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Article

Suggesting a stochastic fractal search paradigm in combination with artificial neural network for early prediction of cooling load in residential buildings

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Abstract: Early prediction of thermal loads plays an essential role in analyzing energy-efficient buildings' energy performance. On the other hand, stochastic algorithms have recently shown high proficiency in dealing with this issue. These are the reasons that this work is dedicated to evaluating an innovative hybrid method for predicting the cooling load (CL) in buildings with residential usage. The proposed model is a combination of artificial neural networks and stochastic fractal search (SFS-ANN). Two benchmark algorithms, namely the grasshopper optimization algorithm (GOA) and firefly algorithm (FA), are also considered to be compared with the SFS. The non-linear effect of eight independent factors on the CL is analyzed using each model's optimal structure. Evaluation of the results outlined that all three metaheuristic algorithms (with more than 90 % correlation) can adequately optimize the ANN. In this regard, this tool's prediction error declined by nearly 23, 18, and 36 % by applying the GOA, FA, and SFS techniques. Also, all used accuracy criteria indicated the superiority of the SFS over the benchmark schemes. Therefore, it is inferred that utilizing the SFS along with ANN provides a reliable hybrid model for the early prediction of CL.

Keywords: Energy-efficiency; HVAC system; Neural network; Cooling load; Metaheuristic search.

1 Introduction

Buildings, vehicles, and industry are the three primary energy consumption sectors globally [1-3]. Among those, buildings are consuming a considerable share, so that it is anticipated to reach over 30 % by 2040 [4]. On the other hand, people's high tendency to dwell in smart cities has resulted in the idea of developing energy-efficient structures [5, 6]. Therefore, accurate analysis of buildings' energy performance (EPB) is a significant step toward this objective. In energy-efficient buildings, heating load (HL) and cooling load (CL) demand

account for system energy consumption and are controlled by heating, ventilating, and air conditioning (HVAC) system [7] to provide convenient indoor air condition.
It is well established that the cost and use of energy affect human lives every day. In this sense, many issues arise from the content of energy consumption such as acid rain, dependency on depleting supplies of fossil fuels, greenhouse gas emissions [8-17], climate change [18-21], as well as environmental concerns that come along with energy power supply [22-35]. In recent years, various techniques have been used for the optimal design of the HVAC system [36-44]. Ghahramani, et al. [45], for instance, use a systematic model to optimize the performance of the HVAC system in office buildings in terms of temperature setpoints. Also, Ferreira, et al. [46] used a soft computing method for controlling the HVAC system. Implemented the proposed model led to about 50 % saving in energy consumption. The effect of façade parameters (e.g., solar reflectance and U-value) was investigated by Ihara, et al. [47], and it was deduced that solar heat gain coefficient (SHGC) could have the most significant impact on energy consumption reduction.

In this way, some drawbacks of forwarding modeling approaches (e.g., modeling in simulation packages), like large dimensions and inadequacy for occupied spaces [48], have driven engineers to employ artificial intelligence approaches for early estimation of energy [49-51]. Artificial intelligence is known as intelligence solutions demonstrated by machines, unlike the natural intelligence provided by animals and humans [52-57]. Artificial neural networks (ANN), as one of the most known AI-based solutions, have received increasing attraction recently [58-62]. More technically, deep learning-based [63-66], machine learning [67-69], decision making-based theories, feature selection-based solutions [70-72], extremer machine learning solutions [73-76], as well as hybrid searching algorithms that enhanced conventional multilayer perceptron like harris hawks optimization [77, 78], whale optimizer [79, 80], bacterial foraging optimization [81], chaos enhanced grey wolf optimization [82], moth-flame optimizer [74, 83], many-objective sizing optimization [84-89], Driven Robust Optimization [90], ant colony optimization [91], and global numerical optimization [92]. These techniques are successfully employed in different aspects such as building design [93-100], image processing/classification [101-108], sustainability, and environmental concerns [24, 109-111]. Various studies are also performed on predicting the HL and CL of residential buildings [41, 43, 44, 112-114]. Zhou, et al. [44] used an ANN and the nonlinear autoregressive with exogenous inputs (NARX) concept for accurate analysis of thermal load in an academic building. In a similar effort, Koschwitz, et al. [115] implemented an approximation of long-term urban heating load using nonlinear autoregressive exogenous recurrent neural networks (NARX RNN). Roy, et al. [116] showed a better performance of neural networks (with a variance accounted for 99.76 %) compared to other conventional methods such as gradient boosted machines.
Other predictors like adaptive neuro-fuzzy inference systems (ANFIS) have shown high robustness for dealing with EPB non-linear problems [117]. Pezeshki and Mazinani [118] concluded the superiority of ANFIS over typical fuzzy logic in buildings' thermal efficiency, as it enjoys the advantages of the ANN as well. Scholars like Naji, et al. [119] and Chou and Bui [120] have demonstrated the applicability of ANFIS and support vector-based methods. More recent studies have suggested utilizing conventional predictors with metaheuristic search schemes for various usages [43, 121]. More significantly, for energy consumption

modeling, such methods have gained high popularity. Satrio, et al. [122] found integrating ANN and multi-objective genetic algorithms a capable tool for optimizing the HVAC system. Moayedi, et al. [4] coupled an ANN with a firefly algorithm based on electromagnetism for predicting building energy consumption. The findings revealed their suggested model's superiority over conventional models like typical ANN, genetic programming, and extreme learning machine. Tien Bui, et al. [43] could reduce the HL prediction error of the ANN from 2.93 to 2.06 and 2.00 by applying the genetic algorithm and imperialist competition algorithm, respectively. This error also fell down from 3.28 to 2.09 and 2.10 for CL estimation. Particle swarm optimization (PSO) is another capable optimizer which has been widely employed for creating hybrid models [123, 124]. Goudarzi, et al. [125] also used the PSO to develop a hybrid of autoregressive integrated moving average and SVR for energy consumption modeling. Moreover, in researches by Moayedi, et al. [126] and Moayedi, et al. [127], novel metaheuristic techniques (e.g., elephant herding optimization, Harris hawks optimization, and grasshopper optimization algorithm) were applied to enhance the prediction capability of the ANN. Despite the wide use of nature-inspired metaheuristic techniques for optimizing the HVAC system, the wide variety of these techniques motivated the authors to investigate the applicability of a novel member of this family, namely stochastic fractal search in this paper. Based on our best knowledge, this algorithm has not been previously used in this field.

2 Methodology

2.1 ANN

As suggested by McCulloch and Pitts [128], the basic idea of ANNs roots in the biological neural system of humans. The structure of this model comprises several processors named neurons connected by so-called synapses "weight." As a potential advantage of this model, the ANNs tries to analyze the non-linear association of a set of input-output data by establishing a stage of mathematical relationships [129]. Figure 1 shows the structure of one of the most popular notions of ANNs, namely multi-layer perceptron (MLP). As is seen, this network is composed of one hidden layer. However, based on the problem's complexity, it can contain two or more hidden layers [130, 131].

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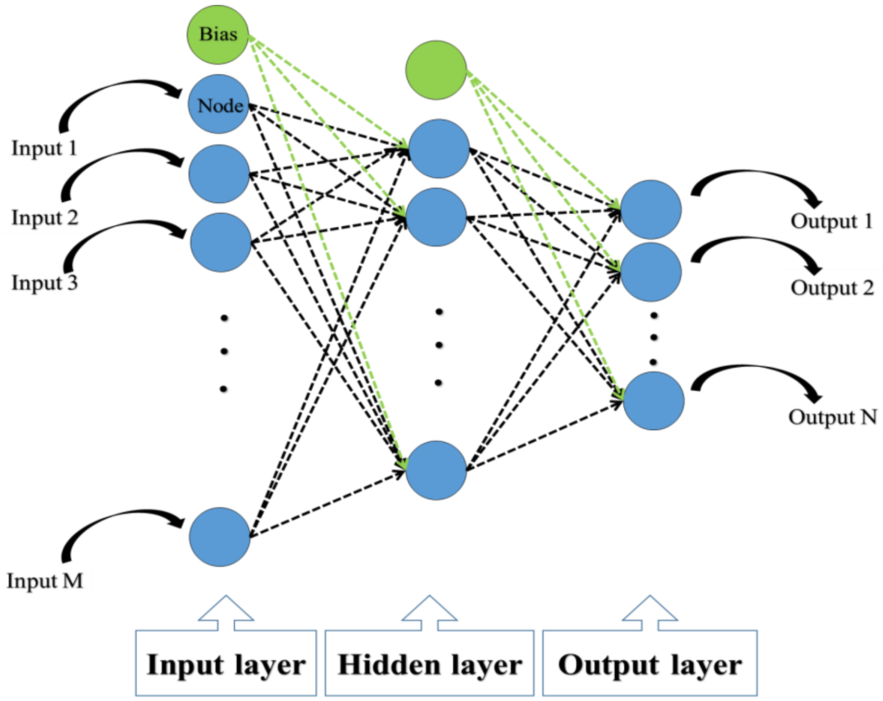

Figure 1: A three-layer MLP.

Input nodes receive the data. Each node assigns (i.e., multiplies) a specific weight factor (*W*), and the obtained value is added to a bias factor (*b*). Lastly, an activation function (*f*) is applied to the whole term to generate the proposed neuron's response. It is mathematically expressed by Equation 1:

$$O = f\left(\sum IW + b\right) \tag{1}$$

2.2 Stochastic fractal search

Proposed by Salimi [132], stochastic fractal search (SFS) is a recently-developed metaheuristic algorithm. This method is based on the fractal mathematical concept and the diffusion feature. Mosbah and El-Hawary [133] used this approach for training an ANN. The SFS draws on two major processes, namely diffusing and appraising, for handling the optimization task. The appraising process is a random manner leading to exploiting features. The diffusing stage is for exploiting features. It increases the chance of a search agent catching the global minimum and also keeps the agent from getting trapped in local solutions. It is carried out by a static diffusion procedure, which indicates that only the elite agent is taken into consideration. Therefore, other solutions (belonging to the rest of the agents) are discarded [134].

Assuming p_b and p_i, respectively, as the elite and typical agent, the Gaussian walk in the diffusion process is expressed as follows:

$$GS_1 = G\,(mn_{Bp}\,,\,\delta) + (a_1\,p_b - a_2\,p_i) \tag{2}$$

$$GS_2 = G\,(mn_p\,,\,\delta) \tag{3}$$

$$\delta = \left|\frac{\log(z)}{z}\,(p_i - p_b)\right| \quad (4)$$

in which $G\,(mn\,,\,\delta)$ indicates the Gaussian distribution function with mean mn and standard deviations δ. z shows the iteration, and two terms a_1 and a_2 are random values varying from 0 to 1. Also, mn_p and mn_{Bp} equal to p_i and p_b, respectively. More information about the SFS algorithms is detailed in similar studies like [135, 136].

2.3 Benchmark optimizers

As mentioned, the grasshopper optimization algorithm (GOA) and the firefly algorithm (FA) is used to create benchmark hybrids of ANN. Like any other algorithms, these techniques implement their certain search method to attain a globally optimal solution for a given problem [137]. As the name implies, the GOA is inspired by the herding behavior of grasshoppers in nature. It was designed by Saremi, et al. [138] in two significant steps, including exploration and exploitation. The herd members (i.e., the grasshoppers) fly to find food (Figure 2), where their swimming movement is affected by three parameters of social relationship, gravity force, and wind advection. More details about the GOA can be found in previous studies [139-141].

