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Application and evaluation of the evolutionary algorithms combined with conventional neural network to determine the building energy consumption of the residential sector

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ABSTRACT

Residential uses a significant amount of energy; hence, encouraging sustainability and lessening environmental effects requires minimizing energy consumption in this sector. This study focuses on applying and evaluating evolutionary algorithms combined with conventional neural networks to predict building energy consumption in the residential sector. The primary objectives were to assess the performance of three evolutionary algorithms – Heap-Based Optimizer (HBO), Multiverse Optimizer (MVO), and Whale Optimization Algorithm (WOA) – in comparison to each other and to determine their effectiveness in predicting energy consumption. Each algorithm was integrated into the neural network framework to optimize the prediction model. Training and testing datasets were employed to evaluate the performance of the models. Two key statistical indices, Root Mean Square Error (RMSE) and R-squared (R^2), were utilized to assess the accuracy of the predictions. The results of the evaluation demonstrated varying performances among the three evolutionary algorithms. MVO achieved the highest scores for both RMSE (48.55082 in training and 68.44517 in testing) and R^2 (0.99184 in training and 0.98236 in testing) on both training and testing datasets, indicating superior predictive accuracy compared to HBO and WOA. These findings underscore the importance of algorithm selection in optimizing predictive models for energy consumption forecasting. Further research may explore hybrid approaches or parameter tuning to enhance the performance of evolutionary algorithms in this domain. Overall, this study contributes to advancing energy forecasting techniques, with potential implications for energy management and conservation efforts in the residential sector.

1. Introduction

With a range of 16–50 percent and a global average of around 30 percent, the residential sector accounts for a sizeable share of the country's total energy consumption [1,2]. To encourage sustainable energy consumption practices given this high level of consumption, it is crucial to gain a thorough understanding of the consumption traits particular to this industry [3–5]. This knowledge should consider issues with energy availability, practical use, and environmental impact. The need to fully comprehend the consumption patterns of the residential sector has grown due to high energy prices, climate change, and variations in energy supply and demand [6,7].

The ultimate goal at this level is to encourage efficiency measures, renewable energy sources, new technology, and conservation practices [8,9]. Residential energy use is less well-studied than energy consumption in industry, commerce, agriculture, and transportation [10]. These elements include centralized ownership, industry experience, strict levels of documentation and control, and self-interest in lowering

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Table 1
Related studies of energy consumption.

References	The subject of research	Methods	Accuracy tool	Accuracy value
Elbeltagi and Wefki [66]	energy consumption for residential buildings	ANN	R^2	0.99
Jogunola et al. [67]	Hybrid Deep Learning Framework for Predicting Energy Consumption	CNN BLSTM-based	MSE	98.7%
Jana et al. [68]	deep learning approach for predicting energy consumption	M-LSTM	RMSE	0.02754
Kim and Cho [69]	residential energy consumption	CNN-LSTM	RMSE	0.6114
Khan et al. [70]	Machine Learning-Based Approach to Predict Energy Consumption of Renewable and Nonrenewable Power Sources	Lasso Ridge GradientBoost MLPRegressor SVR GBoost Proposed	RMSE	73.30541 71.77066 33.46116 72.45894 98.75822 27.88325 21.74774
Ngo et al. [71]	hybrid metaheuristic optimization algorithm and machine learning model for energy use forecast in non-residential buildings	WIO-SVR	R^2	0.90
Alkhazaleh et al. [72]	Thermal Energy Demand	ANFIS-EO ANFIS-GWO ANFIS-HHO ANFIS-SSA	RMSE/ train	2.606 11.144 2.249 2.667
Chou and Ngo [73]	building energy consumption patterns	SARIMA LSSVR MetaFA-LSSVR SARIMA-MetaFA-LSSVR	R^2	0.556 0.375 0.424 0.799
Jamil et al. [74]	energy consumption in Spain		R^2	0.9503
Saberi et al. [75]	Electricity consumption	CBO ECBO IRO	RMSE	30.182 11.773 374.158

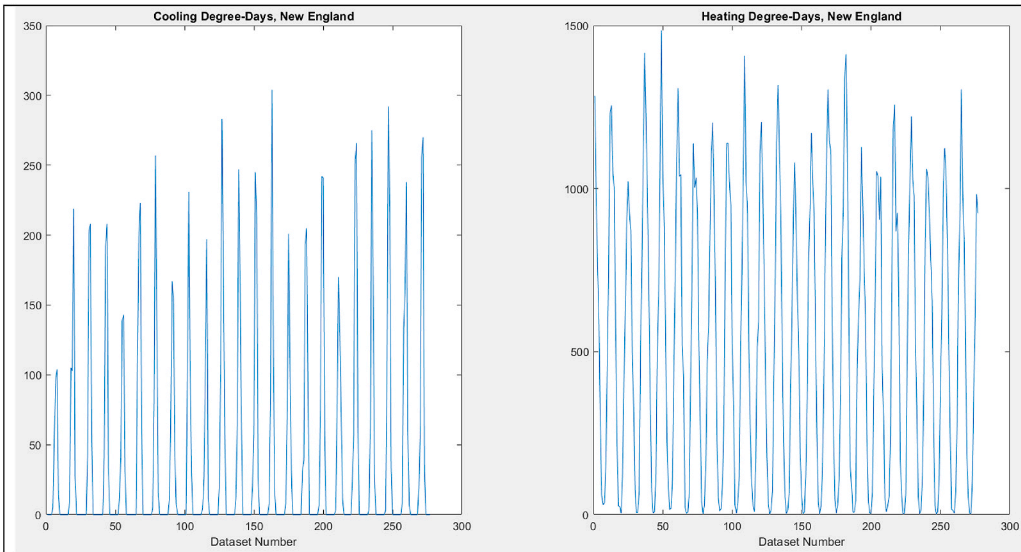
energy use [11]. The residential sector continues to be a significant energy drain due to the following issues. The field includes numerous sizes, shapes, and materials for thermal containment structures. Up to 100% of a home's energy use can be attributed to resident activity [12]. Collecting and sharing energy information about individual households is prohibited due to privacy concerns. Due to the significant expenses, a thorough sub-metering analysis of residential end-uses is not feasible. According to Yu et al. [13], the residential sector uses secondary energy for its energy needs. This kind of energy is produced so that the various systems in residential buildings may use it to sustain the tenants' standard of life [14,15]. The main subcategories of secondary energy end-use in residential contexts are as follows: The energy needed to make up for thermal losses through the building envelope brought on by conduction, radiation, air infiltration, and ventilation is referred to as space cooling (SC) and space heating (SH). This is done to keep the living space comfortable and with good air quality. Appliances and Lighting (AL) is the term used to describe the amount of energy needed to run typical home appliances like refrigerators and coffee machines and to provide suitable lighting. The energy needed to heat water to the proper temperature for residents and appliances is domestic hot water (DHW). The factors that substantially impact how these groups influence overall energy consumption include climate, building characteristics, system and appliance features, ownership, and tenant behavior [16,17].

According to Zhou et al. [18], the overall energy use of a home in terms of domestic energy consumption considers all energy-consuming end uses as well as system and appliance efficiency losses. Complex interactions between these end uses may impact overall energy usage [19]. According to Khedher et al. [20], standard domestic equipment commonly aids in heating the living area. The required energy can be obtained from secondary sources, including on-site production and passive solar gains [21–23]. Understanding each home's energy usage within a particular location is essential to simulate the national or regional residential sector energy usage [24].

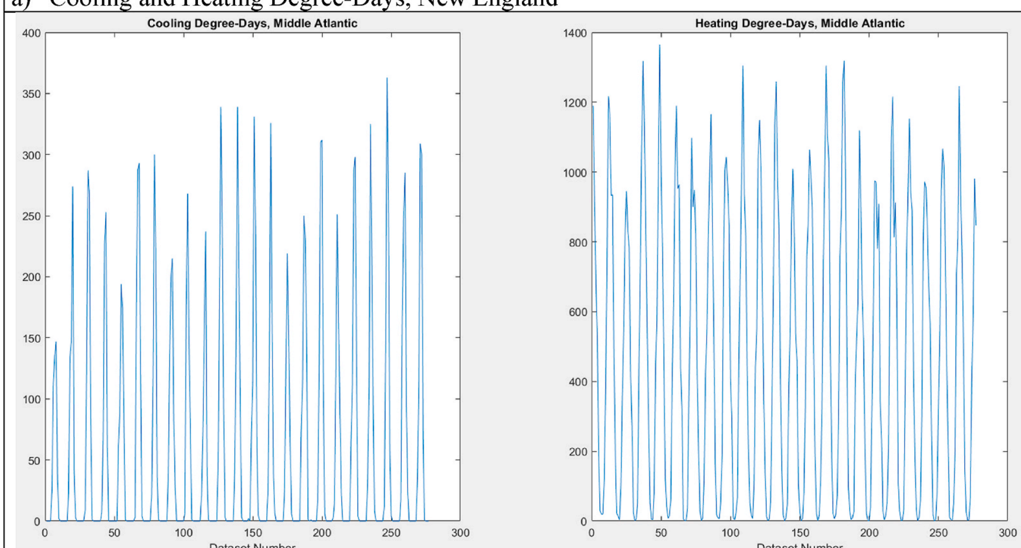
Estimating energy requirements based on input factors is the goal of modeling building energy consumption [25–27]. The models are used for a variety of tasks, such as calculating the macro-scale needs for the nation's or region's energy supply and making micro-scale projections of changes in building energy consumption brought on by new or improved technology [28]. This modeling is helpful because it directs policy choices, including those of new and existing residential structures [29]. If consumption is accurately measured and potential savings from improvements, new materials, and technology are anticipated, decisions about incentives for retrofitting and technology adoption, new building codes, demolition, and reconstruction can be made with confidence [30, 31]. Chen et al. [32] examine the role of building information modeling (BIM) software in streamlining the life cycle assessment (LCA) process to enhance efficiency and accuracy. From a single thermal zone to an entire country, residential energy models can be created at various analytical sizes [33,34]. Several variables, including data accessibility, influence the level of input parameter detail, the model's emphasis and aims, and underlying assumptions [35]. Accurate assumptions can help modeling efforts and produce accurate findings, while increased specificity permits a more in-depth investigation of particular areas.

The novelty of the hybrid approach involving evolutionary algorithms combined with conventional neural networks lies in its ability to leverage the strengths of both methodologies while mitigating their limitations, thereby enhancing the predictive performance and adaptability of energy consumption forecasting models in the residential sector. Evolutionary algorithms (EAs) offer powerful optimization techniques inspired by natural selection and genetic principles [36]. EAs excel in exploring large solution spaces, finding global optima, and handling complex, nonlinear problems. By integrating EAs into the training process of conventional neural networks, the hybrid approach enhances the network's ability to search for optimal weights and biases efficiently, thus improving the model's overall performance and convergence speed. Secondly, conventional neural networks, such as multilayer perceptrons (MLPs), are adept at learning complex patterns and relationships within data [37]. They excel in capturing nonlinear dependencies between input variables and output predictions, making them well-suited for tasks like energy consumption prediction. However, traditional training methods for neural networks, such as gradient descent, may struggle with issues like local optima and slow convergence rates [38]. By combining EAs with MLPs, the hybrid approach addresses these limitations. EAs provide a robust optimization framework that guides the search for optimal network parameters, helping to overcome issues like getting stuck in local optima.

