial neural networks in their analysis. Moon et al. [8] performed a comparative analysis of different typologies of artificial neural networks (ANN) in forecasting electric loads of buildings. In this respect, they investigated the implication of the hyperparameters of the activation functions and hidden layers on the performance of artificial neural network. Results pinpointed that the optimum architecture of artificial neural network comprised five hidden layers with scaled exponential linear activation function. In a second research work, Dong et al. [9] exploited the use of ANN to estimate energy and cost of laminated timber office buildings in cold regions. Latin hypercube sampling was harnessed to maintain a proper uniform distribution of input parameters, and it was urged that ANN models of more than ten hidden neurons were the best-performing ones in terms of mean squared error.

Thirdly, D’Amico et al. [10] leveraged ANN to determine the environmental impacts and energy demands of non-residential buildings. Twenty-nine input variables were defined, including wind velocity, thermal capacity, window transmittance, heating hour, solar gains and internal gains, etc. They experimented three varying architectures of feedforward multi-layer perceptron. The optimal ANN model was found to be composed of two hidden layers with fifty and twenty-five neurons. Biswas et al. [11] used ANN to anticipate annual energy consumption of TxAIRE research house stepping on outdoor temperature, number of days and solar radiation. They tested the training algorithms of OWO-Newton and Levenberg-Marquardt, and they were both perceived to accomplish high determination coefficient values.

A third group of studies compared the predictive abilities of machine learning models. Olu-Ajayi et al. [12] observed the accuracies of seven prediction models, namely linear regression, support vector machine, decision tree, deep neural network, random forest, artificial neural network, K-nearest neighbor, stacking and gradient boosting. The input explanatory features incorporated total floor area, glazed area, temperature, wind speed, number of heated rooms and number of habitable rooms, etc. Deep neural network was determined to be the most efficient model achieving Pearson correlation coefficient, mean absolute error, root mean squared error and mean squared error of 0.95, 0.95, 1.19 and 1.41, respectively. On the same note, Jia et al. [13] studied the capabilities of extreme gradient boosting, artificial neural network, support vector regression and multiple linear regression in anticipating cooling loads of high-rise residential buildings. Input independent parameters comprised of dry bulb temperature, relative humidity, cooling setpoint, floor count, aspect ratio, equipment power density and window energy efficiency, etc. Results exemplified that ANN was the best meta-model, yielding the highest determination coefficient and lowest root mean squared error.

In the same vein, H. Lee et al. [14] deployed multi-layer perceptron and support vector regression to anticipate the consumption of electricity and liquefied natural gas (LNG) in food factories. The key input variables of electricity prediction included production output, operation schedules, outdoor humidity, outdoor temperature besides the previous day's electricity consumption. As for liquified natural gas, the main input parameters involved outdoor temperature, outdoor humidity, production output, previous day's pressure and temperature of LNG, previous day's consumption of LNG, and previous day's flowrate of LNG. It was underlined that multi-layer perceptron was the best-performing model in predicting electricity and LNG consumption.

Roodkoly et al. [15] deployed artificial intelligence models to predict annual primary energy, electricity, and gas consumptions alongside CO_2 emissions and percentage of comfort hours. Among the input parameters, there were U-values of roof, floor, exterior walls, and window alongside window to wall ratio, orientation, and type of HVAC (heating, ventilation, and air-conditioning) system. It was underlined that artificial neural network and random forest models were able to predict the target variables accurately while K-nearest neighbor demonstrated comparatively underperformance. On the same note, Borowski & Zwolińska [16] studied the use of artificial neural networks and support vector machine for analyzing amounts of cooling energy demand in hotels. The used input parameters involved relative humidity, occupancy level, hour, day of the week, average wind speed, speed direction, maximum wind speed, average temperature, and total hourly precipitation. Different configurations of artificial neural network and support vector machine were scrutinized, whereas the best performance scores were achieved using artificial neural network models.

In view of previous research attempts, it can be argued that there is a lack of experimentation of the synergy between machine learning models and state of art meta-heuristics to amplify energy-efficient solutions of residential buildings. Recent advancements in Elman Recurrent Neural Networks have shown promise due to their ability to capture temporal dependencies and nonlinear transformations through recurrent connections [17]. However, ERNNs are prone to suboptimal performance and local minima when hyperparameters (e.g., learning rate, hidden layer size, context layer size, and momentum coefficient) are not meticulously tuned [18,19]. To address this, meta-heuristic algorithms are adopted herein for automated hyperparameter and parameter optimization of ERNN's architecture, handling non-linear and high-dimensional energy datasets besides, which in return, can assist in providing data-driven sustainable and optimal designs that are fundamentally to optimize energy efficiency of residential buildings.

2. MODEL DEVELOPMENT

The utmost objective of this research work is to devise an efficient meta-heuristic-based model for the prediction of HD and CD in residential buildings. This research work predicates on the exploration of nine state of art meta-heuristics to enhance energy efficiency of residential buildings. In this respect, the deployed meta-heuristics to ameliorate the prediction efficiency of Elman neural network through automated tuning of its hyper parameters and parameters. Elman recurrent neural network (ERNN) is a recurrent network that was first introduced by Elman in 1990 and it is marked by its ability to precisely emulate nonlinear and cumbersome processes [17]. Over the past few years, population-based meta-heuristics established themselves as compelling tools to endorse the prediction performance of meta-models [20-24].