The FA is also a capable nature-inspired search scheme proposed by Yang [142]. The FA represents the social flashing behavior of fireflies. The intensity variation of light and attractiveness formulation are two crucial ingredients of this algorithm [143]. Three basic rules of the FA are: (i) the individuals are unisex and are attracted to each other regardless of gender, (ii) the more brightness, the higher attractiveness, and (iii) the objective function of the problem determines the brightness of a firefly. More mathematical information about the fireflies' interaction is well-explained in references like [144-146].

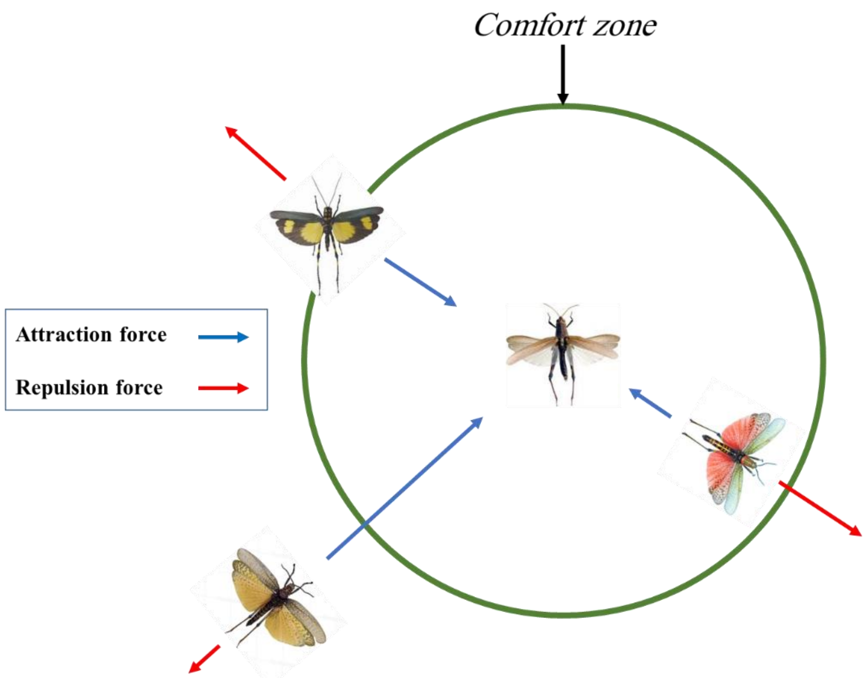

Figure 2: The primitive corrective patterns in the GOA.

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3 Data and statistical analysis

As is known, using reliable data plays an essential role in the proper development of intelligent models. In the case of this study, the information of a residential building is used. The database is produced by a computer simulation in Ecotect [147] environment. Tsanas and Xifara [148] generated it, and it is now available on http://archive.ics.uci.edu/ml/datasets/Energy+efficiency.

By analyzing 12 different buildings (with a total volume of 771.75 m^3), the HL and CL of 768 cases are collected when relative compactness (RC), surface area (SA), wall area (WA), roof area (RA), overall height (OH), orientation, glazing area (GA), and glazing area distribution (GAD) are taken as influential parameters (i.e., independent factors). The statistical description of these parameters (in terms of average value, sample variance, standard error, minimum, and maximum) are presented in Table 1. Figure 3 also illustrates the relationship between the CL and the mentioned parameters.

In order to develop the proposed models, the dataset should be divided into two parts, namely training and testing groups. In this work, it is done with respect to the broadly taken proportion of 80:20. In other words, out of all 768 data, 80 % (i.e., 614 samples) are used in the training phase for analyzing the relationship between the CL and influential parameters, and the remaining 20 % (i.e., 154 samples) are considered as testing data. This group is given to the trained networks to assess their generalization capability.

Table 1: Statistical indices to describe the input/target variable(s).

Features	Descriptive index				
	Mean	Standard Error	Sample Variance	Minimum	Maximum
Relative Compactness	0.76	0.00	0.01	0.62	0.98
Surface Area	671.71	3.18	7759.16	514.50	808.50
Wall Area	318.50	1.57	1903.27	245.00	416.50
Roof Area	176.60	1.63	2039.96	110.25	220.50
Overall Height	5.25	0.06	3.07	3.50	7.00
Orientation	3.50	0.04	1.25	2.00	5.00
Glazing Area	0.23	0.00	0.02	0.00	0.40
Glazing Area distribution	2.81	0.06	2.41	0.00	5.00
Cooling load	24.59	0.34	90.50	10.90	48.03

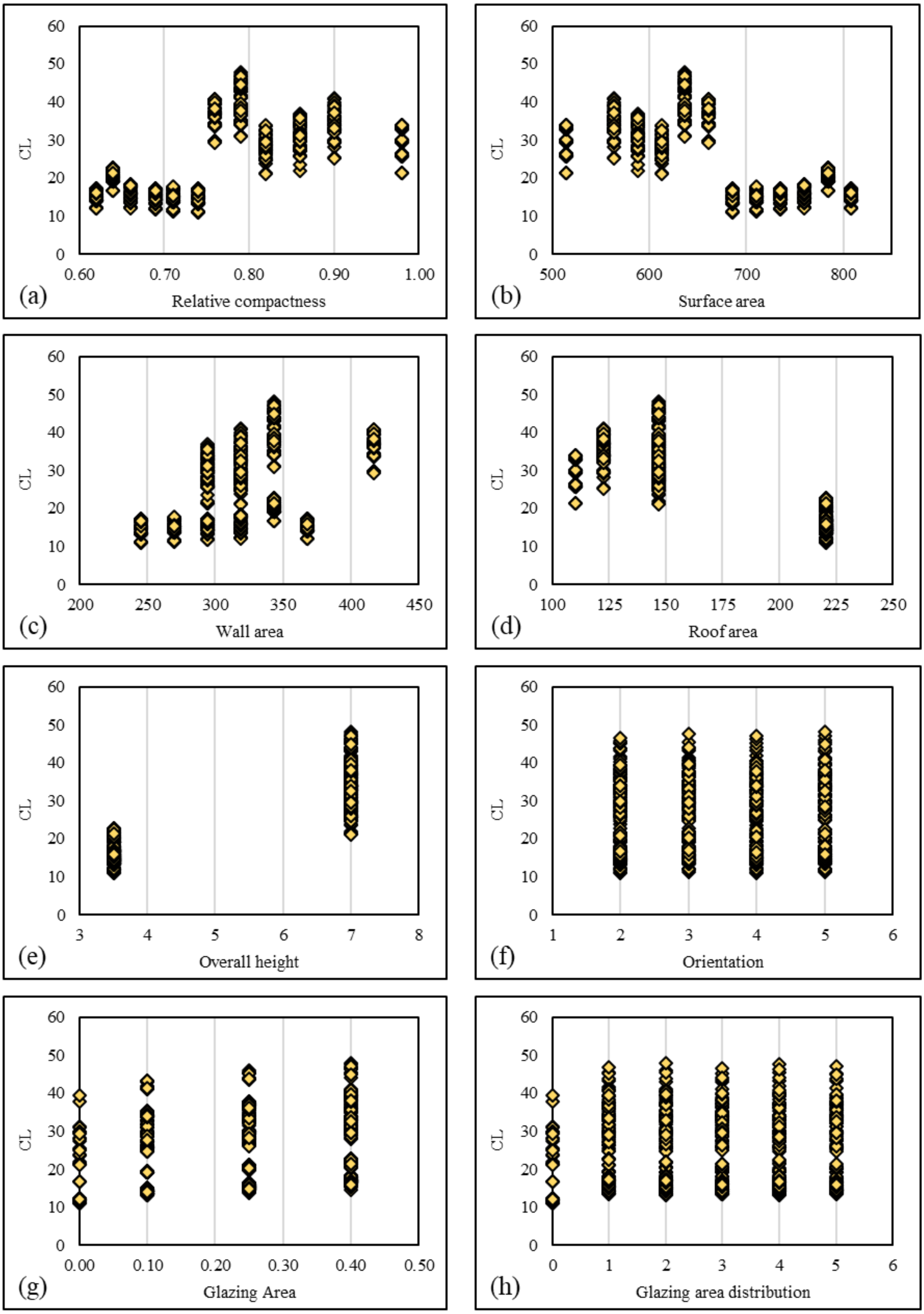

Figure 3: The obtained CL values vs. influential factors.

4 Results and discussion

This study aims to evaluate the applicability of three notions of metaheuristic algorithms, namely stochastic fractal search, grasshopper optimization algorithm, and firefly algorithm in the early estimation of cooling load in energy-efficient buildings. In this research, the algorithms are contributed to the problem through optimizing the parameters of an ANN used for estimating the CL by analyzing environmental parameters. The prediction results of the MLPNN tool, as well as the GOA-ANN, FA-ANN, and SFS-ANN ensembles, are presented and discussed in this part.

4.1 Hybridizing the MLPNN using SFS, FA, and GOA

In order to optimize an ANN using optimizer algorithms, they should be mathematically synthesized [149, 150]. But before doing this, the best structure of the ANN should be determined. To this end, the influential parameters, especially the number of hidden neurons, should be optimized. Based on previous studies, as well as the authors' experience, tangent-sigmoid (Tansig) is selected as the activation function of the ANN neurons. Then, ten different MLPNN structures (with the number of hidden neurons from 1 to 10) are tested, and it was shown that six neurons generate the most reliable hidden layer.

Next, the predictive structure of the proposed MLPNN is given the GOA, FA, and SFS algorithms to construct the hybrid models. Given the training dataset, these algorithms try to find highly optimized weights and biases to build an efficient MLPNN. A total of 1000 repetitions is considered for each algorithm to have enough convergence. For each iteration, an evaluation is carried out by means of an objective function which is set root mean square error (RMSE) in this study. The RMSE is formulated as follows:

$$RMSE = \sqrt{\frac{1}{Q}\sum_{i=1}^{Q}[(CL_{i_{observed}} - CL_{i_{predicted}})]^{2}} \tag{5}$$

where the number of involved data is shown by Q, $CL_{i\ observed}$ and $CL_{i\ predicted}$ stand for the CL values obtained by Tsanas and Xifara [148] and our intelligent models, respectively.

The size of the working population is an influential factor for the performance of the implemented ensemble models. Thus, a trial and error process is taken to ensure that the best population size is used during the optimization. Each model is implemented with nine population sizes of 10, 25, 50, 75, 100, 200, 300, 400, and 500 and the RMSE of the latest iteration is recorded as the best response. The results are shown in Figure 4- (a). As is seen, the best optimization results for the GOA, FA, and SFS algorithms with 400, 100, and 400 population sizes, respectively. The optimization curves of the mentioned structures are also shown in Figure 4 – (b), (c), and (d). These models are then used to estimate the CL.