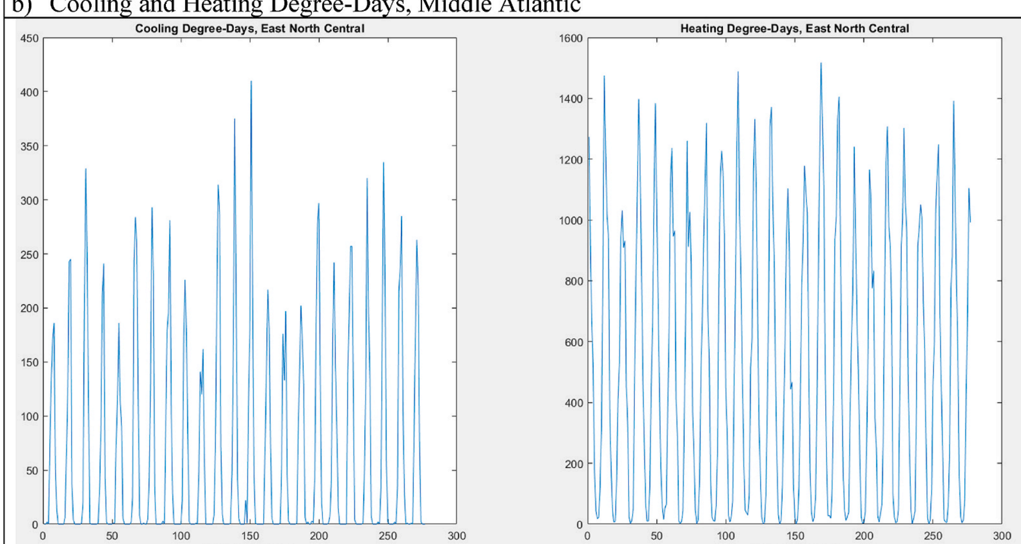
Moreover, the evolutionary process allows for parallel exploration of multiple solutions, speeding up the convergence process and enhancing the overall efficiency of model training [39–42]. Additionally, the hybrid approach offers flexibility and adaptability in model design. Evolutionary algorithms can be tailored to suit specific problem domains, dataset characteristics, and optimization objectives [43]. This flexibility allows researchers and practitioners to customize the hybrid model according to the unique requirements of energy consumption prediction in residential buildings, thus maximizing its effectiveness and applicability. Overall, the novelty of the hybrid approach and optimization algorithms [44–46] lies in its integration of evolutionary optimization techniques with conventional neural networks, synergistically combining their strengths to create robust, efficient, and adaptable



a) Cooling and Heating Degree-Days, New England

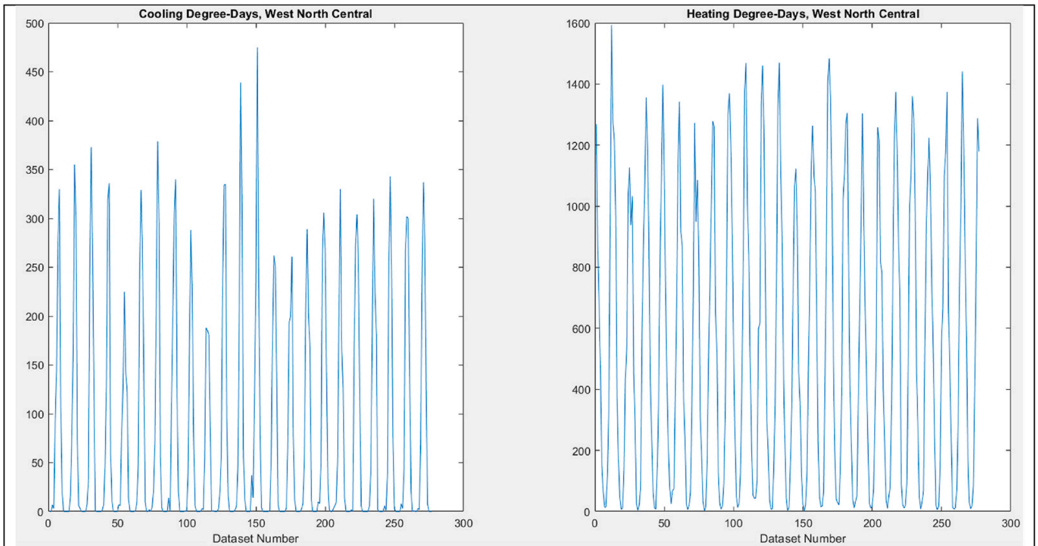


b) Cooling and Heating Degree-Days, Middle Atlantic

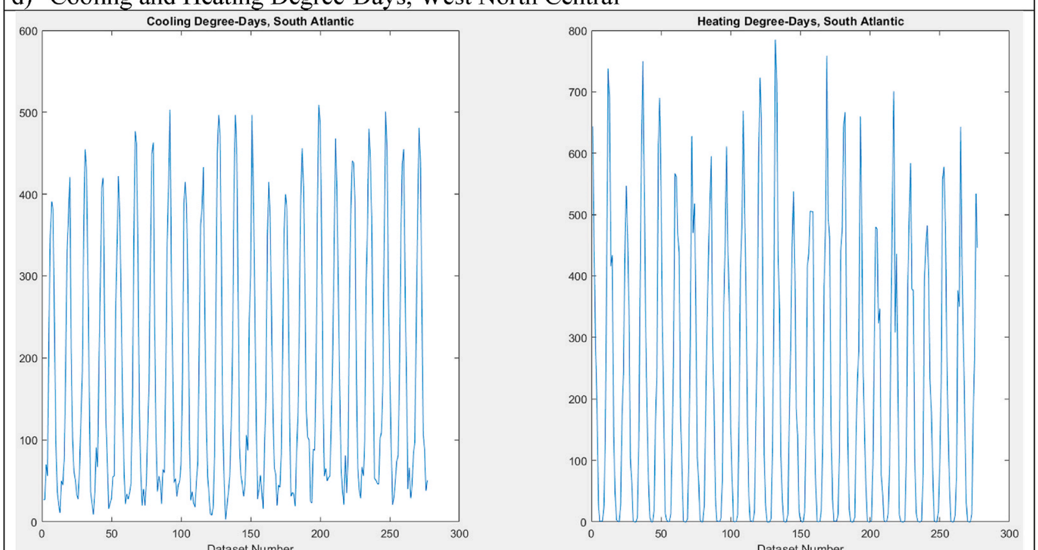


c) Cooling and Heating Degree-Days, East North Central

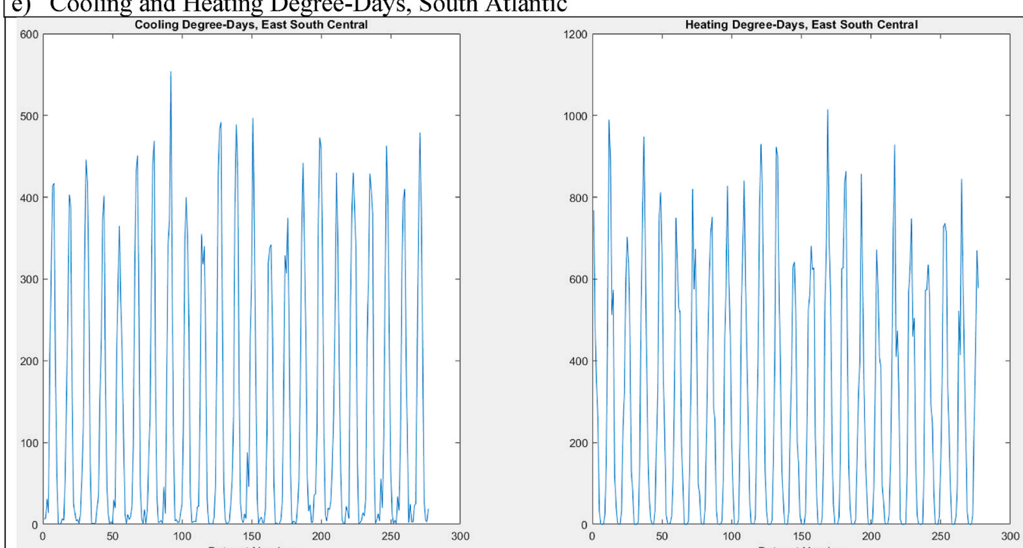
Fig. 1. The variation of variables



d) Cooling and Heating Degree-Days, West North Central



e) Cooling and Heating Degree-Days, South Atlantic



f) Cooling and Heating Degree-Days, East South Central

Fig. 1. (*continued*).

Fig. 1. (*continued*).

Fig. 1. (*continued*).

models for energy management and consumption forecasting in the residential sector [47–51]. This innovative methodology has the potential to revolutionize the field by improving prediction accuracy, scalability, and interpretability, ultimately facilitating more effective energy management and conservation strategies [52,53].

The methods include estimating the housing inventory and determining how much energy each home uses [54–58]. They help develop policy choices for both new and existing residential stock [59]. It is possible to make well-informed decisions that support energy supply, incentives for retrofitting and technology innovation, implementation of new building codes, or possibly demolition and reconstruction through the quantification of consumption and anticipation of the effects or benefits from construction/demolition, retrofits, and novel materials and technology [60]. Several scholars are the studies that have been recently addressed to the issue of energy consumption [61–63]. Hu et al. [64] showed that energy consumption control can be helped by energy extraction and energy recovery from carbon dioxide emissions. As sustainable urban communities continue to seek alternative energy sources, Yang et al. [65] explore the inclusion of renewable resources in the energy mix. This study presents methodologies for residential sector energy modeling, analyzes existing research, and assesses the weaknesses and advantages of the approaches. Table 1 explains recent related studies to compare their results.

This research compares different evolutionary modeling methods for household energy usage. The study finds three techniques: the Whale Optimization Algorithm (WOA), the Multiverse Optimizer (MVO), and the Harris Hawks Optimization (HBO) in combination with an artificial neural network (ANN). Due to different input information levels, simulations, or calculating techniques, each method produces results with diverse applicability. Each strategy is assessed by highlighting its benefits, drawbacks, and intended uses. The inquiry also looks into previously published models.

Integrating evolutionary algorithms with Multilayer Perceptron (MLP) presents a promising approach to address the challenges of predicting building energy consumption in the residential sector [76]. By leveraging evolutionary optimization and neural network modeling capabilities, this study aims to enhance the accuracy and robustness of predictive models, thereby facilitating more effective energy management and conservation strategies. Through a comprehensive evaluation of multiple evolutionary algorithms, including the Heap-Based Optimizer, Multiverse Optimizer, and Whale Optimization Algorithm, this research seeks to identify the most effective optimization technique for

Table 2
Posterior distribution characterization for one-sample mean.

	N	Posterior			95% Credible Interval	
		Mode	Mean	Variance	Lower Bound	Upper Bound
Cooling Degree-Days, New England	277	42.80	42.80	21.189	33.77	51.83
Cooling Degree-Days, Middle Atlantic	277	60.97	60.97	33.726	49.58	72.36
Cooling Degree-Days, East North Central	277	65.25	65.25	33.043	53.98	76.53
Cooling Degree-Days, West North Central	277	81.48	81.48	48.442	67.83	95.13
Cooling Degree-Days, South Atlantic	277	180.74	180.74	88.475	162.29	199.19
Cooling Degree-Days, East South Central	277	139.25	139.25	94.017	120.23	158.26
Cooling Degree-Days, West South Central	277	223.62	223.62	168.910	198.13	249.11
Cooling Degree-Days, Mountain	277	122.57	122.57	72.165	105.91	139.23
Cooling Degree-Days, Pacific	277	75.60	75.60	27.846	65.25	85.95
Cooling Degree-Days, United States	277	115.97	115.97	55.970	101.30	130.65
Heating Degree-Days, New England	277	525.44	525.44	695.037	473.73	577.16
Heating Degree-Days, Middle Atlantic	277	472.66	472.66	628.431	423.49	521.83
Heating Degree-Days, East North Central	277	516.57	516.57	755.418	462.66	570.48
Heating Degree-Days, West North Central	277	541.51	541.51	834.355	484.86	598.17
Heating Degree-Days, South Atlantic	277	218.47	218.47	186.111	191.71	245.23
Heating Degree-Days, East South Central	277	281.18	281.18	309.459	246.67	315.68
Heating Degree-Days, West South Central	277	173.79	173.79	152.954	149.54	198.05
Heating Degree-Days, Mountain	277	414.48	414.48	385.512	375.96	452.99
Heating Degree-Days, Pacific	277	282.08	282.08	168.475	256.62	307.54
Heating Degree-Days, United States	277	355.44	355.44	357.192	318.37	392.51
Average Price of Electricity to Ultimate Customers, Total	277	9.488194945848380	9.488194945848380	0.008	9.311994411008875	9.664395480687887
Average Price of Electricity to Ultimate Customers, Residential	277	11.396570397111912	11.396570397111912	0.014	11.168250991031820	11.624889803192003
Total Energy Consumed by the Residential Sector	277	1748.972317689530400	1748.972317689530400	521.097	1704.196970217471700	1793.747665161588900

Prior on Variance: Diffuse. Prior on Mean: Diffuse.