The dataset used to build and test the developed models is retrieved from the work published by [25]. The explored meta-heuristics herein encompass whale optimization algorithm (WOA) [26], antlion optimization algorithm (ALO) [27], dragonfly algorithm (DA) [28], multiverse optimization algorithm (MVO) [29], mountaineering team-based optimization algorithm (MTBO) [30], chimp optimization algorithm (CHOA) [31], sine–cosine optimization algorithm (SCA) [32], gold rush optimization algorithm (GRO) [33] and dung beetle optimization algorithm (DBO) [34]. The amounts of HD and CD are measured according to the input explanatory variables of orientation, overall height, wall area, roof area, surface area, relative compactness, glazing area distribution and glazing area. The efficacy of the developed meta-heuristic-based models is appraised using six statistical criteria of mean absolute percentage error, relative absolute error, integral absolute error, mean absolute error, root relative squared error, and objective criterion. Min-Max normalization is applied to transform input numerical features to a bounded interval between 0 and 1 (see Equation (1)), which diminishes the impact of feature scale variations and ensures the accuracy and stability of model training.

$$X_{\text{normalized}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

Where;

X_{min} and X_{max} denote the minimum and maximum values in the energy efficacy dataset for a specific feature.

3. MATERIALS AND METHODS

This section briefly overviews the basics and previous applications in this research paper.

3.1. Whale Optimization Algorithm

It imitates the hunting method of humpback whales [26]. This algorithm is initiated by encircling the prey, whilst the present position is assumed as the location of the target prey, and the positions of search agents are updated using position vectors and coefficient vectors. The next step involves the bubble-net attacking method, i.e., the exploitation phase, which considers the two approaches of shrinking encircling mechanism and spiral updating position. The search for prey addresses the exploration phase, whereas the position vectors are mapped according to a randomly selected search agent rather than the best one. Practical applications of WOA included damage identification of framed structures [35], design of water distribution networks [36] and annual forecasting of rainfall [37].

3.2. Antlion Optimization Algorithm

ALO is a bio-inspired algorithm that simulates the relationship between antlions and ants in a trap [27]. In this respect, ants are assumed to probe the search space and antlions are permitted to hunt them and get fitter using the traps. Random walk function that incorporates cumulative sum function, is used to emulate ants' movements. In addition, roulette wheel is adopted to mimic hunting abilities of antlions. Applications of ALO included construction site layout planning [38], structural health monitoring [39] and design of steel planar trusses [40].

3.3. Dragonfly Algorithm

DA was inspired by the dynamic and static swarming behaviours of dragonflies. There are five primary operators that control updating positions of dragonflies in a swarm [28]. They exhibit exploitative and exploratory mechanisms during the search process and they are named: 1) separation, 2) alignment, 3) cohesion, 4) foraging and 5) avoiding. This algorithm adopts Levy flight mechanism to boost exploration, exploitation and random walk of dragonflies in the search space. DA has been used in several engineering areas such as estimation of thickness of damaged zones [41], prediction of concrete compressive strength (Hu, 2023), and determination of footings bearing capacity [43].

3.4. Multiverse Optimization

MVO is a nature-inspired algorithm that uses the doctrines of cosmology: wormhole, black hole, and white hole [29]. In this regard, the operators of white hole and black hole facilitate the exploration of search space while the role of worm hole is to exploit the search space. Each solution vector in the optimization problem is regarded as a universe and each object in the universe is considered as a variable. The following rules are accommodated during the optimization process: a) higher inflation rate implicates higher probability of finding white hole and lower probability of finding black hole, b) universes of higher inflation rates tend to send objects to white holes, c) universes of lower inflation rates tend to collect objects through back holes and d) any object in the universe can perform random search towards the best universe despite its inflation rate. MVO was previously explored for structural damage identification [44] and time-cost optimization of construction projects [45].

3.5. Mountaineering Team-based Optimization

MTBO is originated from the systematized ascent of climbers to reach the mountain's peak taking into consideration the likelihood of natural calamities [30]. In it, the most skilled mountain climber is selected as the leader and guide of the team towards the global optimum point. MTBO also models natural avalanches to allow moving towards global optimization point and evading local minima entrapment. In addition, MTBO imitates the cooperation between team members to save trapped individuals in the case of occurrence of natural disasters. In the case of possible fatalities, a random new member replaces the deceased member. MTBO was proposed for energy storage optimization of microgrids 46] and addressing economic load dispatch problems [47].

3.6. Chimp Optimization

CHOA is a bio-inspired algorithm that mimics the hunting mechanism of chimps of their preys [31]. This algorithm partitions hunting into four basic stages: a) driving, b) chasing, c) blocking and d) attacking. Hence, chimps are divided into four main groups called: a) drivers, b) chasers, c) blockers, and d) attackers. In this context, chimps first pinpoint prey's location using drivers, blockers, and chasers. Afterwards, hunting is performed by the attackers chimps. Over the optimization process, drivers, chasers, blockers and attackers determine possible prey's poisiton and modify their positions from the prey. Eventually, chaotic maps are utilized to simulate social incentive of chimps in an attempt to cirumvent local minima entrapment and slow convergence rates. CHOA was deployed for the anticpation of the compressive strength of high-performance concrete [48] and vibration-based detection of structural damages [49].