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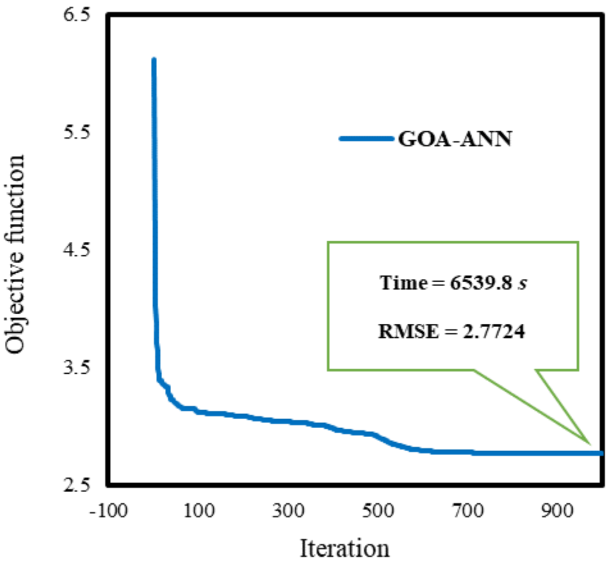

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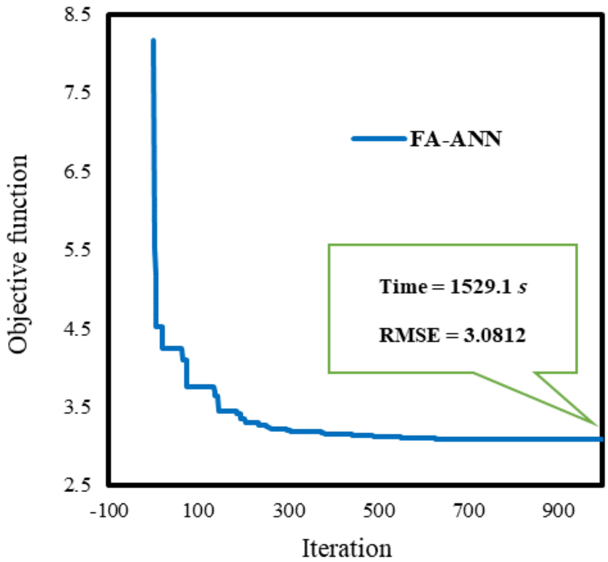

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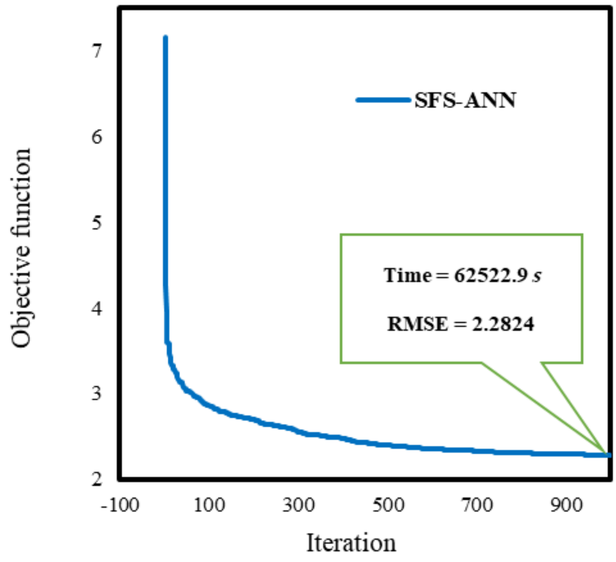

(d)

Figure 4: (a) sensitivity analysis and (b-d) best optimization curves.

4.2 Accuracy criteria

Along with the RMSE, mean absolute error (MAE) is used to report the error of prediction in both training and testing phases. Besides, the accommodation of the results is evaluated by the coefficient of determination (R^2) which varies from 0 to 1. The larger the R^2 is, the higher the regression between the results becomes. These two indices (i.e., MAE and R^2) are expressed by the Equations 6 and 7, respectively.

$$MAE = \frac{1}{Q}\sum_{I=1}^{Q}|CL_{i_{observed}} - CL_{i_{predicted}}| \tag{6}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{Q}(CL_{i_{predicted}} - CL_{i_{observed}})^2}{\sum_{i=1}^{Q}(CL_{i_{observed}} - \overline{CL}_{observed})^2} \tag{7}$$

where the average of $CL_{i\,observed}$ values are addressed by $\overline{CL}_{observed}$.

4.3 Accuracy evaluation

In the training phase, assessing the products showed a good understanding of the relationship between the CL and considered inputs for all used predictors. A comparison between the measured and predicted values of CL is also presented in Figure 5. It can be seen that the models can correctly forecast the overall CL pattern.

In addition, the used error criteria indicate a reasonable error in the learning process. In this regard, the RMSE obtained 3.3916, 2.7725, 3.0812, and 2.2824, respectively, for the MLPNN, GOA-ANN, FA-ANN, and SFS-ANN, respectively. It demonstrates nearly 18 % and 9 % accuracy enhancement by incorporating the GOA and FA, and more considerably, around 33 % by employing the SFS. Reducing the MAE values from 2.6511 to 1.8972 (by 28.44 %), 2.1468 (by 19.02 %), and 1.6272 (by 38.62 %) is another evidence for the efficacy of the applied

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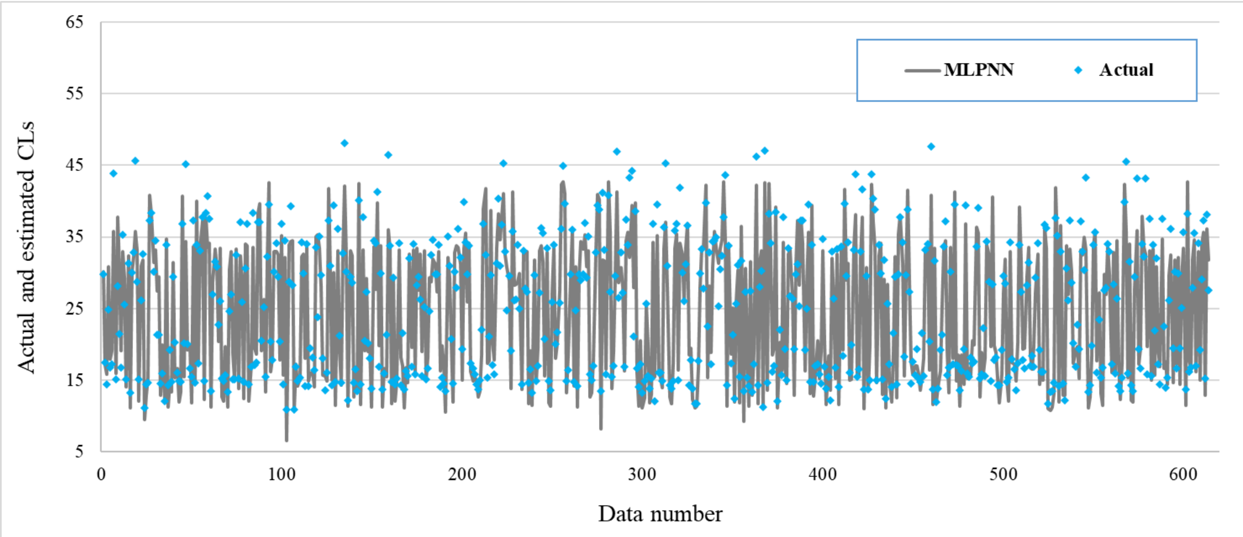
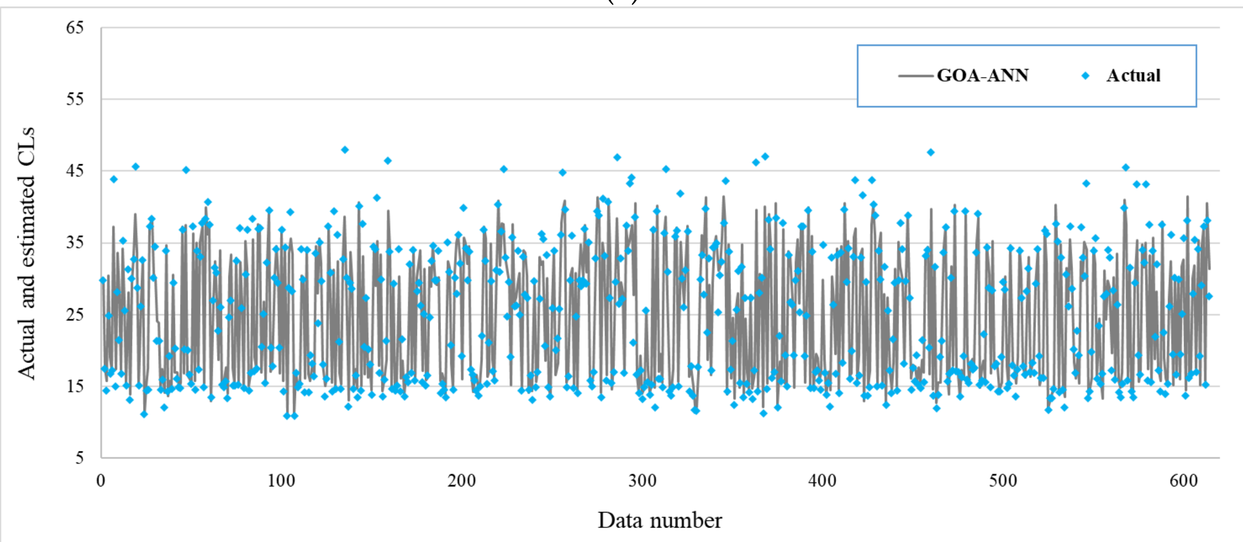
metaheuristic algorithms. Moreover, the correlation for the training results is reported by the obtained R^2s of 0.8804, 0.9156, 0.8957, and 0.9428.



(a)



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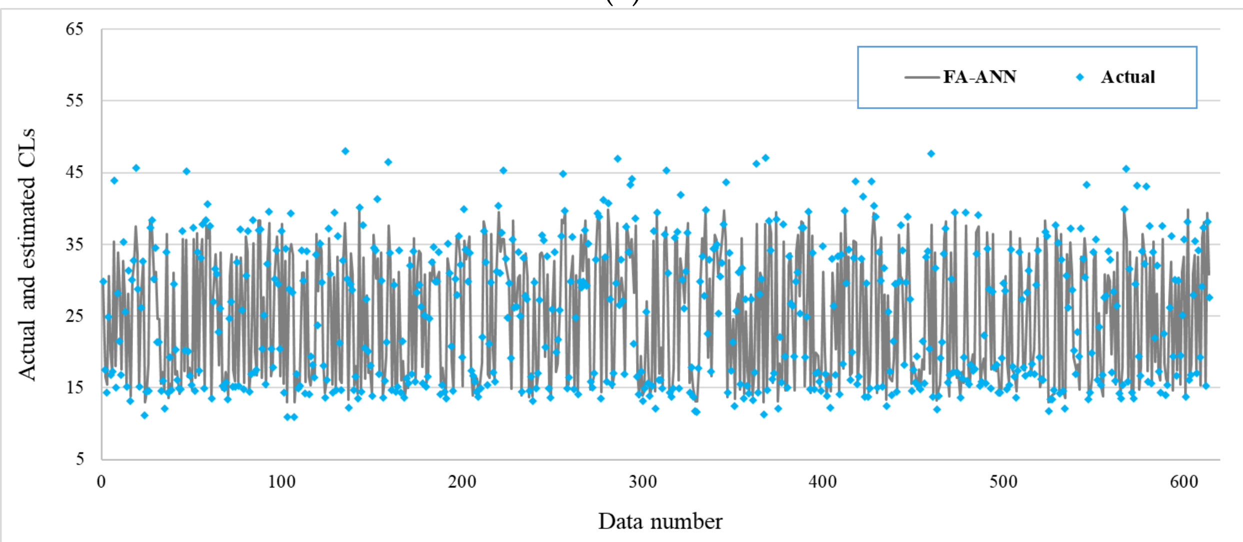