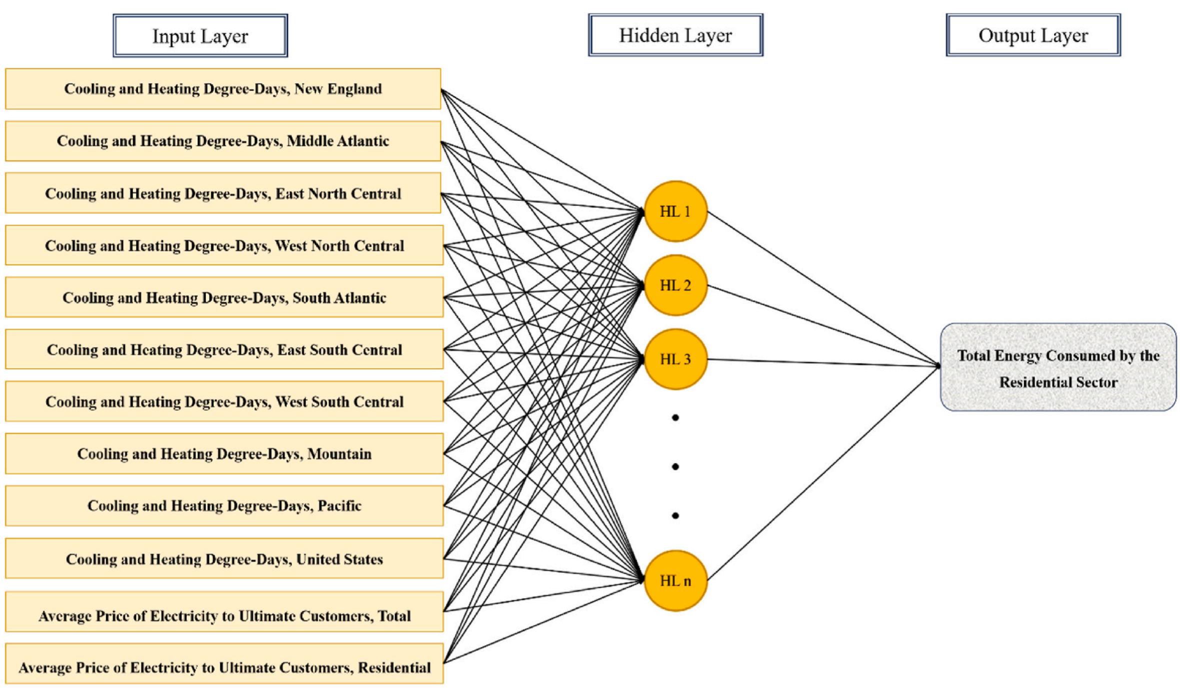


Fig. 2. A simplified structure of ANN with inputs, hidden neurons, and one output.

enhancing the predictive performance of MLP in the context of residential energy consumption prediction. The subsequent sections will delve into the methodology employed, experimental setup, and detailed analysis of results, providing valuable insights into the efficacy of evolutionary algorithms combined with MLP for addressing the complex challenges of energy consumption forecasting in residential buildings.

Furthermore, beyond the scope of this study, promising avenues exist for future research in energy consumption prediction utilizing evolutionary algorithms and MLP. One potential direction involves exploring hybrid approaches that integrate multiple optimization techniques or combine MLP with other machine learning algorithms to capitalize on their complementary strengths. Additionally, the scalability and adaptability of these models to accommodate more significant and diverse datasets warrant investigation, particularly in the context of innovative grid technologies and the integration of renewable energy sources. Furthermore, research efforts could focus on enhancing predictive models' interpretability and explainability, thus fostering stakeholders' trust and understanding and facilitating their adoption in real-world applications. Moreover, investigating the potential impact of socioeconomic factors, policy interventions, and behavioral changes on energy consumption patterns could provide valuable insights for developing more holistic and adaptive energy management strategies. By addressing these future research directions, the field can benefit from more accurate, robust, and actionable predictive models, ultimately contributing to sustainable energy practices and environmental stewardship in the residential sector.

2. Established database

To estimate this parameter accurately, one must look at how it interacts with the variables that affect it. For this reason, it is crucial to offer a reliable dataset. This investigation's model training and validation used two hundred seventy-seven thermal load scenarios. An extensive investigation of the Total Energy Consumption of various structures was carried out by the U.S. Energy Information Administration (EIA), which resulted in the creation of a database that may be accessed at https://www.eia.gov/totalenergy/data/monthly/. (Available as of May 25, 2023. 22 influential independent factors control the output parameter for the Residential Sector's overall energy consumption. These variables consist of cooling and heating degree-days (New England), cooling and heating degree-days (Middle Atlantic), cooling and heating degree-days (East North Central), cooling and heating degree-days (West North Central), cooling and heating degree-days (South Atlantic), cooling and heating degree-days (East South Central), cooling and heating degree-days (West South Central), cooling and heating degree-days (Mountain), cooling and heating degree-days (Pacific), cooling and heating degree-days (United States), average price of electricity to ultimate customers (total), and average price of electricity to ultimate customers (residential). Fig. 1 depicts the variation of the output and input factors, and Table 2 presents the statistical aspects of each variable.

3. Methodology

3.1. Artificial neural network

Due to artificial approaches to capture nonlinear features are employed in anticipating the electricity needs that utilities confront [77,78]. In their literature review, Aydinalp et al. [79] recognize the development of various ANN approaches for electrical load prediction aims. They also claim that ANN modeling for individual building energy usage started in the 1990s with commercial buildings and advanced in complexity. Kreider and Haberl [80] emphasized the significance of employing "connectionist" approaches like artificial neural networks (ANN) in their report on an hourly building energy modeling competition. The best participants employed these strategies and achieved outstanding outcomes.

Fig. 2 illustrates a simpler neural network with interconnected characteristics. This neural network uses hidden neurons. The word "b" biases the coefficients in the vectors "V," which include the coefficients for each input to an output or hidden neuron [81]. Various techniques are utilized to change a specific ANN arrangement's coefficient bias and vector while taking acceptable activation and scaling functions to reduce model faults. Once these numbers have been acquired, the algorithm may determine energy usage based on the function of multiple inputs.

Issa et al. [82] used ANN modeling to examine how much energy homes use in a particular region. To conduct their research, they created an ANN model that contained billing data, the energy performance index (EPI), conditioned floor areas, and a collection of homes. EPI, a score system, measures energy efficiency by looking at a home's structural components. Issa et al.'s ANN approach bridged the gap between actual energy use and expected consumption based on EPI and floor area. However, the authors did not offer any clear findings from their study.

Mihalakakou et al. [83] used the artificial neural network (ANN) methodology to construct an energy technique based on atmospheric states for a residential property in Greece. This model's inputs were solar radiation and air temperature, and it was trained using data on hourly energy use collected over five years. The system was calibrated using a significant amount of hourly "training" data, which is why the results of the predicted energy usage for the residence were considered perfect hourly. Even though multiyear data was available, dates were unfortunately not provided as input to the ANN; as a result, annual changes were not taken into account. However, this strategy can be improved every month by using information from a subset of household energy supplier invoices. It thus becomes a helpful instrument for analyzing differences in energy use between warm and cold years.

Aydinalp and his coworkers developed a neural network methodology-based national home energy use model [79,80,82–84]. Domestic hot water (DHW), space heating (SH), and appliances, lighting, and conditioning (ALC) are the three components that make up the model. To train the ALC module, the researchers only used data from households that use natural gas or oil for heating loads. This allowed them to discriminate between electrical energy use for SH, ALC, and DHW.

3.1.1. Multilayer perceptron (MLP)

MLP is a feedforward artificial neural network characterized by multiple layers of interconnected neurons consisting of an input layer, one or more hidden layers, and an output layer [85]. Each neuron in the network is connected to neurons in the adjacent layers, and these connections are associated with weights that are adjusted during the training process to optimize the network's performance.

Input Layer: The input layer receives the features or variables used for prediction, such as weather data, building characteristics, and occupancy patterns, and is fed into the network for processing.

Hidden Layers: Hidden layers contain neurons that perform nonlinear transformations on the input data. These layers enable the network to learn complex patterns and relationships within the data.

Output Layer: The output layer produces the network's predictions based on the processed input data. In the context of predicting building energy consumption, the output layer would provide estimates of energy usage for residential buildings.

Activation Functions: Activation functions introduce nonlinearity into the network and determine the output of each neuron based on its weighted inputs. Common activation functions include sigmoid, tanh, and ReLU (Rectified Linear Unit).

Weights and Biases: Weights and biases are parameters associated with the connections between neurons in the network. During training, these parameters are adjusted through backpropagation to minimize the difference between the network's predictions and the actual energy consumption values.

MLP is well-suited for predicting building energy consumption in the residential sector due to its ability to capture nonlinear relationships between input variables and energy usage patterns [86]. By training on historical energy consumption data along with relevant predictors such as weather conditions, building characteristics, and occupant behavior, MLP can learn to make accurate predictions of future energy usage. During training, the model's weights and biases are adjusted iteratively using optimization algorithms such as gradient descent to minimize the prediction error. The performance of the trained model is evaluated using statistical metrics such as RMSE (Root Mean Square Error) and R^2 (Coefficient of Determination) on both training and testing datasets to assess its accuracy and generalization ability.