3.7. Sine-cosine Optimization

SCA that is a population-based algorithm that is established based on the mathematical trigonometric functions of sine and cosine [32]. In it, different partitions of search space are explored when the values of since and cosine functions give values greater than 1 or less than -1. On the other sides, exploitation is seconded when sine and cosine functions give values between 1 and -1. Furthermore, the tradeoff between exploration and exploitation is maintained by adaptively modifying the values of sine and cosine functions. SCA was employed for tower crane selection [50], estimation of axial compressive strength of concrete-filled steel tubes [51] and design of truss sections [52].

3.8. Gold Rush Optimization

GRO is a population-based evolutionary algorithm that draws inspiration from the movements of gold prospectors [33]. Upon finding a gold mine, prospectors move to find gold such that the most lucrative gold mine is the optimal location in the search space. In the mathematical modeling of gold mining, the location of gold prospector is considered as approximate position of a gold mine. Three-person collaboration offers adaptive prospection of search region. GRO was adopted in the field of design optimization of symmetric structures [53].

3.9. Dung Beetle Optimization

DBO is a swarm intelligence-based algorithm that is derived from the social behavior of populations of dung beetles [34]. DBO models the habits of 1) ball rolling, 2) dancing, 3) foraging, 4) stealing and 5) reproduction of dung beetles. Over the ball rolling process, dung beetles aim to adopt celestial clues to sustain straight line trajectory. In addition, dung beetles tend to climb on the top of the dung ball in a dancing position when experiencing obstacles that evade them from marching forward. Boundary selection strategy is usually proposed to emulate safe spawning areas, where female dung beetles lay their eggs. DBO was implemented in photovoltaic power modeling [54], network traffic identification [55] and hazard assessment of goaf [55].

4. PERFORMANCE EVALUATION INDICATORS

This research study adopts six performance evaluation measures to gauge the accuracies of the developed heating and cooling prediction models. These measures are mean absolute percentage error, relative absolute error, integral absolute error, mean absolute error, root relative squared error, and objective criterion (see Equations (2)-(7)) [57-61].

$$\mathrm{MAPE} = \frac{100}{\mathrm{N_{tot}}}\sum_{i=1}^{n} \left| \frac{\mathrm{L_i^{Act}} - \mathrm{L_i^{Pre}}}{\mathrm{L_i^{Act}}} \right| \tag{2}$$

$$RAE = \frac{\sum_{i=1}^{n} | L_i^{Act} - L_i^{Pre} |}{\sum_{i=1}^{n} | L_i^{Act} - L^{Ave} |} \quad (3)$$

$$IAE = \frac{\sum_{i=1}^{n} | L_i^{Act} - L_i^{Pre} |}{\sum_{i=1}^{n} L_i^{Act}} \quad (4)$$

$$MAE = \frac{1}{N_{tot}} \sum_{i=1}^{n} | L_i^{Act} - L_i^{Pre} | \quad (5)$$

$$RRSE = \sqrt{\frac{\sum_{i=1}^{n} \left(L_i^{Act} - L_i^{Pre}\right)^2}{\sum_{i=1}^{n} \left(L_i^{Act} - L^{Ave}\right)^2}} \quad (6)$$

$$OBJ = \frac{(N_{tr} - N_{te})}{(N_{tot})} \times \frac{(MAE_{tr})}{(R_{tr}^2)} + \frac{(2 \times N_{test})}{(N_{tot})} \times \frac{(MAE_{te})}{(R_{te}^2)} \quad (7)$$

Where;

L_i^{Act} denotes actual heating or cooling load. L_i^{Pre} stands for heating or cooling load. L^{Ave} is the average of actual HD and CD. N_{tot} is the size of whole dataset. N_{tr} and N_{te} are the sizes of training and testing datasets, respectively. MAE_{tr} and MAE_{te} are the values of mean absolute error for the training and testing partitions, respectively. R_{tr}^2 and R_{te}^2 are the determination coefficients of training and testing subsets, respectively.

5. MODEL IMPLEMENTATION

The developed prediction models were trained and validated using the energy efficiency dataset created by [25]. The used dataset consists of 768 building configurations, whereas training and testing subsets are composed of 614 (80%) and 154 (20%) simulations, respectively. The dataset was created based on simulations of the impact of different designs on energy efficiency using ECOTECT software. The heating and cooling demands are the predicted output features, and the input predictive features are all related to the building's design and envelope, and they represent a mix of continuous and categorical data. The eight input features are (i) relative compactness, (ii) surface area, (iii) wall area, (iv) roof area, (v) overall height, (vi) orientation, (vii) glazing area, and (viii) glazing area distribution. The simulation model was set to reflect residential buildings located in Athens, Greece, assuming an occupancy of seven individuals with a sedentary lifestyle. Further, U-values (thermal transmittance) are 1.78 for the walls, 0.86 for the floors, 0.5 for the roofs, and 2.26 for the windows.