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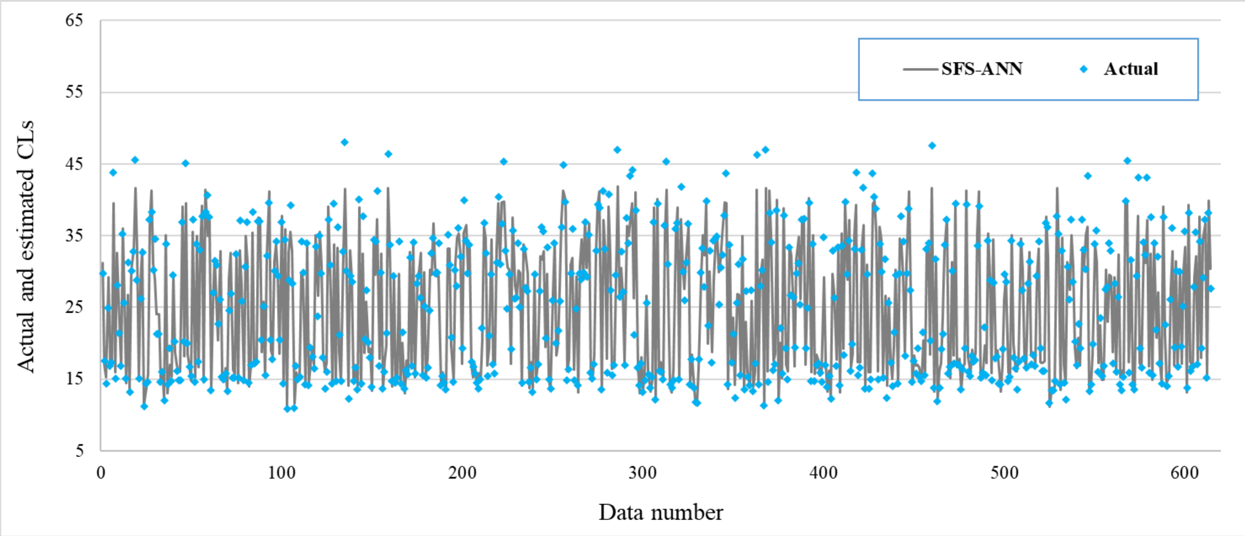


(d)

Figure 5: The measured CLs versus those predicted by (a) MLPNN, (b) GOA-ANN, (c) FA-ANN, and (d) SFS-ANN models.

Figure 6 illustrates the regression chart for the testing data. According to this figure, the correlation of the MLPNN results grew from 88 % to over 90 % after functioning all three metaheuristic algorithms. It is also shown that with an R^2 of 0.9401, the SFS-ANN produced the most consistent outputs, followed by the GOA-ANN with 0.9123 and FA-ANN with 0.9006.

A comparison between the estimated values for the largest and lowest CLs highlights the capability of the models better (Table 2).

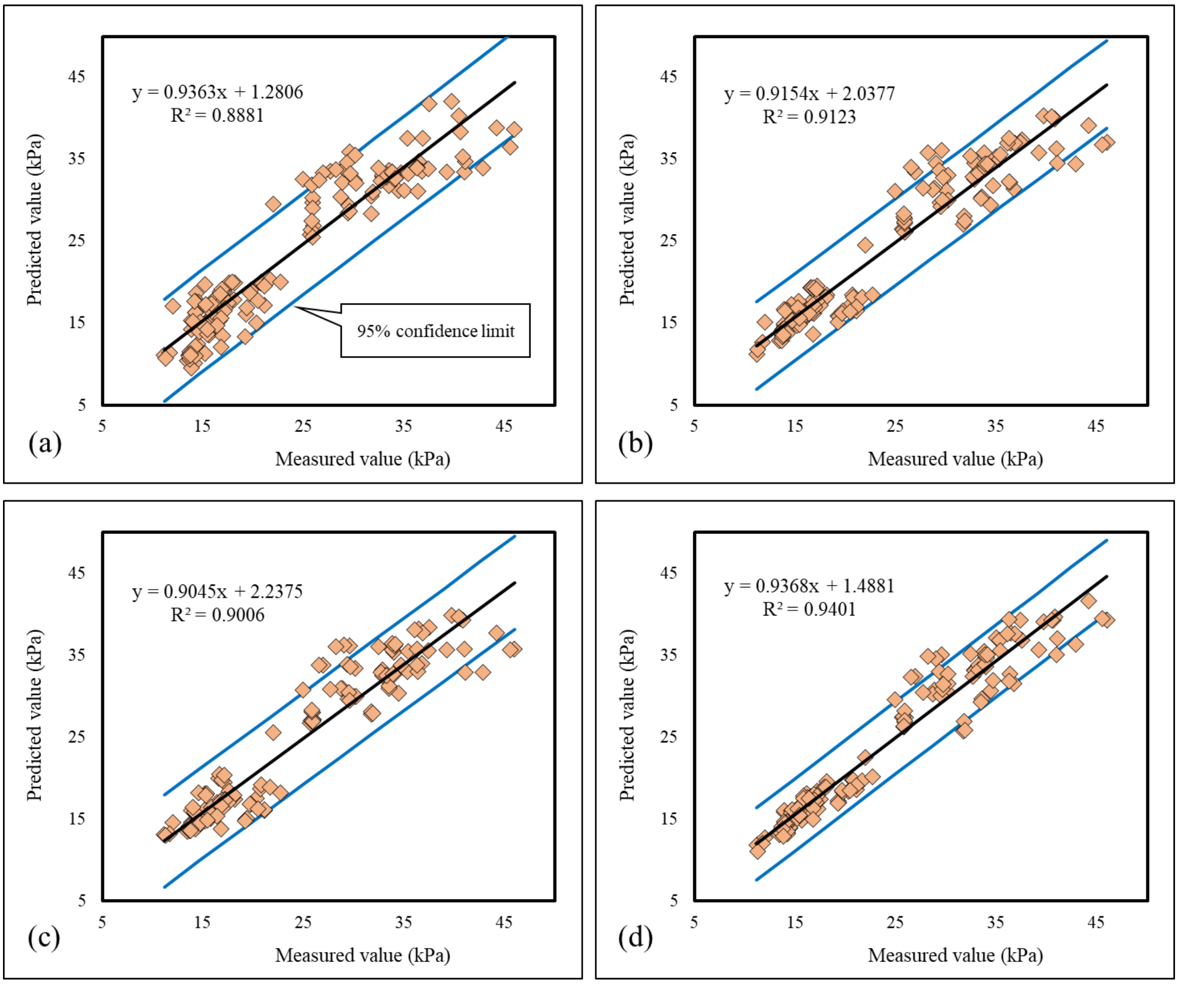
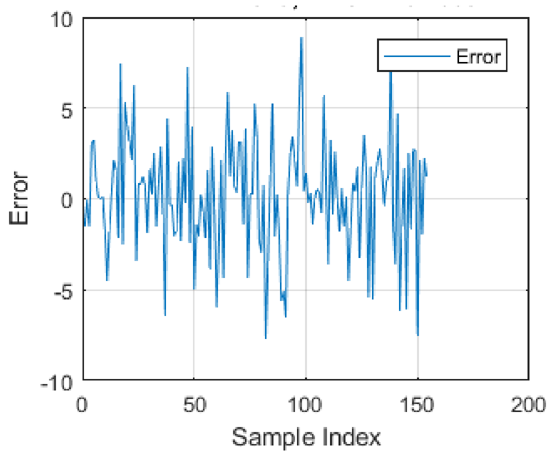


Figure 6: The consistency of the measured CLs with those predicted by (a) MLPNN, (b) GOA-ANN, (c) FA-ANN, and (d) SFS-ANN models in the testing phase.

Table 2: Relative errors for predicting 5 maximum/minimum CL values.

	Measured values	Predicted values				Error (%)			
		MLPNN	GOA-ANN	FA-ANN	SFS-ANN	MLPNN	GOA-ANN	FA-ANN	SFS-ANN
Minimum	11.17	11.07	11.22	13.08	11.82	0.93	0.45	17.14	5.80
	11.27	10.73	11.82	12.96	11.07	4.77	4.92	14.97	1.78
	11.73	11.41	12.67	13.14	12.01	2.70	8.04	12.03	2.40
	12.04	17.11	15.12	14.60	12.65	42.15	25.58	21.28	5.09
	13.43	10.39	12.89	13.52	13.13	22.65	4.03	0.68	2.20
Maximum	41.07	34.85	34.66	32.89	36.96	15.13	15.60	19.91	10.00
	42.86	34.04	34.51	32.83	36.32	20.59	19.49	23.39	15.26
	44.18	38.95	39.27	37.72	41.58	11.83	11.12	14.63	5.89
	45.52	36.61	36.89	35.61	39.45	19.57	18.96	21.77	13.32
	45.97	38.77	37.14	35.72	39.20	15.67	19.21	22.30	14.72

Moreover, the evaluation of the accuracy is done by measuring the error of testing data. In this sense, Figure 7 - (a) to (h) depicts the calculated error (= measured CL – predicted CL) for each sample, along with the histogram them showing the frequency of errors in specific ranges. The calculated RMSEs of 3.1663, 2.7628, 2.9411, and 2.2828 indicate around 12.74 %, 7.11 %, and 27.90 % reduction in generalization error of ANN by using the GOA, FA, and SFS techniques, respectively. As for MAE, these values are 22.89 %, 17.54 %, and 35.56 %, as the mean absolute error fell down from 2.4575 to 1.8951, 2.0265, and 1.5836.