3.2. Heap-Based Optimizer (HBO)

The Heap-Based Optimizer Algorithm (HBO) is based on individuals' social behavior [87]. The corporate rank hierarchy (CRH) concept, used

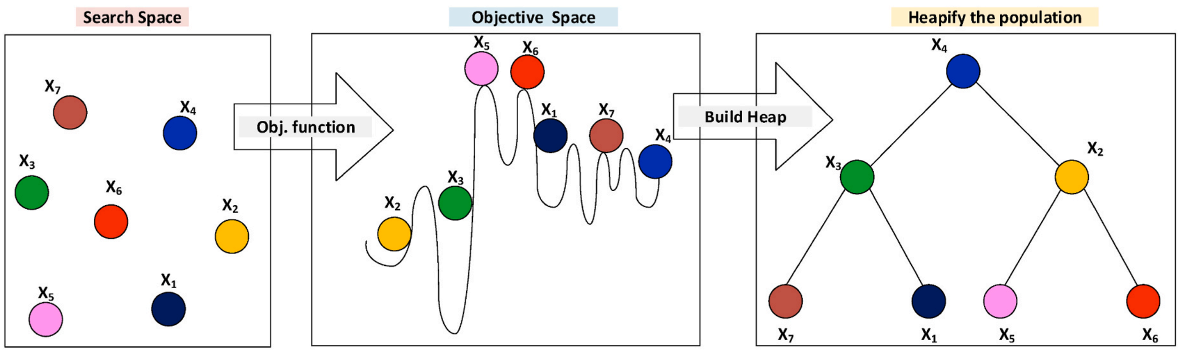
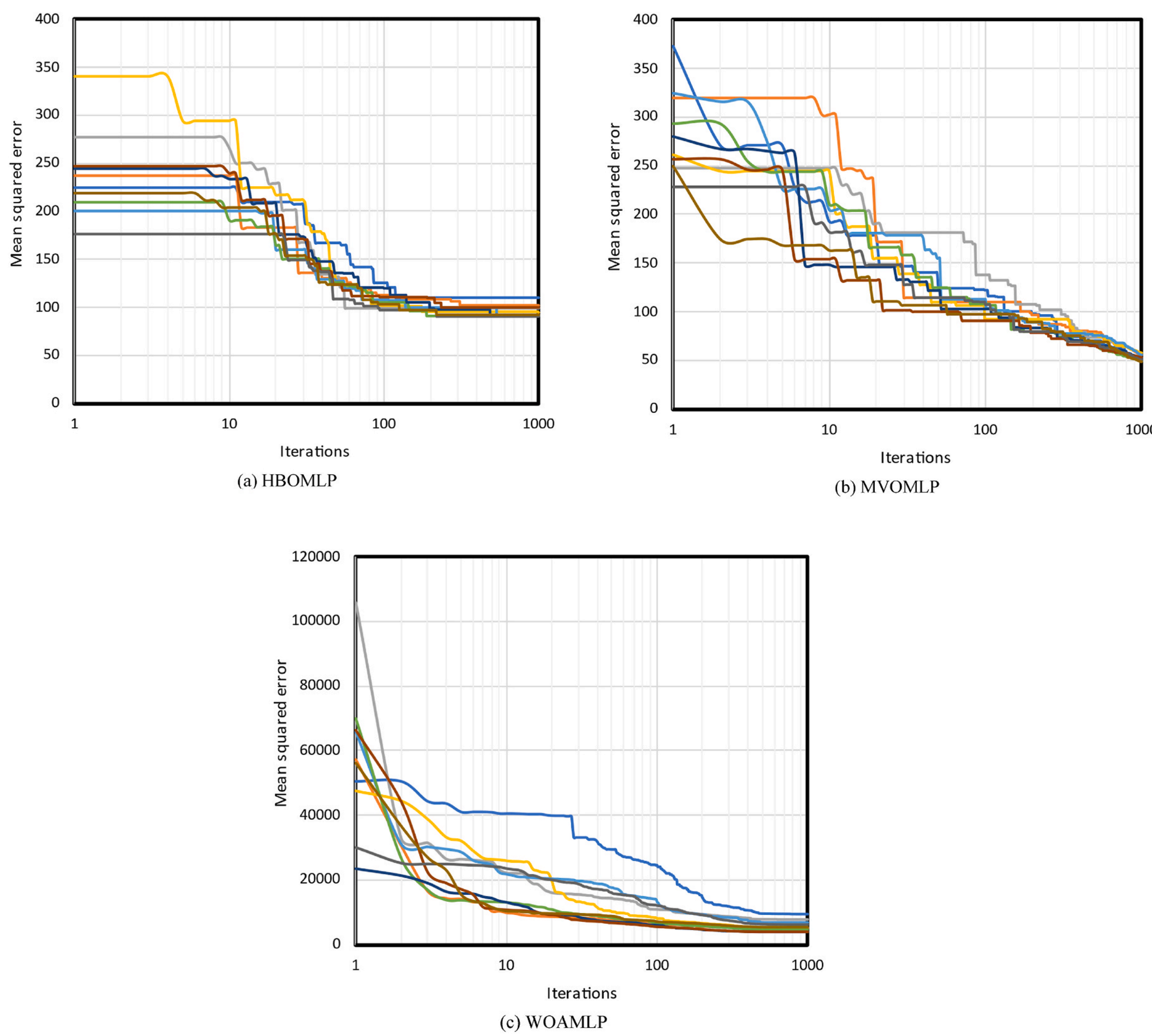


Fig. 3. A demonstration of min-heap in modeling the CRH (after [87]).



(a) HBOMLP

(b) MVOMLP

(c) WOAMLP

Fig. 4. The best-fit model for the (a) HBOMLP, (b) MVOMLP, (c) WOAMLP.

in corporations to organize teams hierarchically to achieve specified goals, is particularly incorporated into the algorithm. To create priority queues, search agents are arranged based on how well they fit into this hierarchy using a heap tree-based data structure. Three main employee behaviors are taken into account by the HBO algorithm: (i) interactions between direct reports and their direct supervisors, (ii) relationships among coworkers, and (iii) individual self-contribution.

Four steps make up the conceptualization of the heap.

3.2.1. *Modeling the corporate rank hierarchy*

A heap data structure is used to implement CRH modeling, as shown in Fig. 3. x_i, where i represents the agent's position in the search and represents the population's search agents. The placements of the agents on this curve, which represents the objective function in the objective space, define the fitness form. The agents were arranged in this shape for the agents' convenience. Fig. 3 shows how to model the CRH using the min-heap technique.

Table 3
The performance of proposed HBOMLP swarm sizes using two statistical indices for network results.

Swarm size	Training dataset		Testing dataset		Scoring				Total Score	Rank
	RMSE	R^2	RMSE	R^2	Training		Testing			
50	109.98689	0.9574	118.0708	0.94654	1	1	4	4	10	10
100	100.45927	0.9646	114.7709	0.94957	2	2	5	5	14	7
150	90.25319	0.9715	96.67639	0.96449	8	8	9	9	34	1
200	93.07152	0.9697	119.5396	0.94517	4	4	2	2	12	8
250	91.21461	0.9709	89.42584	0.9697	5	5	10	10	30	3
300	90.54391	0.9713	99.50127	0.96234	6	6	7	7	26	5
350	87.69568	0.9731	109.7197	0.95401	10	10	6	6	32	2
400	95.03117	0.9684	119.1871	0.9455	3	3	3	3	12	8
450	90.46541	0.9714	98.04474	0.96346	7	7	8	8	30	3
500	90.00907	0.9717	125.9544	0.93893	9	9	1	1	20	6

Table 4
The performance of proposed MVOMLP swarm sizes using two statistical indices for network results.

Swarm size	Training dataset		Testing dataset		Scoring				Total Score	Rank
	RMSE	R^2	RMSE	R^2	Training		Testing			
50	51.72	0.9907	69.716	0.98169	7	7	9	9	32	2
100	55.519	0.9893	78.743	0.97659	4	4	3	3	14	7
150	57.597	0.9885	76.753	0.97777	2	2	4	4	12	8
200	57.895	0.9884	79.303	0.97625	1	1	2	2	6	10
250	55.728	0.9892	70.477	0.98129	3	3	8	8	22	5
300	49.144	0.9916	73.551	0.9796	9	9	6	6	30	3
350	52.820	0.9903	73.977	0.97936	6	6	5	5	22	5
400	53.191	0.9902	88.080	0.97061	5	5	1	1	12	8
450	50.521	0.9912	70.807	0.98111	8	8	7	7	30	3
500	48.550	0.9918	68.445	0.98236	10	10	10	10	40	1

Table 5
The performance of proposed WOAMLP swarm sizes using two statistical indices for network results.

Swarm size	Training dataset		Testing dataset		Scoring				Total Score	Rank
	RMSE	R^2	RMSE	R^2	Training		Testing			
50	97.16696	0.9669	83.52954	0.97361	1	1	5	5	12	8
100	71.46238	0.9822	76.41595	0.97796	7	7	8	8	30	3
150	88.16034	0.9728	113.1167	0.95105	2	2	1	1	6	10
200	72.49368	0.9817	75.73989	0.97836	6	6	9	9	30	3
250	82.8999	0.9760	92.57453	0.96749	3	3	3	3	12	8
300	68.23586	0.9838	80.32591	0.97562	8	8	6	6	28	5
350	63.27109	0.9861	78.48548	0.97674	9	9	7	7	32	2
400	63.19792	0.9861	75.10985	0.97872	10	10	10	10	40	1
450	78.76842	0.9784	87.84525	0.97077	4	4	4	4	16	6
500	73.73122	0.9811	102.9661	0.95962	5	5	2	2	14	7

Table 6
The performance of all three proposed methods using two statistical indices for network results.

	Swarm size	Training dataset		Testing dataset		Scoring				Total Score	Rank
		RMSE	R^2	RMSE	R^2	Training		Testing			
HBOMLP	150	90.25319	0.97150	96.67639	0.96449	1	1	1	1	4	3
MVOMLP	500	48.55082	0.99184	68.44517	0.98236	3	3	3	3	12	1
WOAMLP	400	63.19792	0.98613	75.10985	0.97872	2	2	2	2	8	2

3.2.2. Mathematically modeling the collaboration with the boss

Because of the centralized organizational structure, higher-level policies and rules must be implemented, and subordinates must follow the directives of their immediate superiors. Each search agent's situation is upgraded as follows in the mathematical explanation of this process:

$$x_i^k\ (t+1) = B^k + \gamma\lambda^k \left|B^k - \ x_i k\ (t)\right| \tag{1}$$

$$\gamma = \left|2 - \frac{\left(t \bmod \frac{T}{C}\right)}{\frac{T}{4C}}\right| \tag{2}$$

$$\lambda^k = (2r - 1) \tag{3}$$

The k-th component of a vector is represented by k in the current iteration, denoted by t. B denotes the parent's node, while r is an erroneous number between [0, 1]. T represents the maximum number of repetitions, and C is a user-defined variable.