The population size and number of iterations across all meta-heuristics are set as 200 and 50, respectively. Figures 1-2 illustrate the convergence behaviours of meta-heuristics in the prediction of HD and CD. It is interpreted that ERNN-MVO (9.99%) and ERNN-ALO (10.13%) attained the lowest values of training MAPE in HD prediction. On the contrary, the highest training MAPE was associated with ERNN-MTBO (16.85%) and ERNN-DA (15.14%). In cooling demands, ERNN-MVO (8.05%) and ERNN-DBO (8.67%) exhibited the smallest training MAPE. On the other side, ERNN-DA failed to learn the significant underlying relationships, whereas its training MAPE was 21.29%. Tables (1)-(2) display performance comparisons between meta-heuristics in the prediction of HD and CD, respectively. In HD prediction, it can be observed that ERNN-MVO was able to attain the lowest values of MAPE (9.8%), RAE (0.249), IAE (0.102), MAE (2.275) and RRSE (0.333). On the other hand, ERNN-MTBO had the highest values of MAPE (17.73%), RAE (0.424), IAE (0.174), MAE (3.881) and RRSE (0.528). It is also noted that ERNN-ALO was able to attain respectable prediction performance reflected in the form of MAPE (9.93%), RAE (0.282), IAE (0.116), MAE (2.582) and RRSE (0.347). In addition to that, ERNN-MTBO wasn't able to predict HD such that it achieved MAPE, RAE, IAE, MAE, and RRSE of 17.73%, 0.424, 0.174, 3.881, and 0.528, respectively.

As for CD, ERNN-MVO provides the lowest MAPE (8.17%) while ERNN-MTBO obtains the smallest RAE (0.26), IAE (0.091), MAE (2.233) and RRSE (0.437). On the other side, ERNN-DA yields the largest MAPE (23.17%), RAE (0.691), IAE (0.241), MAE (5.926) and RRSE (1.012). It is also observed that ERNN-MTBO obtained acceptable prediction patterns with MAPE (8.56%), RAE (0.26), IAE (0.091), MAE (2.233) and RRSE (0.437), Table 3 expounds relevant scores of OBJ criterion of developed prediction models. It is shown that ERNN-MVO (2.51), ERNN-ALO (2.56) and ERNN-WOA

(2.99) had the smallest scores of OBJ criterion, which marks that ERNN-MVO is the best fitted model in HD prediction. On the flip side, ERNN-DA (5.34) and ERNN-MTBO (5.14) obtained the highest values, demonstrating their deficient performance. In relation with CD, it is viewed that the smallest values of OBJ criterion were linked with ERNN-MTBO (2.51), ERNN-DBO (2.68) and ERNN-MVO (2.69), which implies that ERNN-MTBO is the best performing model. On the other hand, ENN-DA (10.55) and ENN-SCA (4.87) instilled the largest values of OBJ criterion in CD prediction, appending them as the least preferred models.