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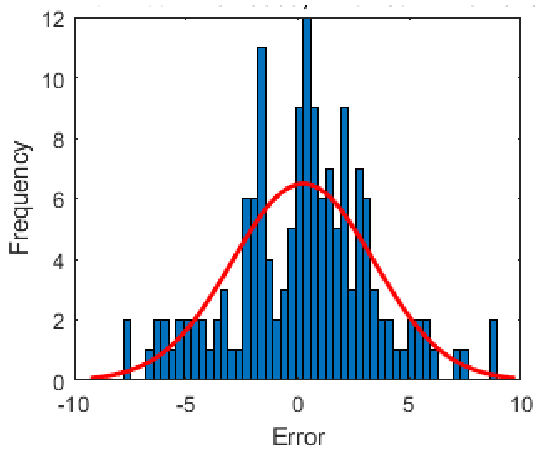

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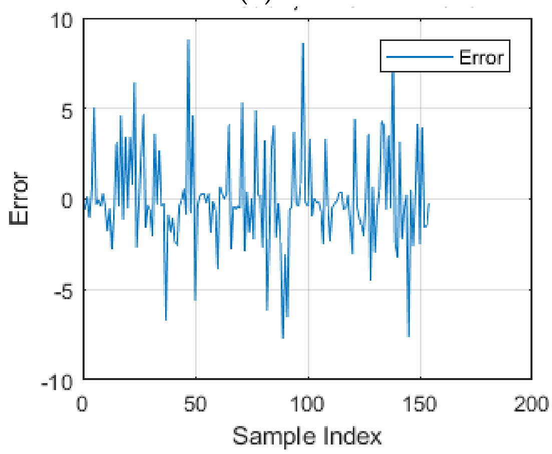

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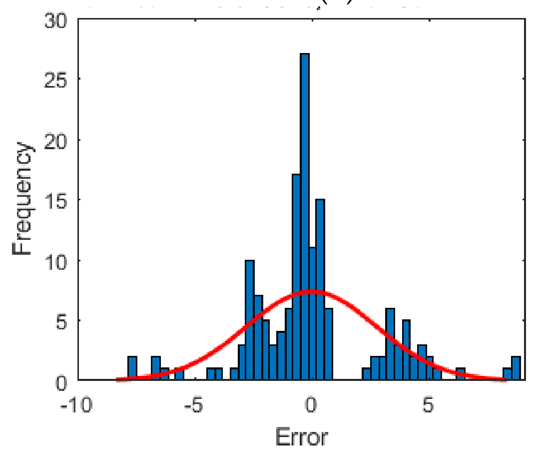

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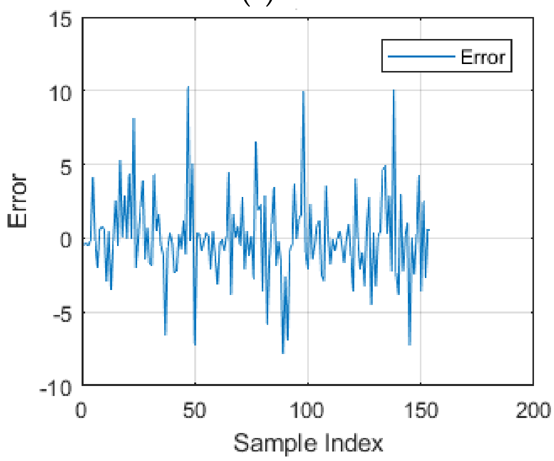

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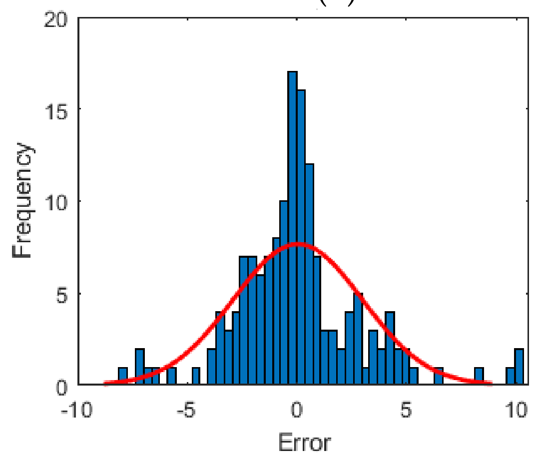

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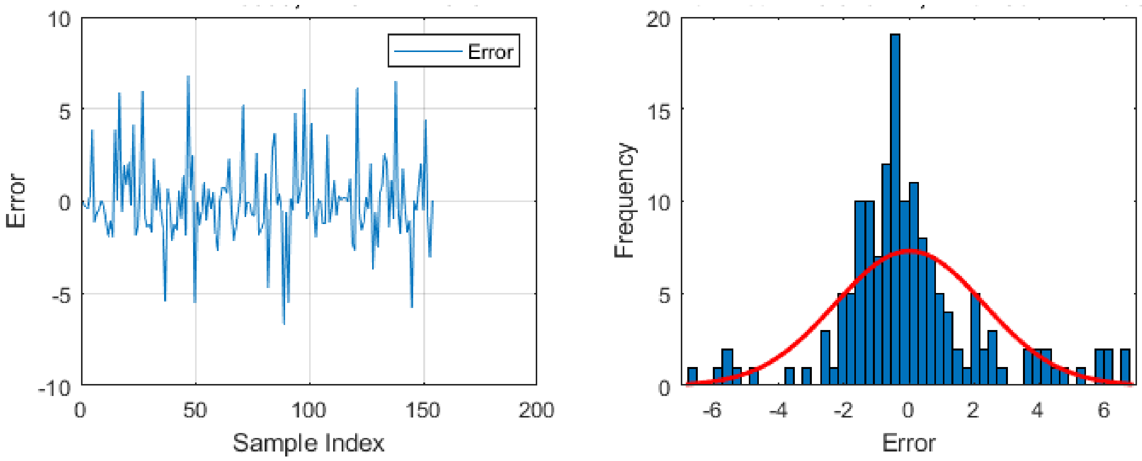

(g) (h)

Figure 7: Direct errors and their frequency drawn for the testing results of (a and b) MLPNN, (c and d) GOA-ANN, (e and f) FA-ANN, and (g and h) SFS-ANN.

Table 3 gives a summary of the results. Based on the resulted accuracy criteria, three major points can be deduced:

(i): All used artificial intelligence models are capable enough to learn properly, and subsequently, estimate the CL pattern for buildings with unseen conditions.

(ii): Synthesizing with three metaheuristic algorithms of GOA, FA, and SFS can significantly improve the regular ANN competency.

(iii): Comparing the efficiency of the used algorithms reveals the outstanding optimization capability of the SFS in optimizing the ANN. After the SFS, GOA outperforms the FA.

Table 3: A summary of accuracy indices obtained in this work.

Models	Network results					
	Training			Testing		
	RMSE	MAE	R^2	RMSE	MAE	R^2
MLPNN	3.3916	2.6511	0.8804	3.1663	2.4575	0.8881
GOA-ANN	2.7725	1.8972	0.9156	2.7628	1.8951	0.9123
FA-ANN	3.0812	2.1468	0.8957	2.9411	2.0265	0.9006
SFS-ANN	2.2824	1.6272	0.9428	2.2828	1.5836	0.9401

4.4 Presenting the neural predictive formula

As explained, all evidence asserted the superiority of the SFS technique in optimizing the ANN in this study. It means that the solution matrix (i.e., ANN weights and biases) proffered by this scheme develops a more flexible neural network. Therefore, in this section, the SFS-ANN ensemble is presented in the form of a neural-metaheuristic formulation to predict the HL by taking the effective parameters into the equation. It is expressed by Equation 8, which is made of six weights and one bias term belonging to the unique output neuron. As can be seen, this formula needs to receive some inputs shown by *A*, *B*, …, *F*. These parameters symbolize the response of the hidden neurons (see Figure 1), which are calculated by Equation 9. Considering the number of input parameters and hidden neurons, the main matrix comprises eight columns and six rows which are multiplied by the inputs matrix. Next, the bias matrix is added, and the Tansig activation function is applied.

$$CL_{SFS\text{-}ANN} = 0.1898 \times A + 0.9542 \times B - 0.3437 \times C + 0.0578 \times D + 0.8368 \times E - 0.8240 \times F - 0.2414 \tag{8}$$

$$\begin{bmatrix} A \\ B \\ C \\ D \\ E \\ F \end{bmatrix} = Tansig\left(\left(\begin{bmatrix} 1.0336 & 0.2712 & -0.9112 & 0.6027 & 0.8083 & 0.1966 & 0.1951 & 0.0468 \\ 0.7463 & -0.4399 & -0.6948 & -0.6665 & -0.7741 & -0.5713 & 0.4305 & -0.5282 \\ 0.2431 & -0.8419 & 0.3706 & -0.4923 & -0.5359 & -0.0527 & -1.0335 & 0.7495 \\ 0.4635 & 0.9505 & 0.6423 & -0.0044 & -1.0053 & -0.5465 & -0.3986 & 0.2620 \\ -0.2864 & 0.1648 & -0.6859 & -1.1583 & -0.4441 & 0.1043 & 0.1328 & -0.9595 \\ 0.4652 & 0.9660 & 0.8049 & -0.8814 & 0.1853 & -0.5100 & -0.4416 & 0.0622 \end{bmatrix}\begin{bmatrix} RC \\ SA \\ WA \\ RA \\ OH \\ Orientation \\ GA \\ GAD \end{bmatrix}\right) + \begin{bmatrix} -1.7514 \\ -1.0509 \\ -0.3503 \\ 0.3503 \\ -1.0509 \\ 1.7514 \end{bmatrix}\right) \tag{9}$$

5 Conclusions

In this work, for the first time, three robust optimizers of stochastic fractal search, grasshopper optimization algorithm, and firefly algorithm were applied to the problem of the cooling load early prediction. These algorithms were used to optimize the performance of a neural network by adjusting the computational parameters. The findings revealed, first, the applicability of neural computing for analyzing the non-linear relationship between the CL and eight environmental parameters. Secondly, all three metaheuristic algorithms could promisingly optimize the ANN for the betterment of accuracy. Last but not least, from a comparison among the results, it was concluded that the SFS-based hybrid model enjoys more accuracy than GOA and FA. The governing neural-metaheuristic relationship of the SFS-ANN was also presented in the form of a viable formula for mathematically predicting the CL.

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6 References

1. Al-Homoud, M. S., Computer-aided building energy analysis techniques. *Building and Environment* **2001,** 36, (4), 421-433.
2. Yang, C.; Gao, F.; Dong, M., Energy Efficiency Modeling of Integrated Energy System in Coastal Areas. *Journal of Coastal Research* **2020,** 103, (SI), 995-1001.
3. Zuo, X.; Dong, M.; Gao, F.; Tian, S., The Modeling of the Electric Heating and Cooling System of the Integrated Energy System in the Coastal Area. *Journal of Coastal Research* **2020,** 103, (SI), 1022-1029.
4. Moayedi, H.; Gör, M.; Lyu, Z.; Bui, D. T., Herding Behaviors of grasshopper and Harris hawk for hybridizing the neural network in predicting the soil compression coefficient. *Measurement* **2020,** 152, 107389.
5. Ahmadi-Karvigh, S.; Ghahramani, A.; Becerik-Gerber, B.; Soibelman, L., Real-time activity recognition for energy efficiency in buildings. *Applied energy* **2018,** 211, 146-160.
6. Bibri, S. E.; Krogstie, J., Smart sustainable cities of the future: An extensive interdisciplinary literature review. *Sustainable cities and society* **2017,** 31, 183-212.
7. McQuiston, F. C.; Parker, J. D., Heating, ventilating, and air conditioning: analysis and design. **1982**.
8. Chen, Y.; He, L.; Guan, Y.; Lu, H.; Li, J., Life cycle assessment of greenhouse gas emissions and water-energy optimization for shale gas supply chain planning based on multi-level approach: Case study in Barnett, Marcellus, Fayetteville, and Haynesville shales. *Energy Conversion and Management* **2017,** 134, 382-398.