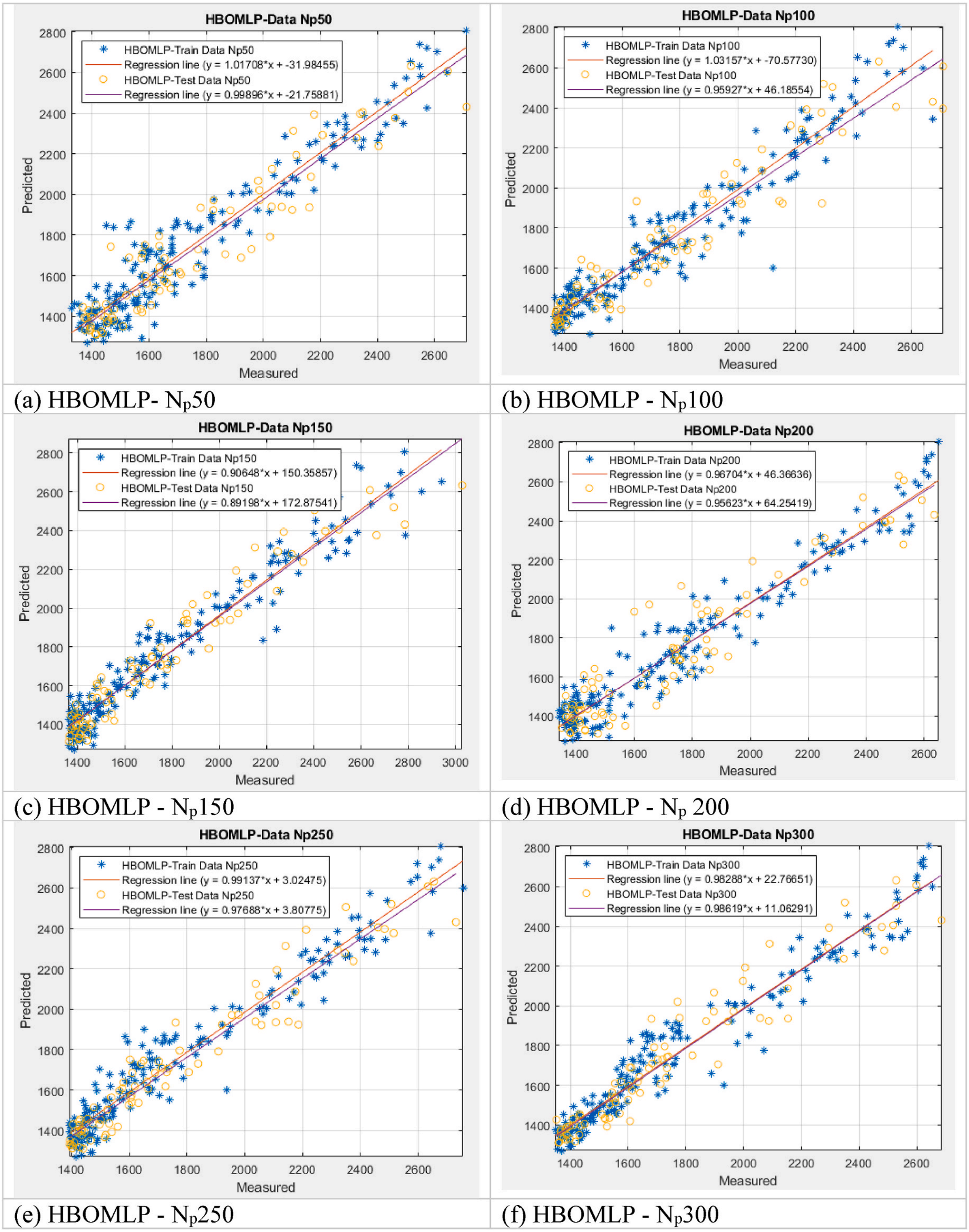


Fig. 5. The accuracy outcomes of the testing and training datasets for various proposed structures of HBOMLP

3.2.3. *Mathematically modeling the interaction between the colleagues*

Colleagues work together to complete duties at work in a cooperative manner. Nodes in a particular system at the same levels in the hierarchy are deemed colleagues. Each search agent (x_i), improves its position by relying on a haphazard colleague, (S_r). The agent explicitly improves its standing in the light of the chosen companion.

$$x_i^k\,(t+1) = \begin{cases} s_r^k + \gamma\lambda^k \left|s_r^k - x_i^k(t)\right|, f(Sr) < f(x_i\,(t)) \\ x_i^k + \gamma\lambda^k \left|s_r^k - x_i^k(t)\right|, f(Sr) \geq f(x_i(t)) \end{cases} \tag{4}$$

3.2.4. *Self-contribution of an employee to accomplish a task*

During this stage, an individual laborer's self-contribution is charted in the following manner:

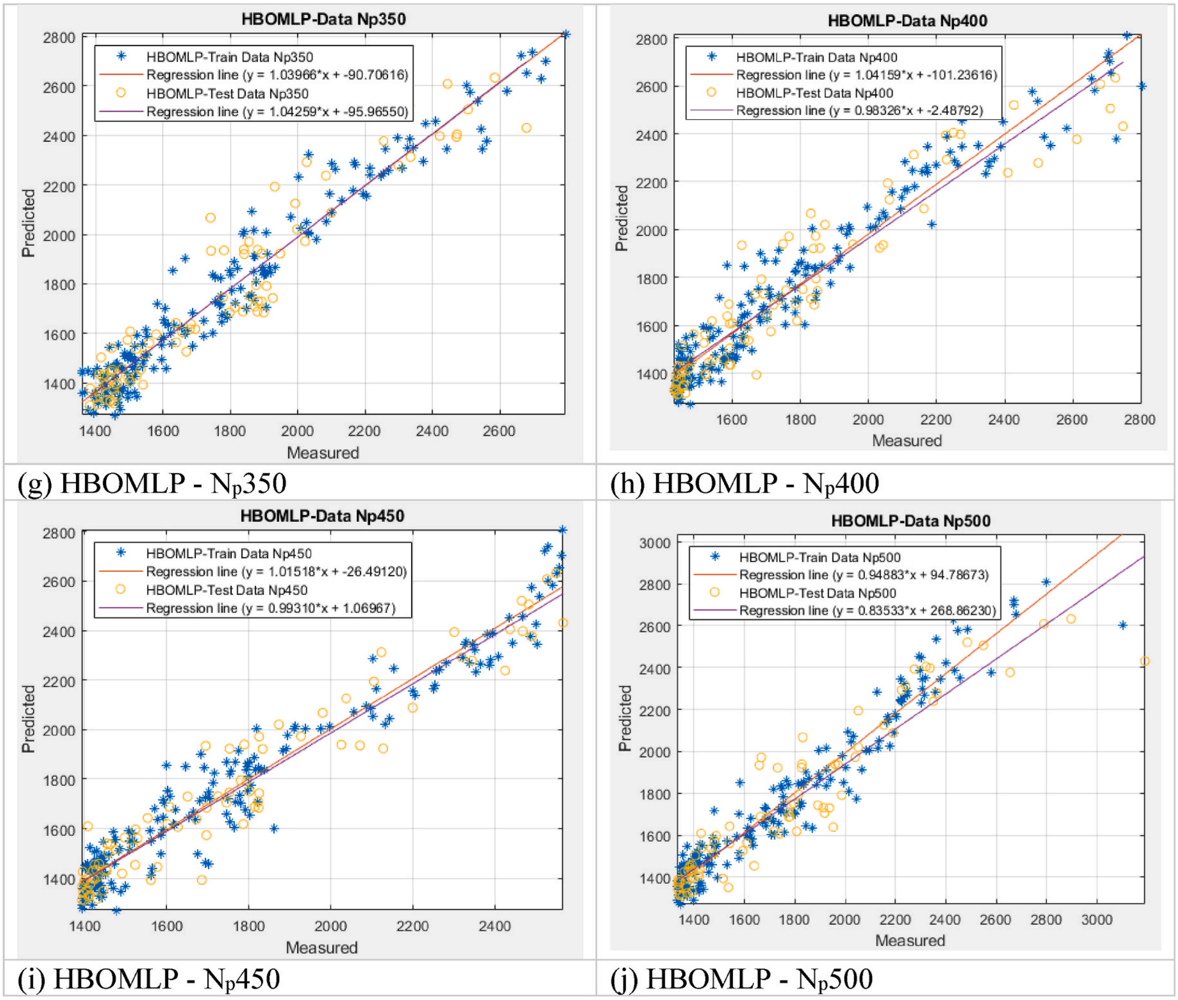


Fig. 5. (*continued*).

$$x_i^k(t+1) = x_i^k(t) \tag{5}$$

The subsequent section elaborates on how the equation can regulate exploration.

3.2.5. Putting all together

In the academic context, the main obstacle is identifying appropriate selection probabilities for the three equations that effectively manage exploitation and exploration. The roulette wheel is partitioned into three distinct sections: $p1$, $p2$, and $p3$. The value of $p1$ plays a crucial role in population changes and can be calculated using the subsequent equation:

$$p_1 = 1 - \frac{t}{T} \tag{6}$$

The computation of p_2 selection is achieved through the utilization of the subsequent equation.

$$p_2 = p_1 - \frac{1 - p_1}{2} \tag{7}$$

The final step is to determine the value of $p3$, which can be computed in the following manner:

$$p_3 = p_2 - \frac{1 - p_1}{2} = 1 \tag{8}$$

The HBO algorithm's mechanism for updating positions can be mathematically represented as a general formula.

$$xi\ k\ (t+1) = \begin{cases} x_i^k\ (t), p \le p_1 \\ B^k + \gamma\lambda^k\ \left|B^k - x_i^k(t)\right|, p\ >\ p_1 and\ p \le p_2 \\ s_r^k + \gamma\lambda^k\ \left|s_r^k -\ x_i^k(t)\right|, p\ >\ p_2 and\ p \le p_3 and\ f(S_r) <\ f(x_i(t)) \\ x_i^k + \gamma\lambda^k\ \left|s_r^k -\ x_i^k(t)\right|, p\ >\ p_2 and\ p \le p_3 and\ f(S_r) \ge f(x_i(t)) \end{cases} \tag{9}$$

The variable p is a stochastic quantity that takes values in the interval (0, 1).

3.3. Multiverse optimizer (MVO)

Mirjalili et al. [88] introduced the multiverse optimizer (MVO) method, founded on the multiverse physics theory. According to the multiverse hypothesis, multiple great bangs create a universe [88,89]. It creates a mathematical approach of the wormhole (white/black) tunnels connecting two worlds and the wheel mechanism for transferring universe products. In each iteration, the inflation rates of the universes are ranked, and a roulette wheel chooses the universe with the highest inflation rate to contain a white hole. The following is a mathematical description of the MVO model:

Consider the subsequent:

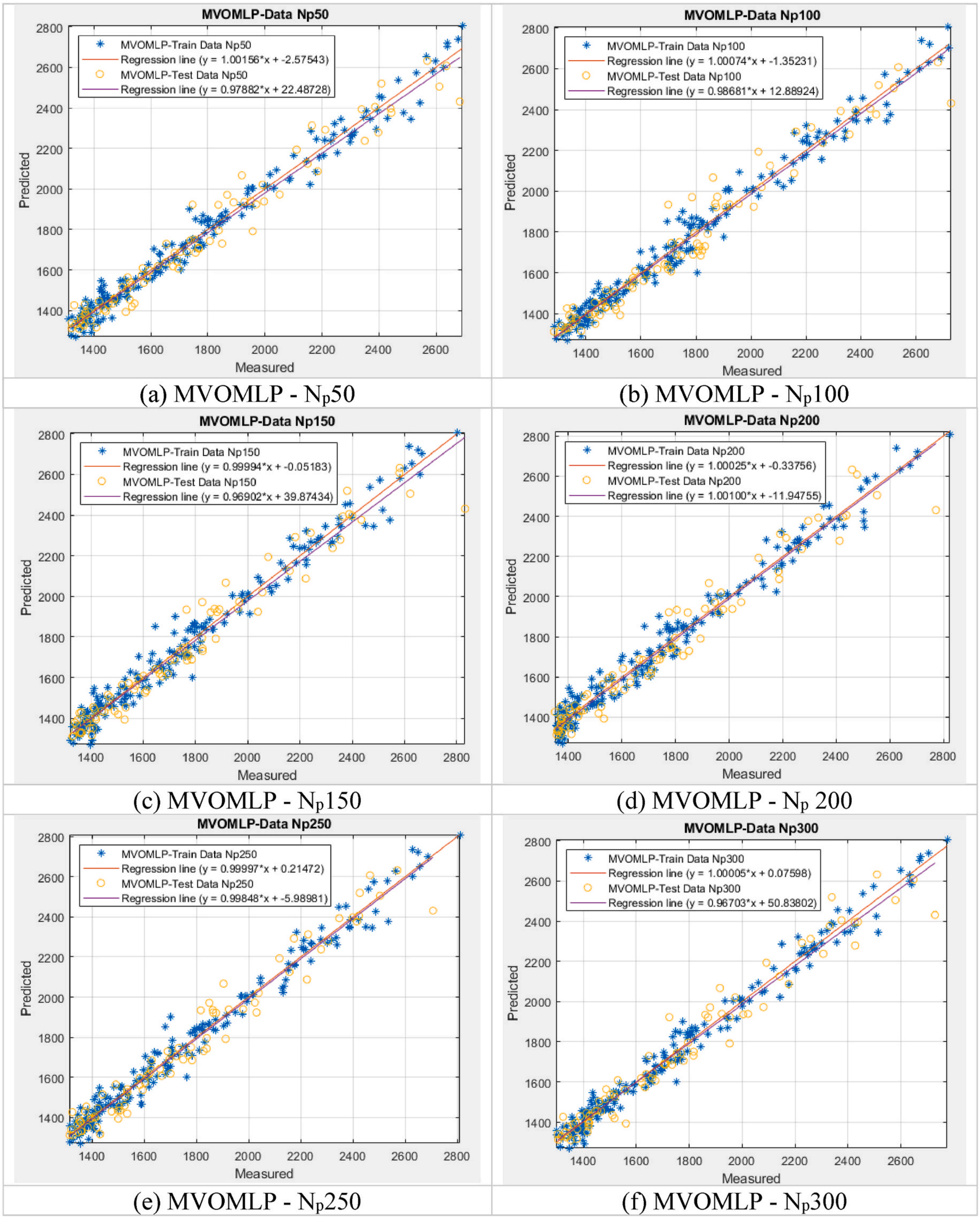


Fig. 6. The accuracy outcomes of the testing and training datasets for various proposed structures of MVOMLP

$$u = \begin{bmatrix} x_1^1 & x_1^2 & \cdots & x_1^d \\ x_2^1 & x_2^2 & \cdots & x_2^d \\ \vdots & \vdots & \vdots & \vdots \\ x_n^1 & x_n^1 & \cdots & x_n^d \end{bmatrix} \tag{10}$$

If n is the total universes' number (possible solutions) and d is the total parameters' number (variables), then:

$$x_k^j = \begin{cases} x_k^j \; r_1 < NI(u_i) \\ x_i^j \; r_1 \geq NI(u_i) \end{cases} \tag{11}$$

Where r_1 is an integer between 0 and 1, u_i is the i-th universe, $NI(u_i)$ is the normalized rate of inflation for the i-th universe, and x_i^j is the j-th parameter of the i-th world.