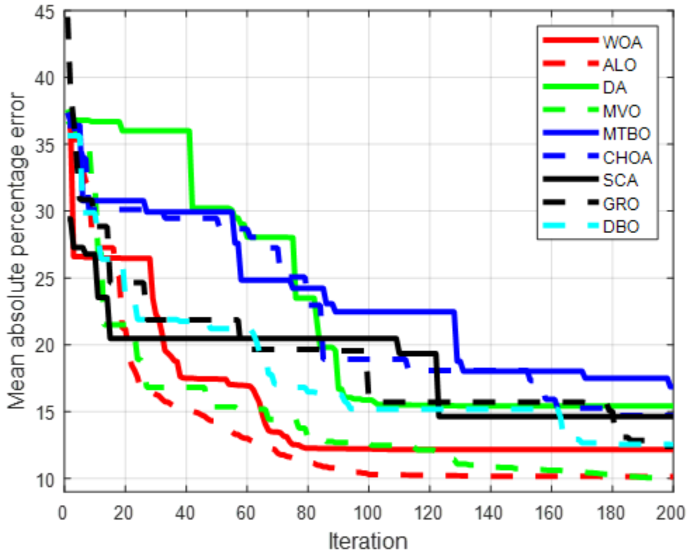

Fig. 1. Convergence behaviours of meta-heuristics in projecting HD

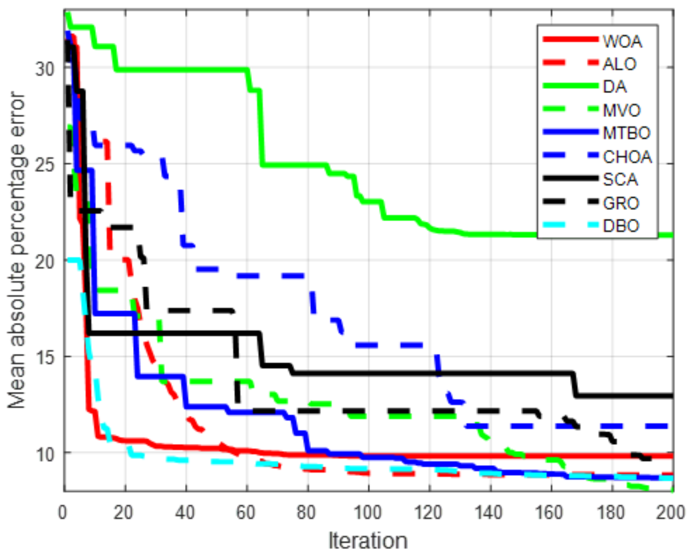

Fig. 2. Convergence behaviours of meta-heuristics in projecting CD

Table 1. Performance comparison between meta-heuristics in anticipating HD

Metric	ERNN-WOA	ERNN -ALO	ERNN-DA	ERNN-MVO	ERNN-MTBO	ERNN-CHOA	ERNN-SCA	ERNN-GRO	ERNN-DBO
MAPE	12.33%	9.93%	15.9%	9.8%	17.73%	14.62%	14.07%	12.31%	13.43%
RAE	0.282	0.249	0.401	0.249	0.424	0.361	0.339	0.326	0.342
IAE	0.116	0.102	0.164	0.102	0.174	0.148	0.139	0.133	0.14
MAE	2.582	2.279	3.665	2.275	3.881	3.299	3.102	2.977	3.123
RRSE	0.347	0.334	0.51	0.333	0.528	0.445	0.428	0.441	0.428

Table 2. Performance comparison between meta-heuristics in anticipating CD

Metric	ERNN-WOA	ERNN-ALO	ERNN-DA	ERNN-MVO	ERNN-MTBO	ERNN-CHOA	ERNN-SCA	ERNN-GRO	ERNN-DBO
MAPE	9.95%	8.99%	23.17%	8.17%	8.56%	12.47%	13.86%	10.10%	8.58%
RAE	0.307	0.28	0.691	0.264	0.26	0.379	0.447	0.291	0.275
IAE	0.107	0.098	0.241	0.092	0.091	0.132	0.156	0.101	0.096
MAE	2.635	2.406	5.926	2.261	2.233	3.253	3.831	2.492	2.362
RRSE	0.5	0.464	1.012	0.47	0.437	0.592	0.696	0.449	0.47

Table 3. Results of OBJ criterion in the anticipation of HD and CD

Model	OBJ criterion (HD)	OBJ criterion (CD)
ERNN-WOA	2.99	3.11
ERNN-ALO	2.56	2.79
ERNN-DA	5.34	10.55
ERNN-MVO	2.51	2.69
ERNN-MTBO	5.14	2.51
ERNN-CHOA	3.99	4.37
ERNN-SCA	3.51	4.87
ERNN-GRO	3.61	2.94
ERNN-DBO	3.96	2.68

Figures 3-6 demonstrate visual comparisons between some of the developed prediction models. It can be observed that the developed ERNN-ALO generated HD near to the actual ones. In addition, the forecasted CD by ERNN-MVO exhibited close proximity to the actual values. On the contrary, ERNN-CHOA and ERNN-DA obtained quite far HD and CD from the actual data.