9. Chen, Y.; He, L.; Li, J.; Zhang, S., Multi-criteria design of shale-gas-water supply chains and production systems towards optimal life cycle economics and greenhouse gas emissions under uncertainty. *Computers & Chemical Engineering* **2018,** 109, 216-235.
10. Chen, Y.; Li, J.; Lu, H.; Yan, P., Coupling system dynamics analysis and risk aversion programming for optimizing the mixed noise-driven shale gas-water supply chains. *Journal of Cleaner Production* **2021,** 278, 123209.
11. Cheng, X.; He, L.; Lu, H.; Chen, Y.; Ren, L., Optimal water resources management and system benefit for the Marcellus shale-gas reservoir in Pennsylvania and West Virginia. *Journal of Hydrology* **2016,** 540, 412-422.
12. Han, X.; Zhang, D.; Yan, J.; Zhao, S.; Liu, J., Process development of flue gas desulphurization wastewater treatment in coal-fired power plants towards zero liquid discharge: Energetic, economic and environmental analyses. *Journal of Cleaner Production* **2020,** 261, 121144.
13. He, L.; Chen, Y.; Li, J., A three-level framework for balancing the tradeoffs among the energy, water, and air-emission implications within the life-cycle shale gas supply chains. *Resources, Conservation and Recycling* **2018,** 133, 206-228.
14. He, L.; Chen, Y.; Zhao, H.; Tian, P.; Xue, Y.; Chen, L., Game-based analysis of energy-water nexus for identifying environmental impacts during Shale gas operations under stochastic input. *Science of The Total Environment* **2018,** 627, 1585-1601.
15. Li, Z.-G.; Cheng, H.; Gu, T.-Y., Research on dynamic relationship between natural gas consumption and economic growth in China. *Structural Change and Economic Dynamics* **2019,** 49, 334-339.
16. Liu, E.; Lv, L.; Yi, Y.; Xie, P., Research on the Steady Operation Optimization Model of Natural Gas Pipeline Considering the Combined Operation of Air Coolers and Compressors. *IEEE Access* **2019,** 7, 83251-83265.
17. Su, Z.; Liu, E.; Xu, Y.; Xie, P.; Shang, C.; Zhu, Q., Flow field and noise characteristics of manifold in natural gas transportation station. *Oil & Gas Science and Technology–Revue d'IFP Energies nouvelles* **2019,** 74, 70.
18. He, L.; Shen, J.; Zhang, Y., Ecological vulnerability assessment for ecological conservation and environmental management. *Journal of Environmental Management* **2018,** 206, 1115-1125.
19. Lu, H.; Tian, P.; He, L., Evaluating the global potential of aquifer thermal energy storage and determining the potential worldwide hotspots driven by socio-economic, geo-hydrologic and climatic conditions. *Renewable and Sustainable Energy Reviews* **2019,** 112, 788-796.
20. Tian, P.; Lu, H.; Feng, W.; Guan, Y.; Xue, Y., Large decrease in streamflow and sediment load of Qinghai–Tibetan Plateau driven by future climate change: A case study in Lhasa River Basin. *CATENA* **2020,** 187, 104340.
21. Zhang, K.; Ruben, G. B.; Li, X.; Li, Z.; Yu, Z.; Xia, J.; Dong, Z., A comprehensive assessment framework for quantifying climatic and anthropogenic contributions to streamflow changes: A case study in a typical semi-arid North China basin. *Environmental Modelling & Software* **2020,** 128, 104704.
22. Chen, H.; Chen, A.; Xu, L.; Xie, H.; Qiao, H.; Lin, Q.; Cai, K., A deep learning CNN architecture applied in smart near-infrared analysis of water pollution for agricultural irrigation resources. *Agricultural Water Management* **2020,** 240, 106303.
23. Feng, S.; Lu, H.; Tian, P.; Xue, Y.; Lu, J.; Tang, M.; Feng, W., Analysis of microplastics in a remote region of the Tibetan Plateau: Implications for natural environmental response to human activities. *Science of The Total Environment* **2020,** 739, 140087.
24. He, L.; Shao, F.; Ren, L., Sustainability appraisal of desired contaminated groundwater remediation strategies: an information-entropy-based stochastic multi-criteria preference model. *Environment, Development and Sustainability* **2020**, 1-21.
25. Huang, Z.; Zheng, H.; Guo, L.; Mo, D., Influence of the Position of Artificial Boundary on Computation Accuracy of Conjugated Infinite Element for a Finite Length Cylindrical Shell. *Acoustics Australia* **2020,** 48, (2), 287-294.
26. Jia, L.; Liu, B.; Zhao, Y.; Chen, W.; Mou, D.; Fu, J.; Wang, Y.; Xin, W.; Zhao, L., Structure design of MoS_2@Mo_2C on nitrogen-doped carbon for enhanced alkaline hydrogen evolution reaction. *Journal of Materials Science* **2020,** 55, (34), 16197-16210.
27. Li, X.; Zhang, R.; Zhang, X.; Zhu, P.; Yao, T., Silver-Catalyzed Decarboxylative Allylation of Difluoroarylacetic Acids with Allyl Sulfones in Water. *Chemistry – An Asian Journal* **2020,** 15, (7), 1175-1179.
28. Lv, Q.; Liu, H.; Yang, D.; Liu, H., Effects of urbanization on freight transport carbon emissions in China: Common characteristics and regional disparity. *Journal of Cleaner Production* **2019,** 211, 481-489.
29. Quan, Q.; Hao, Z.; Xifeng, H.; Jingchun, L., Research on water temperature prediction based on improved support vector regression. *Neural Computing and Applications* **2020**, 1-10.
30. Yang, M.; Sowmya, A., An Underwater Color Image Quality Evaluation Metric. *IEEE Transactions on Image Processing* **2015,** 24, (12), 6062-6071.
31. Yang, W.; Zhao, Y.; Wang, D.; Wu, H.; Lin, A.; He, L., Using Principal Components Analysis and IDW Interpolation to Determine Spatial and Temporal Changes of Surface Water Quality of Xin'anjiang River in Huangshan, China. *International Journal of Environmental Research and Public Health* **2020,** 17, (8), 2942.
32. Zhang, B.; Xu, D.; Liu, Y.; Li, F.; Cai, J.; Du, L., Multi-scale evapotranspiration of summer maize and the controlling meteorological factors in north China. *Agricultural and Forest Meteorology* **2016,** 216, 1-12.

33. Zhang, D.; Han, X.; Wang, H.; Yang, Q.; Yan, J., Experimental study on transient heat/mass transfer characteristics during static flash of aqueous NaCl solution. *International Journal of Heat and Mass Transfer* **2020,** 152, 119543.
34. Liu, J.; Liu, Y.; Wang, X., An environmental assessment model of construction and demolition waste based on system dynamics: a case study in Guangzhou. *Environmental Science and Pollution Research* **2020,** 27, (30), 37237-37259.
35. Zhang, W., Parameter Adjustment Strategy and Experimental Development of Hydraulic System for Wave Energy Power Generation. *Symmetry* **2020,** 12, (5), 711.
36. Bui, X.-N.; Moayedi, H.; Rashid, A. S. A., Developing a predictive method based on optimized M5Rules–GA predicting heating load of an energy-efficient building system. *Engineering with Computers* **2019**, 1-10.
37. Gao, W.; Alsarraf, J.; Moayedi, H.; Shahsavar, A.; Nguyen, H., Comprehensive preference learning and feature validity for designing energy-efficient residential buildings using machine learning paradigms. *Applied Soft Computing* **2019,** 84, 105748.
38. Guo, Z.; Moayedi, H.; Foong, L. K.; Bahiraei, M., 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* **2020**, 109866.
39. Le, L. T.; Nguyen, H.; Zhou, J.; Dou, J.; Moayedi, H., Estimating the Heating Load of Buildings for Smart City Planning Using a Novel Artificial Intelligence Technique PSO-XGBoost. *Applied Sciences* **2019,** 9, (13).
40. Moayedi, H.; Bui, T. D.; Dounis, A.; Lyu, Z.; Foong, K. L., Predicting Heating Load in Energy-Efficient Buildings Through Machine Learning Techniques. *Applied Sciences* **2019,** 9, (20).
41. Moayedi, H.; Mu'azu, M. A.; Foong, L. K., Novel Swarm-based Approach for Predicting the Cooling Load of Residential Buildings Based on Social Behavior of Elephant Herds. *Energy and Buildings* **2019,** 206, 109579.
42. Moayedi, H.; Nguyen, H.; Kok Foong, L., Nonlinear evolutionary swarm intelligence of grasshopper optimization algorithm and gray wolf optimization for weight adjustment of neural network. *Engineering with Computers* **2019**.
43. Tien Bui, D.; Moayedi, H.; Anastasios, D.; Kok Foong, L., Predicting heating and cooling loads in energy-efficient buildings using two hybrid intelligent models. *Applied Sciences* **2019,** 9, (17), 3543.
44. Zhou, G.; Moayedi, H.; Bahiraei, M.; Lyu, Z., 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* **2020,** 254(inpress).
45. Ghahramani, A.; Zhang, K.; Dutta, K.; Yang, Z.; Becerik-Gerber, B., Energy savings from temperature setpoints and deadband: Quantifying the influence of building and system properties on savings. *Applied Energy* **2016,** 165, 930-942.
46. Ferreira, P.; Ruano, A.; Silva, S.; Conceicao, E., Neural networks based predictive control for thermal comfort and energy savings in public buildings. *Energy and buildings* **2012,** 55, 238-251.
47. Ihara, T.; Gustavsen, A.; Jelle, B. P., Effect of facade components on energy efficiency in office buildings. *Applied energy* **2015,** 158, 422-432.
48. Park, J.; Lee, S. J.; Kim, K. H.; Kwon, K. W.; Jeong, J.-W., Estimating thermal performance and energy saving potential of residential buildings using utility bills. *Energy and buildings* **2016,** 110, 23-30.
49. Wang, Y.; Yao, M.; Ma, R.; Yuan, Q.; Yang, D.; Cui, B.; Ma, C.; Liu, M.; Hu, D., Design strategy of barium titanate/polyvinylidene fluoride-based nanocomposite films for high energy storage. *Journal of Materials Chemistry A* **2020,** 8, (3), 884-917.
50. Zhao, X.; Ye, Y.; Ma, J.; Shi, P.; Chen, H., Construction of electric vehicle driving cycle for studying electric vehicle energy consumption and equivalent emissions. *Environmental Science and Pollution Research* **2020**, 1-15.
51. Zhu, L.; Kong, L.; Zhang, C., Numerical Study on Hysteretic Behaviour of Horizontal-Connection and Energy-Dissipation Structures Developed for Prefabricated Shear Walls. *Applied Sciences* **2020,** 10, (4), 1240.
52. Chao, L.; Zhang, K.; Li, Z.; Zhu, Y.; Wang, J.; Yu, Z., Geographically weighted regression based methods for merging satellite and gauge precipitation. *Journal of Hydrology* **2018,** 558, 275-289.
53. Li, T.; Xu, M.; Zhu, C.; Yang, R.; Wang, Z.; Guan, Z., A Deep Learning Approach for Multi-Frame In-Loop Filter of HEVC. *IEEE Transactions on Image Processing* **2019,** 28, (11), 5663-5678.
54. Xu, M.; Li, T.; Wang, Z.; Deng, X.; Yang, R.; Guan, Z., Reducing Complexity of HEVC: A Deep Learning Approach. *IEEE Transactions on Image Processing* **2018,** 27, (10), 5044-5059.
55. Fu, X.; Pace, P.; Aloi, G.; Yang, L.; Fortino, G., Topology Optimization Against Cascading Failures on Wireless Sensor Networks Using a Memetic Algorithm. *Computer Networks* **2020**, 107327.
56. Fu, X.; Yang, Y., Modeling and analysis of cascading node-link failures in multi-sink wireless sensor networks. *Reliability Engineering & System Safety* **2020,** 197, 106815.
57. Li, C.; Hou, L.; Sharma, B. Y.; Li, H.; Chen, C.; Li, Y.; Zhao, X.; Huang, H.; Cai, Z.; Chen, H., Developing a new intelligent system for the diagnosis of tuberculous pleural effusion. *Computer methods and programs in biomedicine* **2018,** 153, 211-225.
58. Cao, B.; Zhao, J.; Lv, Z.; Gu, Y.; Yang, P.; Halgamuge, S. K., Multiobjective Evolution of Fuzzy Rough Neural Network via Distributed Parallelism for Stock Prediction. *IEEE Transactions on Fuzzy Systems* **2020,** 28, (5), 939-952.