The method of transportation is as follows, assuming a wormhole tunnel connects one world to the best universe:

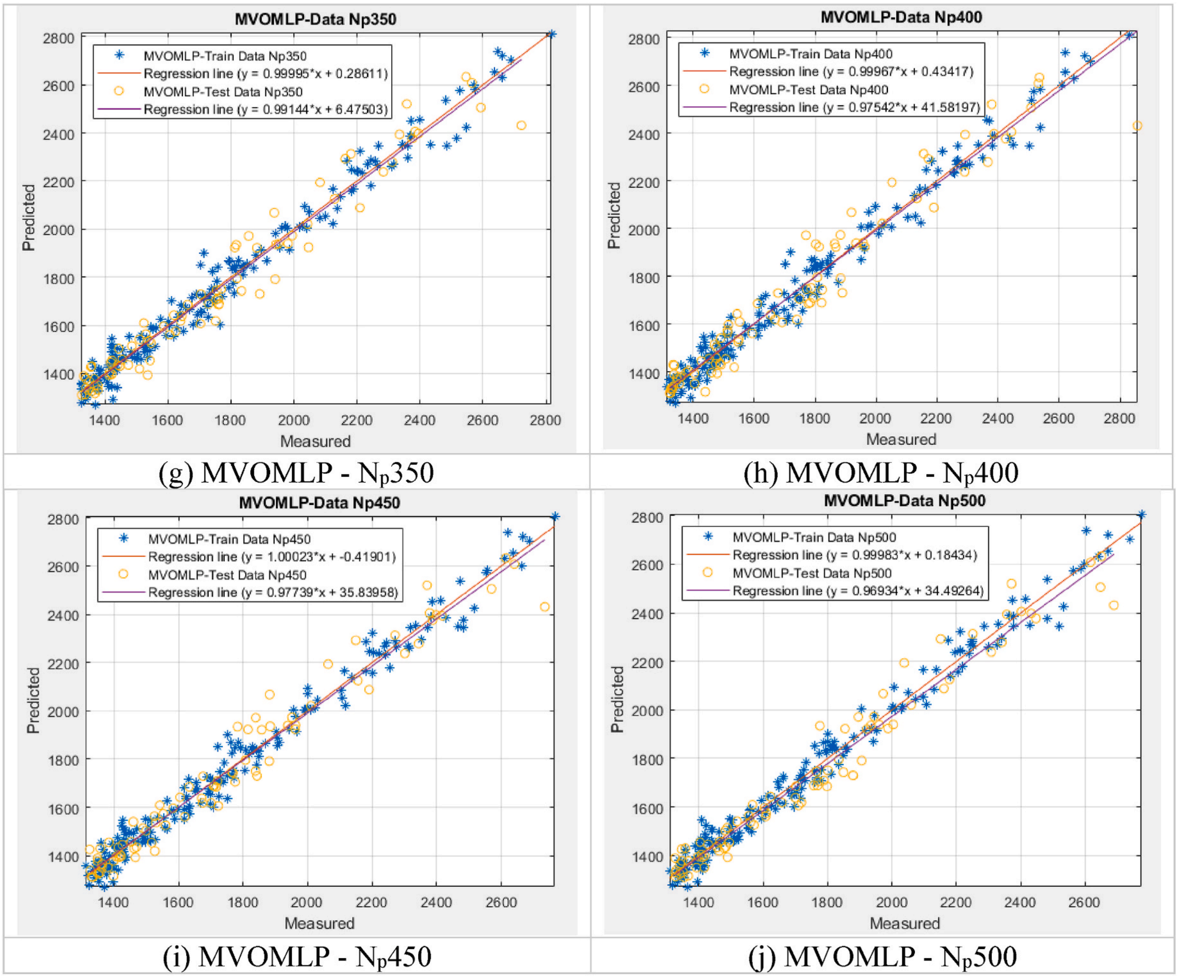


Fig. 6. (*continued*).

$$x_i^j = \begin{cases} \begin{cases} x_j + TDR + \left(\left(ub_j - lb_j\right) * r_4 + lb_j\right) & if\ r_3 < 0.5 \\ x_j - TDR + \left(\left(ub_j - lb_j\right) * r_4 + lb_j\right) & if\ r_3 \geq 0.5 \end{cases} & r_2 < WEP \\ x_i^j \quad r_2 \geq WEP \end{cases} \tag{12}$$

Where lb_j and ub_j are the lower and upper bounds of the j-th variable, x_j is the j-th parameter of the best universe, WEP and TDR are the worm existence probability and traveling distance rate, respectively, and r_2, r_3, and r_4 are random values between [0, 1]. The WEP and TDR formulas are as follows:

$$WEP = MIN + l \times \left(\frac{max - min}{L}\right) \tag{13}$$

$$TDR = 1 - \frac{l^{1/p}}{L^{1/p}} \tag{14}$$

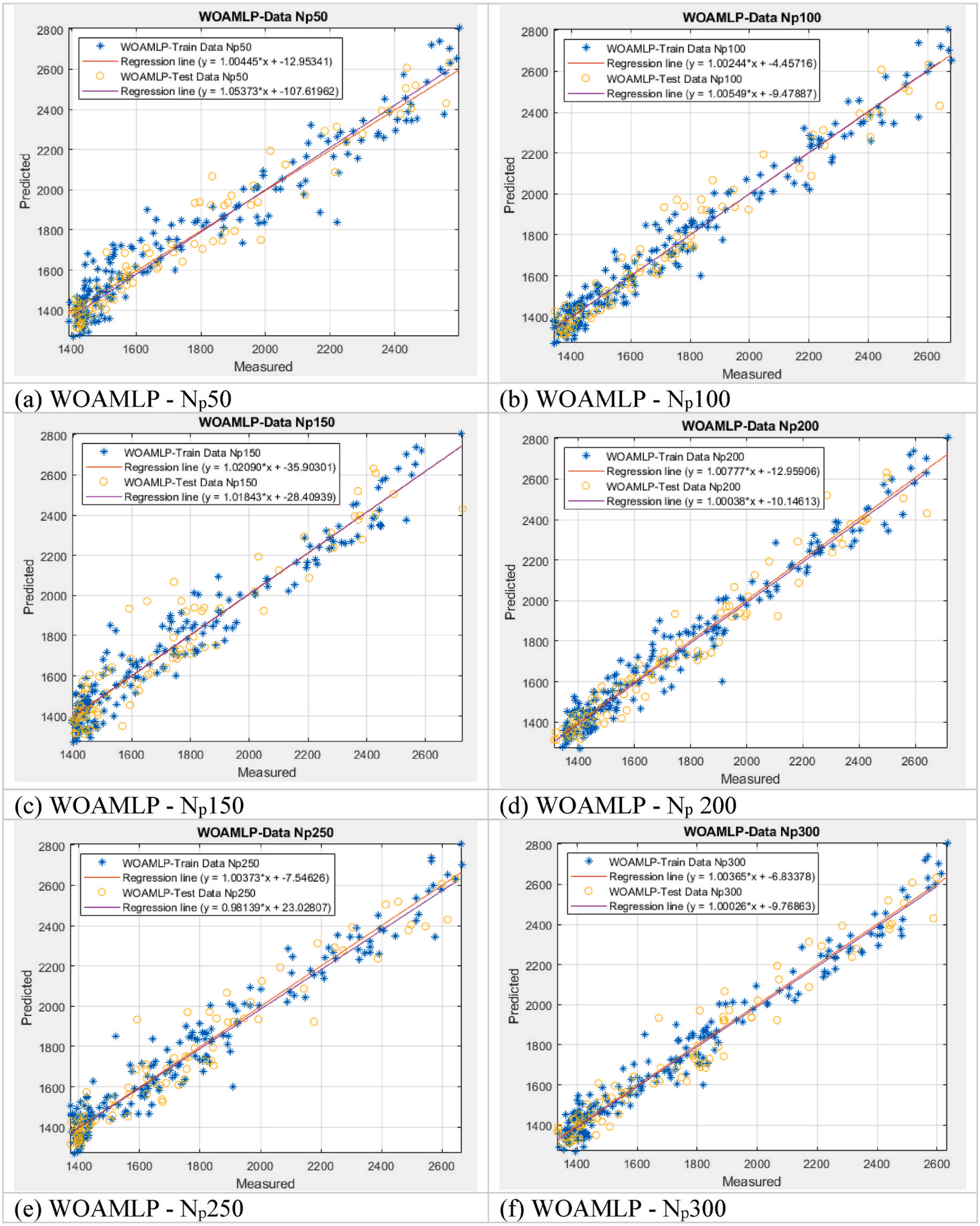
Where l is the iteration currently being performed, L denotes the number of iterations that can be performed in total, p denotes the exploitation accuracy over iterations, which is set at 6, and min and max denote the minimum and maximum values, respectively, which are set at 0.2 and 1, respectively. This study's maximum number of iterations is 500, using 30 universes.

3.4. Whale optimization algorithm (WOA)

A ground-breaking meta-heuristic system called the whale optimization algorithm simulates the social behavior of humpback whales [90, 91]. This meta-heuristic approach was developed by Mirjalili and Lewis [92]. The spiral bubble-net feeding maneuver theoretically represents this method of optimization. It's important to note that humpback whales are the only species known to engage in bubble-net feeding [92, 93]. Two behaviors have been identified to update the whales' location during optimization: the decreasing encircling mechanism and the spiral bubble-net feeding maneuver. The fundamental WOA method assumes that the best candidate solution at the moment is optimum or very close to it because the precise location of the optimal design in the search space is unknown [92]. It also assumes that the other search agents will move to match the best search agent. The following WOA procedure is briefly explained from Ref. [92].

The WOA starts with a set of populations that were created at random. Search agents modify their placements at each iteration using the A vector value. The following parts go over the update process. Until the termination condition is satisfied, this procedure is repeated.