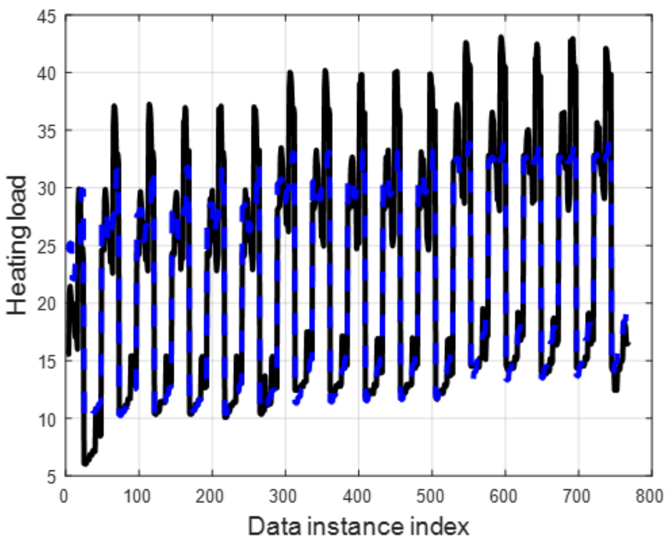

Fig. 3. Actual and predicted HD using ERNN-ALO

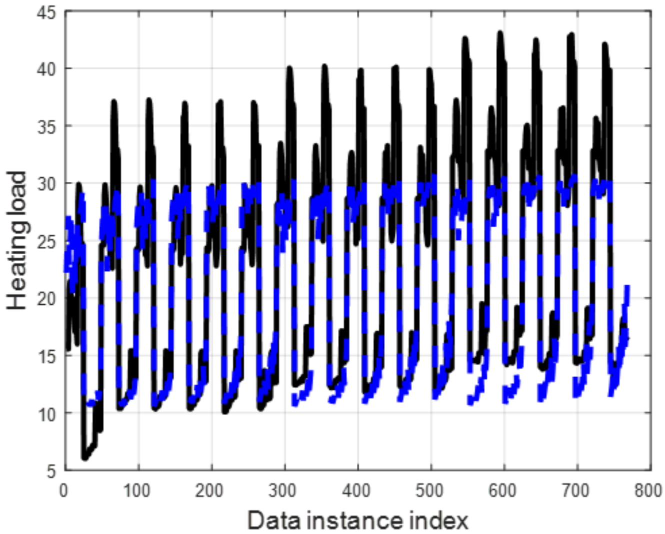

Fig. 4. Actual and predicted HD using ERNN-CHOA

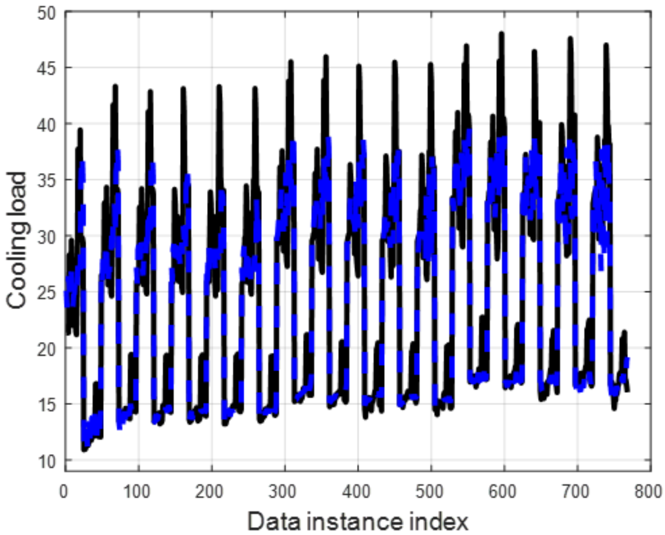

Fig. 5. Actual and predicted CD using ERNN-MVO

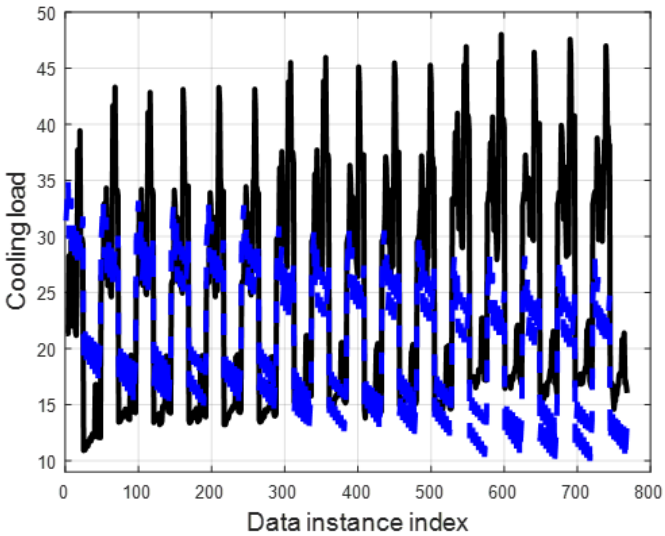

Fig. 6. Actual and predicted CD using ERNN-DA

Figures 7-10 depict correlation charts of ERNN-MVO, ERNN-DA, ERNN-MTBO and ERNN-SCA. It is shown that the predicted HD by ERNN-MVO were concordant with the real values (R^2=0.894). Furthermore, it can be said high consistencies were observed between forecasted CD by ERNN-MTBO (R^2=0.879) and their counterpart actual values.