59. Shi, K.; Wang, J.; Tang, Y.; Zhong, S., Reliable asynchronous sampled-data filtering of T–S fuzzy uncertain delayed neural networks with stochastic switched topologies. *Fuzzy Sets and Systems* **2020,** 381, 1-25.
60. Shi, K.; Wang, J.; Zhong, S.; Tang, Y.; Cheng, J., Non-fragile memory filtering of T-S fuzzy delayed neural networks based on switched fuzzy sampled-data control. *Fuzzy Sets and Systems* **2020,** 394, 40-64.
61. Zhu, Q., Research on Road Traffic Situation Awareness System Based on Image Big Data. *IEEE Intelligent Systems* **2020,** 35, (1), 18-26.
62. Zhang, X.; Wang, Y.; Chen, X.; Su, C.-Y.; Li, Z.; Wang, C.; Peng, Y., Decentralized adaptive neural approximated inverse control for a class of large-scale nonlinear hysteretic systems with time delays. *IEEE Transactions on Systems, Man, and Cybernetics: Systems* **2018,** 49, (12), 2424-2437.
63. Lv, Z.; Qiao, L., Deep belief network and linear perceptron based cognitive computing for collaborative robots. *Applied Soft Computing* **2020,** 92, 106300.
64. Qian, J.; Feng, S.; Li, Y.; Tao, T.; Han, J.; Chen, Q.; Zuo, C., Single-shot absolute 3D shape measurement with deep-learning-based color fringe projection profilometry. *Optics Letters* **2020,** 45, (7), 1842-1845.
65. Qian, J.; Feng, S.; Tao, T.; Hu, Y.; Li, Y.; Chen, Q.; Zuo, C., Deep-learning-enabled geometric constraints and phase unwrapping for single-shot absolute 3D shape measurement. *APL Photonics* **2020,** 5, (4), 046105.
66. Qiu, T.; Shi, X.; Wang, J.; Li, Y.; Qu, S.; Cheng, Q.; Cui, T.; Sui, S., Deep Learning: A Rapid and Efficient Route to Automatic Metasurface Design. *Advanced Science* **2019,** 6, (12), 1900128.
67. Hu, L.; Hong, G.; Ma, J.; Wang, X.; Chen, H., An efficient machine learning approach for diagnosis of paraquat-poisoned patients. *Computers in Biology and Medicine* **2015,** 59, 116-124.
68. Shen, L.; Chen, H.; Yu, Z.; Kang, W.; Zhang, B.; Li, H.; Yang, B.; Liu, D., Evolving support vector machines using fruit fly optimization for medical data classification. *Knowledge-Based Systems* **2016,** 96, 61-75.
69. Zhang, X.; Wang, D.; Zhou, Z.; Ma, Y., Robust Low-Rank Tensor Recovery with Rectification and Alignment. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **2019**, 1-1.
70. Zhang, X.; Fan, M.; Wang, D.; Zhou, P.; Tao, D., Top-k Feature Selection Framework Using Robust 0-1 Integer Programming. *IEEE Transactions on Neural Networks and Learning Systems* **2020**, 1-15.
71. Zhao, X.; Li, D.; Yang, B.; Chen, H.; Yang, X.; Yu, C.; Liu, S., A two-stage feature selection method with its application. *Computers & Electrical Engineering* **2015,** 47, 114-125.
72. Liu, S.; Yu, W.; Chan, F. T.; Niu, B., A variable weight-based hybrid approach for multi-attribute group decision making under interval-valued intuitionistic fuzzy sets. *International Journal of Intelligent Systems* **2020**.
73. Chen, H.-L.; Wang, G.; Ma, C.; Cai, Z.-N.; Liu, W.-B.; Wang, S.-J., An efficient hybrid kernel extreme learning machine approach for early diagnosis of Parkinson′ s disease. *Neurocomputing* **2016,** 184, 131-144.
74. Wang, M.; Chen, H.; Yang, B.; Zhao, X.; Hu, L.; Cai, Z.; Huang, H.; Tong, C., Toward an optimal kernel extreme learning machine using a chaotic moth-flame optimization strategy with applications in medical diagnoses. *Neurocomputing* **2017,** 267, 69-84.
75. Wang, S.-J.; Chen, H.-L.; Yan, W.-J.; Chen, Y.-H.; Fu, X., Face recognition and micro-expression recognition based on discriminant tensor subspace analysis plus extreme learning machine. *Neural processing letters* **2014,** 39, (1), 25-43.
76. Xia, J.; Chen, H.; Li, Q.; Zhou, M.; Chen, L.; Cai, Z.; Fang, Y.; Zhou, H., Ultrasound-based differentiation of malignant and benign thyroid Nodules: An extreme learning machine approach. *Computer methods and programs in biomedicine* **2017,** 147, 37-49.
77. Chen, H.; Heidari, A. A.; Chen, H.; Wang, M.; Pan, Z.; Gandomi, A. H., Multi-population differential evolution-assisted Harris hawks optimization: Framework and case studies. *Future Generation Computer Systems* **2020,** 111, 175-198.
78. Zhang, Y.; Liu, R.; Wang, X.; Chen, H.; Li, C., Boosted binary Harris hawks optimizer and feature selection. *Engineering with Computers* **2020**.
79. Wang, M.; Chen, H., Chaotic multi-swarm whale optimizer boosted support vector machine for medical diagnosis. *Applied Soft Computing Journal* **2020,** 88.
80. Cao, Y.; Li, Y.; Zhang, G.; Jermsittiparsert, K.; Nasseri, M., An efficient terminal voltage control for PEMFC based on an improved version of whale optimization algorithm. *Energy Reports* **2020,** 6, 530-542.
81. Xu, X.; Chen, H.-L., Adaptive computational chemotaxis based on field in bacterial foraging optimization. *Soft Computing* **2014,** 18, (4), 797-807.
82. Zhao, X.; Zhang, X.; Cai, Z.; Tian, X.; Wang, X.; Huang, Y.; Chen, H.; Hu, L., Chaos enhanced grey wolf optimization wrapped ELM for diagnosis of paraquat-poisoned patients. *Computational Biology and Chemistry* **2019,** 78, 481-490.
83. Xu, Y.; Chen, H.; Luo, J.; Zhang, Q.; Jiao, S.; Zhang, X., Enhanced Moth-flame optimizer with mutation strategy for global optimization. *Information Sciences* **2019,** 492, 181-203.
84. Cao, B.; Dong, W.; Lv, Z.; Gu, Y.; Singh, S.; Kumar, P., Hybrid Microgrid Many-Objective Sizing Optimization With Fuzzy Decision. *IEEE Transactions on Fuzzy Systems* **2020,** 28, (11), 2702-2710.
85. Cao, B.; Fan, S.; Zhao, J.; Yang, P.; Muhammad, K.; Tanveer, M., Quantum-enhanced multiobjective large-scale optimization via parallelism. *Swarm and Evolutionary Computation* **2020,** 57, 100697.
86. Cao, B.; Wang, X.; Zhang, W.; Song, H.; Lv, Z., A Many-Objective Optimization Model of Industrial Internet of Things Based on Private Blockchain. *IEEE Network* **2020,** 34, (5), 78-83.

87. Cao, B.; Zhao, J.; Gu, Y.; Fan, S.; Yang, P., Security-Aware Industrial Wireless Sensor Network Deployment Optimization. *IEEE Transactions on Industrial Informatics* **2020,** 16, (8), 5309-5316.
88. Cao, B.; Zhao, J.; Gu, Y.; Ling, Y.; Ma, X., Applying graph-based differential grouping for multiobjective large-scale optimization. *Swarm and Evolutionary Computation* **2020,** 53, 100626.
89. Cao, B.; Zhao, J.; Yang, P.; Gu, Y.; Muhammad, K.; Rodrigues, J. J. P. C.; Albuquerque, V. H. C. d., Multiobjective 3-D Topology Optimization of Next-Generation Wireless Data Center Network. *IEEE Transactions on Industrial Informatics* **2020,** 16, (5), 3597-3605.
90. Qu, S.; Han, Y.; Wu, Z.; Raza, H., Consensus Modeling with Asymmetric Cost Based on Data-Driven Robust Optimization. *Group Decision and Negotiation* **2020**.
91. Zhao, X.; Li, D.; Yang, B.; Ma, C.; Zhu, Y.; Chen, H., Feature selection based on improved ant colony optimization for online detection of foreign fiber in cotton. *Applied Soft Computing* **2014,** 24, 585-596.
92. Sun, G.; Yang, B.; Yang, Z.; Xu, G., An adaptive differential evolution with combined strategy for global numerical optimization. *Soft Computing* **2019**, 1-20.
93. Abedini, M.; Zhang, C., Performance Assessment of Concrete and Steel Material Models in LS-DYNA for Enhanced Numerical Simulation, A State of the Art Review. *Archives of Computational Methods in Engineering* **2020**.
94. Gholipour, G.; Zhang, C.; Mousavi, A. A., Numerical analysis of axially loaded RC columns subjected to the combination of impact and blast loads. *Engineering Structures* **2020,** 219, 110924.
95. Liu, J.; Wu, C.; Wu, G.; Wang, X., A novel differential search algorithm and applications for structure design. *Applied Mathematics and Computation* **2015,** 268, 246-269.
96. Mou, B.; Zhao, F.; Qiao, Q.; Wang, L.; Li, H.; He, B.; Hao, Z., Flexural behavior of beam to column joints with or without an overlying concrete slab. *Engineering Structures* **2019,** 199, 109616.
97. Wang, J.; Huang, Y.; Wang, T.; Zhang, C.; Liu, Y. h., Fuzzy finite-time stable compensation control for a building structural vibration system with actuator failures. *Applied Soft Computing* **2020,** 93, 106372.
98. Wu, C.; Wu, P.; Wang, J.; Jiang, R.; Chen, M.; Wang, X., Critical review of data-driven decision-making in bridge operation and maintenance. *Structure and Infrastructure Engineering* **2020**, 1-24.
99. Zhang, C.; Abedini, M.; Mehrmashhadi, J., Development of pressure-impulse models and residual capacity assessment of RC columns using high fidelity Arbitrary Lagrangian-Eulerian simulation. *Engineering Structures* **2020,** 224, 111219.
100. Zhang, C.; Wang, H., Swing vibration control of suspended structures using the Active Rotary Inertia Driver system: Theoretical modeling and experimental verification. *Structural Control and Health Monitoring* **2020,** 27, (6), e2543.
101. Zenggang, X.; Zhiwen, T.; Xiaowen, C.; Xue-min, Z.; Kaibin, Z.; Conghuan, Y., Research on Image Retrieval Algorithm Based on Combination of Color and Shape Features. *Journal of Signal Processing Systems* **2019**.
102. Chao, M.; Kai, C.; Zhiwei, Z., Research on tobacco foreign body detection device based on machine vision. *Transactions of the Institute of Measurement and Control* **2020,** 42, (15), 2857-2871.
103. Liu, D.; Wang, S.; Huang, D.; Deng, G.; Zeng, F.; Chen, H., Medical image classification using spatial adjacent histogram based on adaptive local binary patterns. *Computers in biology and medicine* **2016,** 72, 185-200.
104. Xu, M.; Li, C.; Zhang, S.; Callet, P. L., State-of-the-Art in 360° Video/Image Processing: Perception, Assessment and Compression. *IEEE Journal of Selected Topics in Signal Processing* **2020,** 14, (1), 5-26.
105. Yue, H.; Wang, H.; Chen, H.; Cai, K.; Jin, Y., Automatic detection of feather defects using Lie group and fuzzy Fisher criterion for shuttlecock production. *Mechanical Systems and Signal Processing* **2020,** 141, 106690.
106. Zenggang, X.; Zhiwen, T.; Xiaowen, C.; Xue-min, Z.; Kaibin, Z.; Conghuan, Y., Research on Image Retrieval Algorithm Based on Combination of Color and Shape Features. *Journal of Signal Processing Systems* **2019**, 1-8.
107. Zhang, X.; Wang, T.; Wang, J.; Tang, G.; Zhao, L., Pyramid Channel-based Feature Attention Network for image dehazing. *Computer Vision and Image Understanding* **2020,** 197-198, 103003.
108. Zhang, X.; Jiang, R.; Wang, T.; Wang, J., Recursive Neural Network for Video Deblurring. *IEEE Transactions on Circuits and Systems for Video Technology* **2020**, 1-1.
109. Hu, X.; Chong, H.-Y.; Wang, X., Sustainability perceptions of off-site manufacturing stakeholders in Australia. *Journal of Cleaner Production* **2019,** 227, 346-354.
110. Feng, W.; Lu, H.; Yao, T.; Yu, Q., Drought characteristics and its elevation dependence in the Qinghai–Tibet plateau during the last half-century. *Scientific Reports* **2020,** 10, (1), 14323.
111. Keshtegar, B.; Heddam, S.; Sebbar, A.; Zhu, S.-P.; Trung, N.-T., SVR-RSM: a hybrid heuristic method for modeling monthly pan evaporation. *Environmental Science and Pollution Research* **2019,** 26, (35), 35807-35826.
112. Seo, B.; Yoon, Y. B.; Cho, S. S. S. In *ANN-based thermal load prediction approach for advanced controls in building energy systems*, ARCC Conference Repository, 2019.
113. Halon, T.; Pelinska-Olko, E.; Szyc, M.; Zajaczkowski, B., Predicting Performance of a District Heat Powered Adsorption Chiller by Means of an Artificial Neural Network. *Energies* **2019,** 12, (17), 3328.
114. Nguyen, H.; Moayedi, H.; Sharifi, A.; Amizah, W. J. W.; Safuan, A. R. A., Proposing a novel predictive technique using M5Rules-PSO model estimating cooling load in energy-efficient building system. *Engineering with Computers* **2019,** 35, 1-11.