The two steps of the WOA algorithm are exploitation and exploration. This approach smoothly moves from the discovery phase to the exploitation phase. The change in the A vector's value causes the transition to occur. A vector's value decreases over time; half of the iterations are used for exploration while $|A| \geq 1$ and the other half are used for exploitation when $|A| < 1$. The letter jj stands for the absolute value. As seen below, the vector A is calculated:



(a) WOAMLP - N_p50 (b) WOAMLP - N_p100
(c) WOAMLP - N_p150 (d) WOAMLP - N_p 200
(e) WOAMLP - N_p250 (f) WOAMLP - N_p300

Fig. 7. The accuracy outcomes of the testing and training datasets for various proposed structures of WOAMLP

$$\vec{A} = 2\vec{a} \bullet \vec{r} - \vec{a} \tag{15}$$

Where $\vec{a}$ decreases linearly over iterations from 2 to 0, and r is a random vector with a range of [0, 1].

4. Results

The present study examines the effectiveness of three innovative optimization techniques for approximating total energy using a neural network. This objective is achieved by integrating the algorithms with an MLP neural network. Each algorithm employs a specific search strategy to determine the MLP's optimal computational weights.

The Multilayer Perceptron (MLP) is structured based on the size of its hidden layer and the number of neurons within it. Therefore, optimizing these parameters is crucial. Previous research has demonstrated that one hidden layer is sufficient for modeling complex phenomena [94]. However, determining the optimal number of hidden neurons required a trial-and-error approach. The outcomes reveal that among the tested

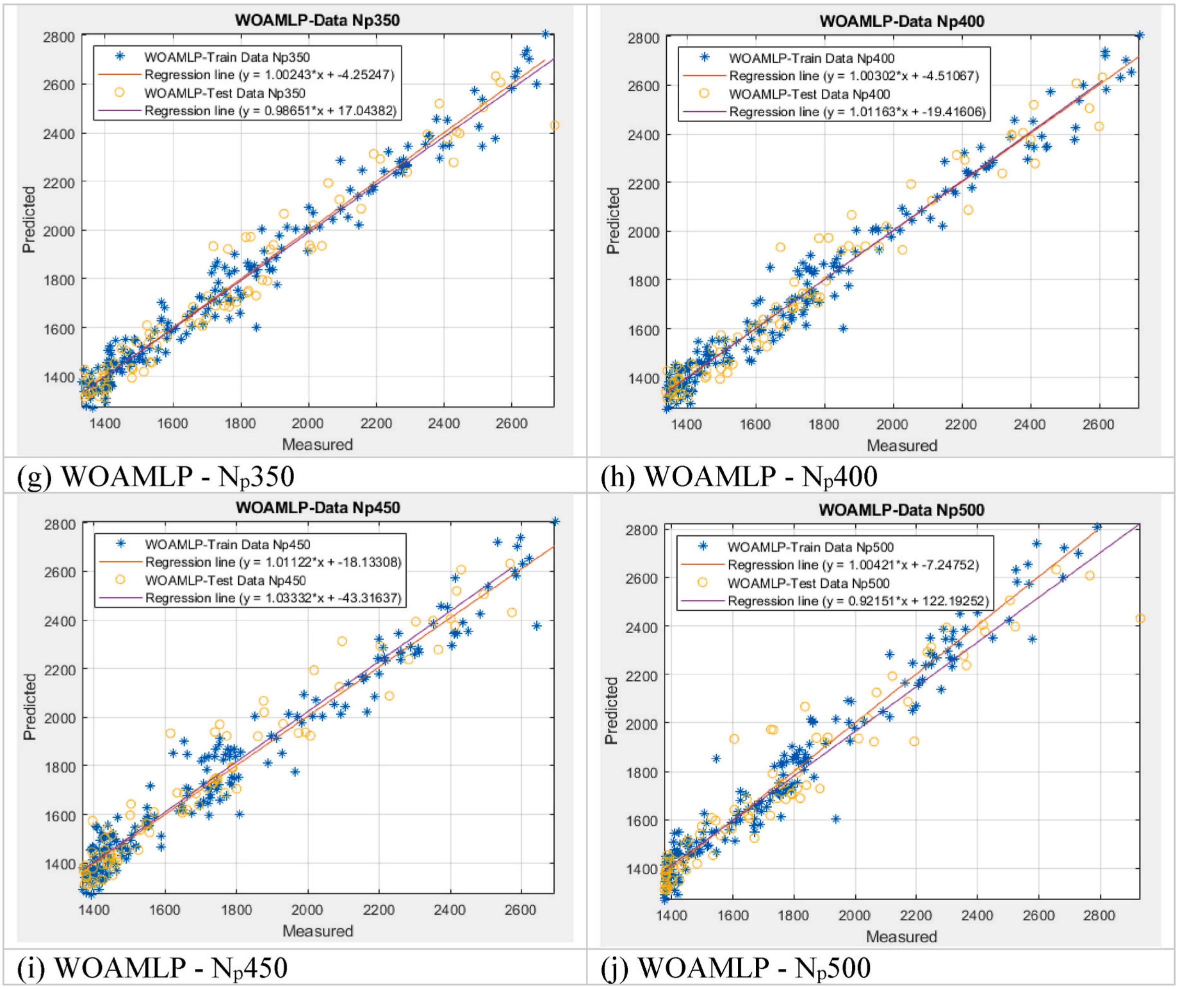


Fig. 7. (*continued*).

structures, where the middle layer ranges from 1 to 10 neurons, a structure with 22 × 5 × 1 neurons exhibited promising performance.

There are two data sets: the training set and the test set. A portion of the training set was separated and used as the validation set to fine-tune the algorithms. Based on the original versus resampled train data, any of the three strategies mentioned above can be identified as the most cost-effective model for all techniques. We initialize our convolutional neural network with random weights. In addition, we train the network with dropout using stochastic gradient descent by multiplying random Bernoulli variables by the input of the final layer. Consequently, there will be some variation in the network after each training session. To control the impact of randomness on our results, we repeat the complete experiment ten times and report the standard deviation and average of the ten acquired R^2 values.

4.1. Accuracy indicators

In the academic field of learning and prediction, mean absolute error (MAE) and root mean square error (RMSE) are error measurement metrics. Equations (16) and (17) are utilized to formulate these metrics. Additionally, Equation (18) defines the coefficient of determination (R^2), which determines the compatibility between predicted and estimated total energy.

$$MAE = \frac{1}{U}\sum_{i=1}^{U}\left|S_{i_{observed}} - S_{i_{predicted}}\right| \tag{16}$$

$$RMSE = \sqrt{\frac{1}{U}\sum_{i=1}^{U}\left[\left(S_{i_{observed}} - S_{i_{predicted}}\right)\right]^2} \tag{17}$$

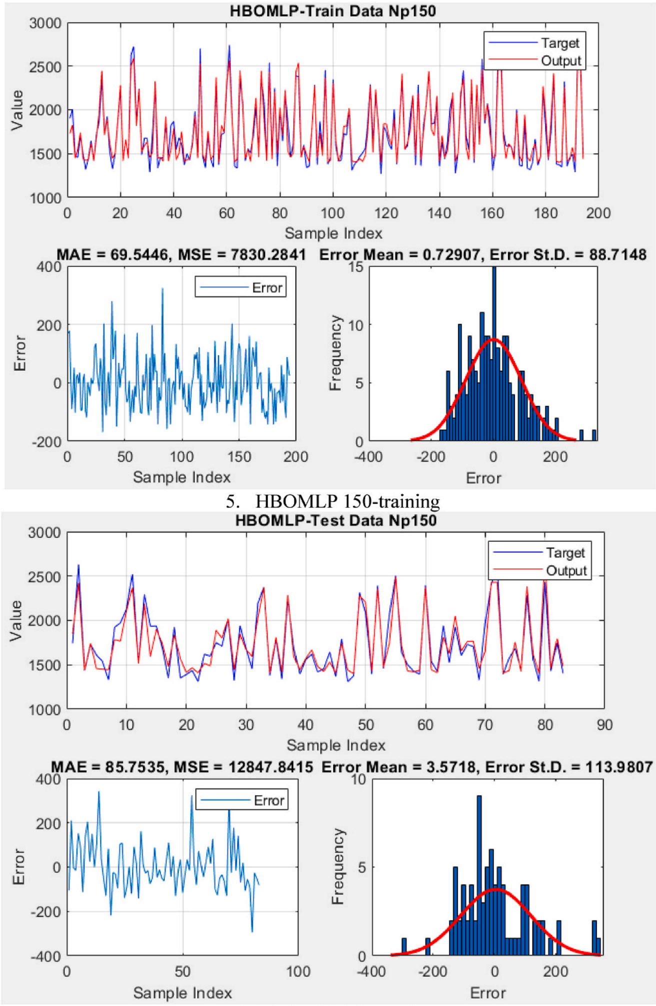
$$R^2 = 1 - \frac{\sum_{i=1}^{U}\left(S_{i_{predicted}} - S_{i_{observed}}\right)^2}{\sum_{i=1}^{U}\left(S_{i_{observed}} - \underline{S}_{i_{observed}}\right)^2} \tag{18}$$

The equations presented involve two variables, $S_{i_{observed}}$ and $S_{i_{predicted}}$, which represent the measured and predicted total energy, respectively. Additionally, U denotes the quantity of data records utilized in the analysis. Moreover, $\underline{S}_{i_{observed}}$ refers to the mean value of the observed total energy.

4.2. Incorporated MLP with optimizers

After synthesizing the metaheuristic approaches with the MLP, three methods are derived: HBO-MLP, MVO-MLP, and WOA-MLP. These ensembles are trained with samples to establish a relationship between the total energy and the corresponding variables. To evaluate the optimization behavior of the methods, each model undergoes 1000 repetitions for implementation. The objective function is reported by calculating the RMSE of results at each repetition. It should be noted that this stage focuses on pattern recognition and reports RMSE of training data.

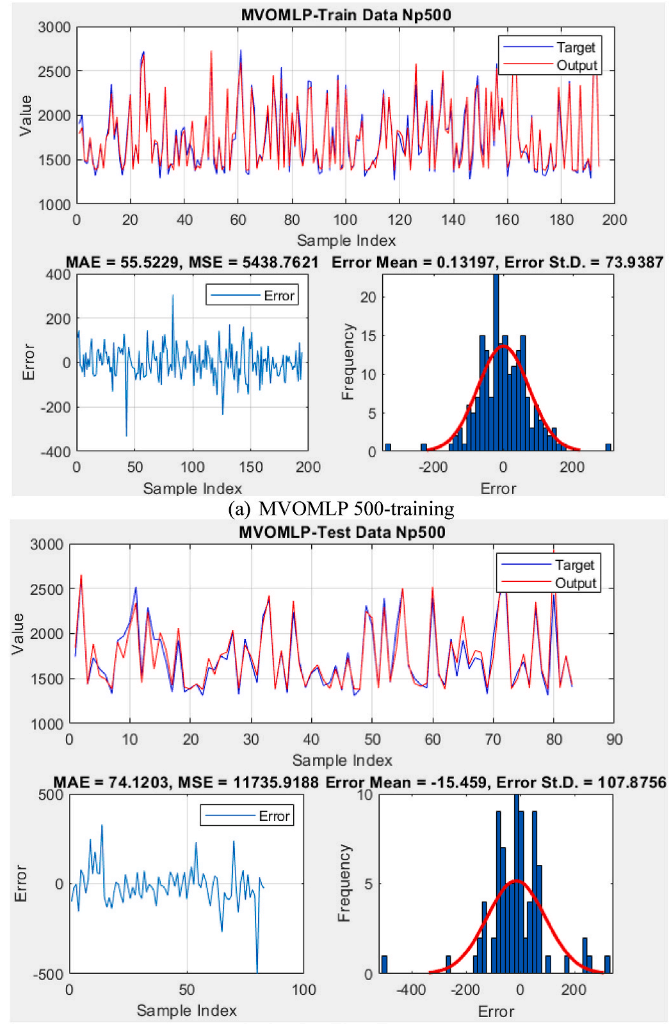
The swarm-based algorithms rely significantly on the number of participants involved. The present study explores the performance of



5. HBOMLP 150-training

(b) HBOMLP 150-Testing

Fig. 8. The proposed HBOMLP model in terms of its Mean Absolute Error (MAE) and frequency of occurrence of errors.