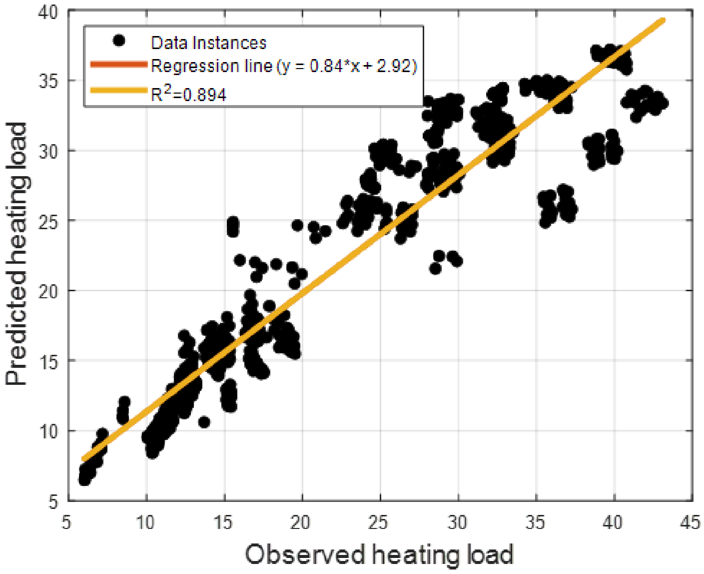

Fig. 7. Correlation analysis of HD using ERNN-MVO

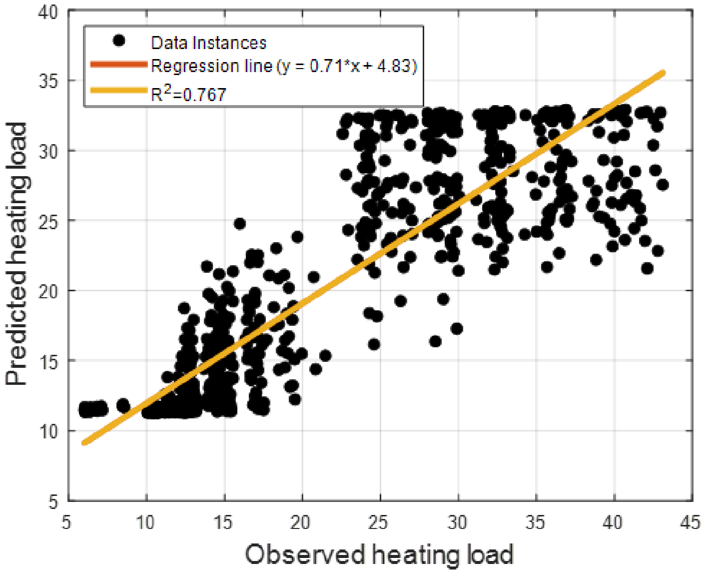

Fig. 8. Correlation analysis of HD using ERNN-DA

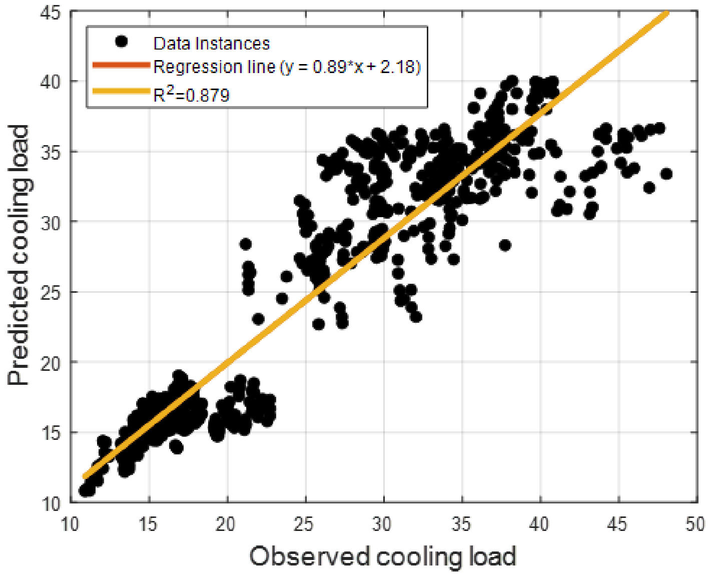

Fig. 9. Correlation analysis of CD using ERNN-MTBO

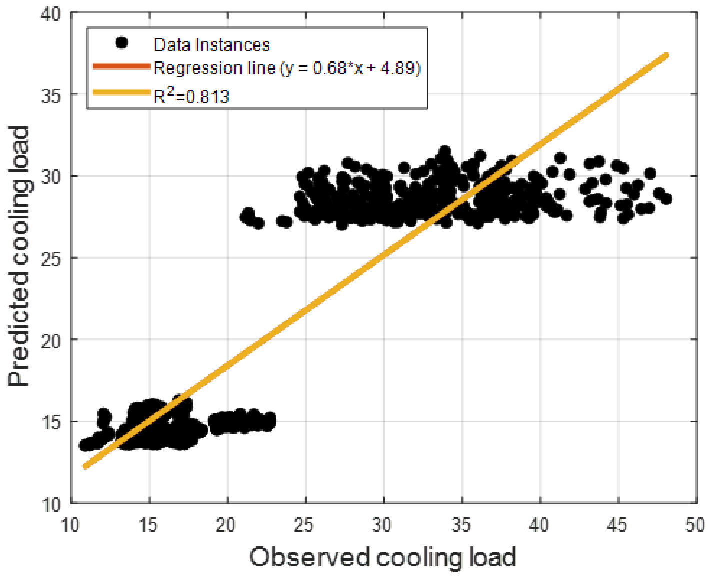

Fig. 10. Correlation analysis of CD using ERNN-SCA

Box plots of observed and predicted distributions of HD and CD are expounded in Figures 11-12. Visual comparison reveals that ERNN-MVO and ERNN-ALO are the most accurate predictive models of HD. Moreover, it is manifested that mean and spread of predicted CD by ERNN-MTBO and ERNN-MVO are pretty close to the actual values. Conversely, ERNN-DA, ERNN-CHOA and ERNN-SCA produced quite CD that are quite departed from the actual targets.