115. Koschwitz, D.; Spinnräker, E.; Frisch, J.; van Treeck, C., Long-term urban heating load predictions based on optimized retrofit orders: A cross-scenario analysis. *Energy and Buildings* **2020,** 208, 109637.
116. Roy, S. S.; Samui, P.; Nagtode, I.; Jain, H.; Shivaramakrishnan, V.; Mohammadi-ivatloo, B., Forecasting heating and cooling loads of buildings: a comparative performance analysis. *Journal of Ambient Intelligence and Humanized Computing* **2019**, 1-12.
117. Nilashi, M.; Dalvi-Esfahani, M.; Ibrahim, O.; Bagherifard, K.; Mardani, A.; Zakuan, N., A soft computing method for the prediction of energy performance of residential buildings. *Measurement* **2017,** 109, 268-280.
118. Pezeshki, Z.; Mazinani, S. M., Comparison of artificial neural networks, fuzzy logic and neuro fuzzy for predicting optimization of building thermal consumption: a survey. *Artificial Intelligence Review* **2019,** 52, (1), 495-525.
119. Naji, S.; Shamshirband, S.; Basser, H.; Keivani, A.; Alengaram, U. J.; Jumaat, M. Z.; Petković, D., Application of adaptive neuro-fuzzy methodology for estimating building energy consumption. *Renewable and Sustainable Energy Reviews* **2016,** 53, 1520-1528.
120. Chou, J.-S.; Bui, D.-K., Modeling heating and cooling loads by artificial intelligence for energy-efficient building design. *Energy and Buildings* **2014,** 82, 437-446.
121. Moayedi, H.; Tien Bui, D.; Dounis, A.; Ngo, P. T. T., A Novel Application of League Championship Optimization (LCA): Hybridizing Fuzzy Logic for Soil Compression Coefficient Analysis. *Applied Sciences* **2020,** 10, (1), 67.
122. Satrio, P.; Mahlia, T. M. I.; Giannetti, N.; Saito, K., Optimization of HVAC system energy consumption in a building using artificial neural network and multi-objective genetic algorithm. *Sustainable Energy Technologies and Assessments* **2019,** 35, 48-57.
123. Le, L. T.; Nguyen, H.; Zhou, J.; Dou, J.; Moayedi, H., Estimating the Heating Load of Buildings for Smart City Planning Using a Novel Artificial Intelligence Technique PSO-XGBoost. *Applied Sciences* **2019,** 9, (13), 2714.
124. Nguyen, H.; Moayedi, H.; Jusoh, W. A. W.; Sharifi, A., Proposing a novel predictive technique using M5Rules-PSO model estimating cooling load in energy-efficient building system. *Engineering with Computers* **2019**, 1-10.
125. Goudarzi, S.; Anisi, M. H.; Kama, N.; Doctor, F.; Soleymani, S. A.; Sangaiah, A. K., Predictive modelling of building energy consumption based on a hybrid nature-inspired optimization algorithm. *Energy and Buildings* **2019,** 196, 83-93.
126. Moayedi, H.; Mu'azu, M. A.; Foong, L. K., Novel Swarm-based Approach for Predicting the Cooling Load of Residential Buildings Based on Social Behavior of Elephant Herds. *Energy and Buildings* **2019**, 109579.
127. Moayedi, H.; Nguyen, H.; Foong, L., Nonlinear evolutionary swarm intelligence of grasshopper optimization algorithm and gray wolf optimization for weight adjustment of neural network. *Engineering with Computers.* **2019**.
128. McCulloch, W. S.; Pitts, W., A logical calculus of the ideas immanent in nervous activity. *The bulletin of mathematical biophysics* **1943,** 5, (4), 115-133.
129. Moayedi, H.; Osouli, A.; Bui, D. T.; Kok Foong, L.; Nguyen, H.; Kalantar, B., Two novel neural-evolutionary predictive techniques of dragonfly algorithm (DA) and biogeography-based optimization (BBO) for landslide susceptibility analysis. *Geomatics, Natural Hazards and Risk* **2019,** 10, (1), 2429-2453.
130. Cybenko, G., Approximation by superpositions of a sigmoidal function. *Mathematics of control, signals and systems* **1989,** 2, (4), 303-314.
131. Hornik, K.; Stinchcombe, M.; White, H., Multilayer feedforward networks are universal approximators. *Neural networks* **1989,** 2, (5), 359-366.
132. Salimi, H., Stochastic fractal search: a powerful metaheuristic algorithm. *Knowledge-Based Systems* **2015,** 75, 1-18.
133. Mosbah, H.; El-Hawary, M., Optimization of neural network parameters by Stochastic Fractal Search for dynamic state estimation under communication failure. *Electric Power Systems Research* **2017,** 147, 288-301.
134. Akar, H. A.; Mahdi, F. R., Research Article Trajectory Tracking Controller of Mobile Robot under Time Variation Parameters based on Neural Networks and Stochastic Fractal Algorithm. *Research Journal of Applied Sciences, Engineering and Technology* **2016,** 13, (11), 871-878.
135. Padhy, S.; Panda, S., A hybrid stochastic fractal search and pattern search technique based cascade PI-PD controller for automatic generation control of multi-source power systems in presence of plug in electric vehicles. *CAAI Transactions on Intelligence Technology* **2017,** 2, (1), 12-25.
136. Mellal, M. A.; Zio, E., A penalty guided stochastic fractal search approach for system reliability optimization. *Reliability Engineering & System Safety* **2016,** 152, 213-227.
137. Yang, X.-S., *Nature-inspired metaheuristic algorithms*. Luniver press: 2010.
138. Saremi, S.; Mirjalili, S.; Lewis, A., Grasshopper optimisation algorithm: theory and application. *Advances in Engineering Software* **2017,** 105, 30-47.
139. Mafarja, M.; Aljarah, I.; Faris, H.; Hammouri, A. I.; Ala'M, A.-Z.; Mirjalili, S., Binary grasshopper optimisation algorithm approaches for feature selection problems. *Expert Systems with Applications* **2019,** 117, 267-286.
140. Mirjalili, S. Z.; Mirjalili, S.; Saremi, S.; Faris, H.; Aljarah, I., Grasshopper optimization algorithm for multi-objective optimization problems. *Applied Intelligence* **2018,** 48, (4), 805-820.

141. Aljarah, I.; Ala'M, A.-Z.; Faris, H.; Hassonah, M. A.; Mirjalili, S.; Saadeh, H., Simultaneous feature selection and support vector machine optimization using the grasshopper optimization algorithm. *Cognitive Computation* **2018,** 10, (3), 478-495.
142. Yang, X.-S., Firefly algorithm. *Nature-inspired metaheuristic algorithms* **2008,** 20, 79-90.
143. Gálvez, A.; Iglesias, A., Firefly algorithm for polynomial Bézier surface parameterization. *Journal of Applied Mathematics* **2013,** 2013.
144. Yang, X.-S., Firefly algorithm, stochastic test functions and design optimisation. *arXiv preprint arXiv:1003.1409* **2010**.
145. Yang, X.-S. In *Firefly algorithms for multimodal optimization*, International symposium on stochastic algorithms, 2009; Springer: pp 169-178.
146. Yang, X.-S., Multiobjective firefly algorithm for continuous optimization. *Engineering with Computers* **2013,** 29, (2), 175-184.
147. Roberts, A.; Marsh, A., ECOTECT: environmental prediction in architectural education. **2001**.
148. Tsanas, A.; Xifara, A., Accurate quantitative estimation of energy performance of residential buildings using statistical machine learning tools. *Energy and Buildings* **2012,** 49, 560-567.
149. Nguyen, H.; Mehrabi, M.; Kalantar, B.; Moayedi, H.; Abdullahi, M. a. M., Potential of hybrid evolutionary approaches for assessment of geo-hazard landslide susceptibility mapping. *Geomatics, Natural Hazards and Risk* **2019,** 10, (1), 1667-1693.
150. Bahiraei, M.; Heshmatian, S.; Moayedi, H., Artificial intelligence in the field of nanofluids: A review on applications and potential future directions. *Powder Technology* **2019**.