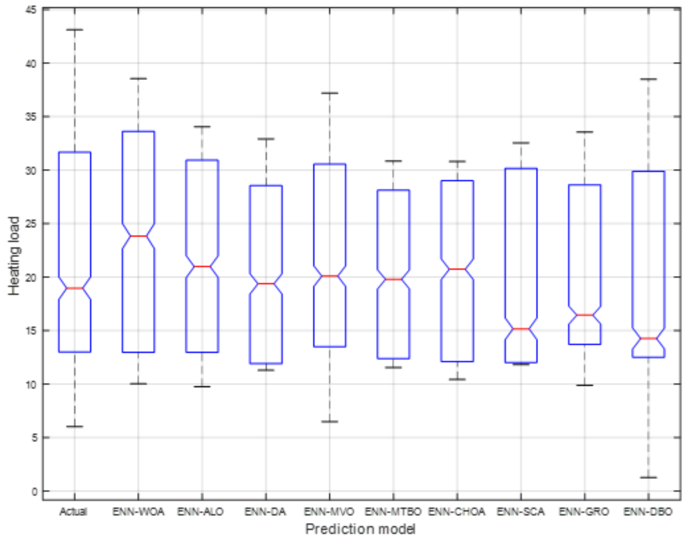

Fig. 11. Box plot analysis of HD

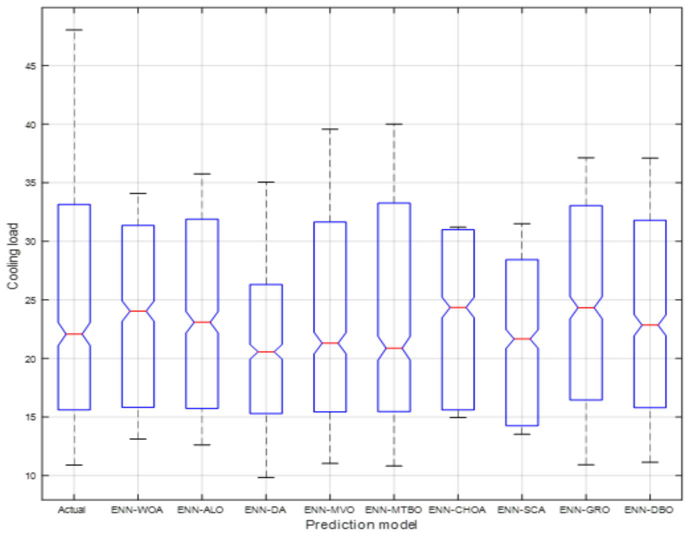

Fig. 12. Box plot analysis of CD

In light of above analysis, it is evident that MVO and MTBO demonstrate superior performance compared to other metaheuristic algorithms in terms of solution accuracy and robustness. The high accuracies of MVO in HD prediction stems from its ability to exhibit a well-tuned balance between exploration and exploitation phases. Further, it is primarily inspired by three cosmological phenomena: white holes, black holes, and wormholes [62]. These concepts are mathematically modelled to drive exploration, exploitation, and local search, respectively. In addition, MVO has fewer hyperparameters compared to some other algorithms, making it more stable across different problems [62]. Similarly, MVO demonstrated consistent dominance over other optimization algorithms (particle swarm, genetic algorithm, firefly algorithm, bat algorithm, and gravitational search algorithm) when evaluated on multimodal benchmark functions, further underscoring its effectiveness in evading local minima solutions and premature convergence [62]. MTBO's improved effectiveness in CD prediction arises from its faster convergence to global optimum solutions due to its team-based collaboration mechanism 30]. Additionally, MTBO offers enhanced population diversity, and its dynamic mechanism assists in coordinating exploratory and exploitative behaviors, which systematically aids in efficiently locating globally optimal solutions [46].

6. CONCLUSIONS

Surging escalations in energy consumption and CO_2 emissions call for designing energy-efficient buildings. With that in mind, this paper introduced a pile of meta-heuristic-based models for assessing magnitudes of HD and CD. Nine population-based meta-heuristics were experimented and compared based on statistical indicators and visual diagrams. Results explicated that ERNN-MVO (OBJ=2.51) and ERNN-ALO (OBJ=2.56) had the best performances in predicting amounts of HD while ERNN-MTBO (OBJ=5.14) and ERNN-DA (OBJ=5.34) were the least efficient models. At the level of CD, ERNN-MTBO (OBJ=2.51) and ERNN-MVO (OBJ=2.69) were able to address the issue of its accurate anticipation while ERNN-DA (OBJ=10.55) and ERNN-SCA (OBJ=4.87) failed in its emulation. The results of performance indicators complied with the outputs of OBJ criterion. In this context, the developed ERNN-MVO was found to be the best model of HD with MAPE, RAE, IAE, MAE, and RRSE of 9.8%, 0.249, 0.102, 2.275, and 0.333, respectively. Moreover, ERNN-MTBO was the most accurate prediction model of CD, whereas it yielded MAPE, RAE, IAE, MAE, and RRSE of 8.56%, 0.26, 0.091, 2.233, and 0.437 respectively. Counting on the obtained results, the developed models can assist architects in endorsing early designs of energy-efficient buildings.

Despite their promising results, the proposed meta-heuristic-based ERNN models are subject to some limitations. It is important to note that the developed models are specifically designed and validated for residential buildings. Application to commercial, institutional or industrial buildings would require architectural and operational adjustments to the input parameters of the energy prediction models. Future research may accommodate the integration of advanced meteorological data to ameliorate the robustness and efficaciousness of energy prediction models. Consequently, the selection of appropriate climatic variables, such as dry bulb temperature, solar irradiance, relative humidity, and wind speed and direction, can potentially enhance the model's accuracy for future-year energy simulations. Another potential research avenue is creating a larger and more diverse dataset encompassing a wider range of climates, architectural styles, construction materials, occupancy patterns, and HVAC system types which would be necessary to bolster the models' reliability and reduce the risk of overfitting to specific data characteristics.

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