(a) MVOMLP 500-training

(b) MVOMLP 500-Testing

Fig. 9. The proposed MVOMLP model in terms of its Mean Absolute Error (MAE) and frequency of occurrence of errors.

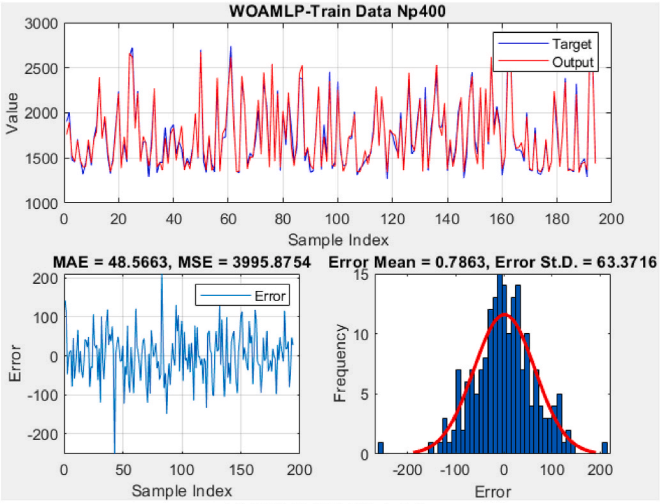
nine different population sizes (ranging from 50 to 500) for each model, intending to identify the most optimal complexity that results in the lowest Mean Squared Error (MSE). The findings reveal that 150, 500, and 400 populations deliver the lowest MSE values (7830.2841, 5438.7621, and 3995.8754) for HBO-MLP, MVO-MLP, and WOA-MLP, respectively. These results are depicted in Fig. 4.

The developed models are dependable, straightforward, and conform to laboratory results. This demonstrates that the developed approach is a versatile and dependable instrument. This study employed parametric research to evaluate the optimal swarm size and number of nations. Various MLP analyses were conducted on populations of 500, 450, 400, 350, 300, 250, 200, 150, 100 and 50 members.

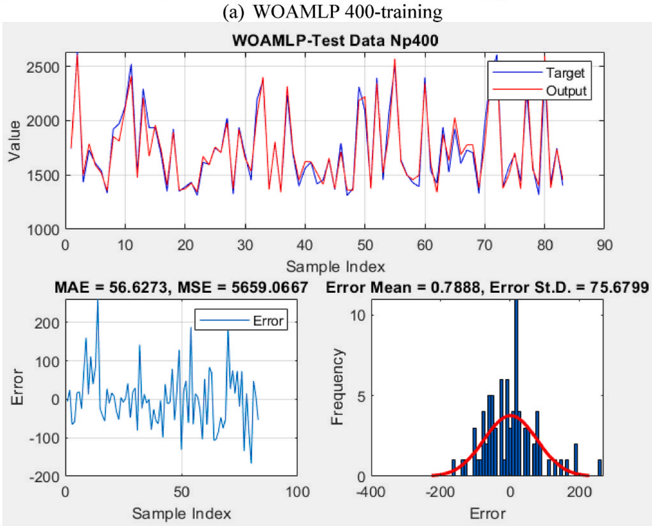
To determine the optimal MLP architecture, a predictive neural network with a double hidden layer was trained with varying numbers of nodes. To demonstrate the repeatability of the learning system, the training process was repeated multiple times for each structure. The same method was applied to the three models in Tables 3–6. The correlation between the number of neurons and the precision and complexity of network structures is notable. According to the findings, 150, 500, and 400 populations have the lowest MAE values (69.5446, 55.5229, and 48.5663) for HBO-MLP, MVO-MLP, and WOA-MLP, respectively. The testing outputs accuracy outcomes, a minor increase in the amount of testing R^2, and a negligible reduction in the RMSE amount led the authors to choose a structure with four nodes as the fittest. Consequently, a 22 × 5× 1 structure for the MLP network was chosen as the optimal MLP structure for the entire further hybridizing process (such as HBO-MLP, MVO-MLP, and WOA-MLP).

4.3. Prediction results

A scatter plot denotes a graphical representation that effectively showcases the correlation between two variables. Scatter plots are a tool for visualizing data in two dimensions, wherein each data point is depicted using a dot or symbol. One factor is plotted along the horizontal axis, while the other is plotted along the vertical axis. Such plots can be employed to discern patterns and trends within the data. These variables can demonstrate both the magnitude and orientation of their relationship. If the dots on the scatter plot tend to form a straight line, this indicates a strong correlation between the two variables. If the dots are scattered randomly around the graph, this indicates a weak or no correlation. Scatter plots can also show any outliers or unusual values in the data. In the data analysis, an outlier refers to a specific data point that deviates considerably from the remaining dataset. These points can be crucial in identifying unusual trends or errors in the data. Figs. 5–7 show the scatter plots for HBO-MLP, MVO-MLP, and WOA-MLP methods. The calculated R^2s (0.9715, 0.99184, and 0.98613 in training and 0.96449, 0.98236, and 0.97872 in the testing phase) accurately predict the total energy. It is comparable to the R^2 values derived from the scatter plots in Tables 3–5 for population sizes 500, 450, 400, 350, 250, 300, 200, 150,



(a) WOAMLP 400-training



(b) WOAMLP 400-Testing

Fig. 10. The proposed WOAMLP model in terms of its Mean Absolute Error (MAE) and frequency of occurrence of errors.

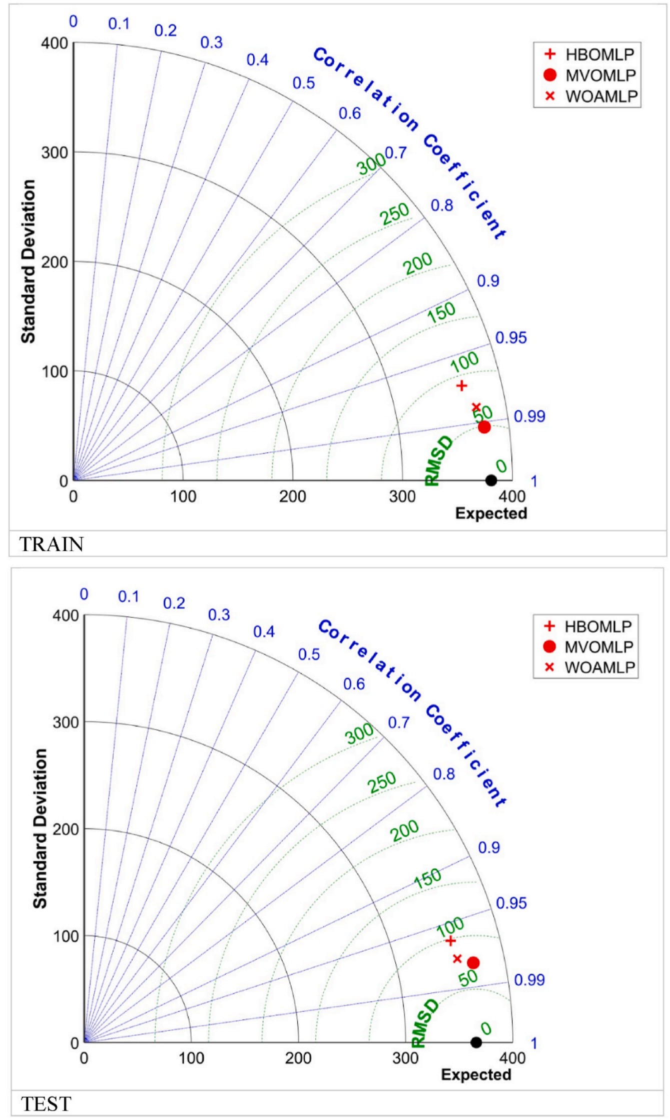


Fig. 11. Taylor diagrams for proposed methods in predicting total energy.

100, and 50. The iteration results revealed that MVO-MLP's prediction modeling was superior.

The accuracy of models in predicting total energy was evaluated based on their RMSE and R^2 values during both the learning and prediction phases. Tables 3–6 present all accuracy criteria obtained, with models exhibiting lower RMSE and higher R^2 selected as the most accurate predictors. Among these, the MLP constructed using weights and biases from MVO demonstrated the highest reliability and accuracy in predicting total energy without any discrepancy. Following this, MVO-MLP emerged as a promising optimizer for prediction, with HBO-MLP and WOA-MLP following behind.

The evaluation of evolutionary algorithms combined with multilayer perceptron neural networks for predicting building energy consumption in the residential sector reveals distinct performances across the tested methodologies, as indicated by their RMSE, R^2 values, and ranks. Multiverse Optimizer with Multilayer Perceptron (MVOMLP) emerges as the most effective approach, boasting the lowest RMSE of 48.55082 on the training dataset and the highest R^2 of 0.99184. This stellar performance translates to the top rank across training and testing datasets, solidifying its dominance with an overall rank of 1. While competitive, heap-based Optimizer with Multilayer Perceptron (HBOMLP) trails behind MVOMLP with an RMSE of 90.25319 and R^2 of 0.9715 on the training dataset, resulting in a corresponding rank 3. The Whale Optimization Algorithm with Multilayer Perceptron (WOAMLP) demonstrates intermediate performance, with an RMSE of 63.19792 and R^2 of 0.98613 on the training dataset, securing a rank of 2. These results underscore MVOMLP's exceptional predictive prowess, highlighting its potential to enhance energy consumption prediction models in residential settings significantly. However, further exploration of the nuanced interplay between algorithmic design, parameter optimization, and dataset characteristics is warranted to unlock the full potential of these methodologies and drive advancements in energy forecasting and conservation initiatives.

This study segment evaluates the implemented models' efficacy by comparing their predicted total energy output to the measured target values. The outcomes of the training and testing phases are depicted in Figs. 8–10, illustrating the variance between each set of output and the total energy target. During the training phase, HBO-MLP, MVO-MLP, and WOA-MLP predictions produced error values within ranges of [0.72907, 88.7148], [0.13197, 73.9387] and [0.7863, 63.3716], respectively.

The preceding section stated that the MSE values for four models were 7830.2841, 5438.7621, and 3995.8754. Furthermore, the MAEs calculated for each model were low (69.5446, 55.5229, and 48.5663), indicating minimal training error for all four approaches. The R^2 values obtained demonstrate high consistency between the target and output total energy, with over 98% agreement observed. The testing outcomes

Table 7
Crucial elements in building models to estimate energy consumption.

elements in building models	Key notes	description
Energy Economics	**Demand-Side Factors**	Consider economic factors that influence residential energy consumption, such as household income, energy prices, and the cost of energy-efficient appliances. Economic theory, such as the theory of consumer behavior and demand elasticity, can guide the modeling of energy consumption patterns.
	Policy Analysis	Assess the impact of energy policies, regulations, and incentives on residential energy consumption. Economic models, such as cost-benefit analysis or economic optimization models, can help evaluate the effectiveness of different policy interventions.
	Energy Market Dynamics	Understand how energy markets operate and how changes in supply and demand affect energy prices and consumption patterns. Consider factors like peak/off-peak pricing, time-of-use tariffs, and the integration of renewable energy sources into the grid.
	Lifecycle Cost Analysis	Evaluate the lifecycle costs of energy-efficient technologies and investments in residential buildings. Assess the economic feasibility of energy efficiency upgrades and renewable energy installations over the long term.
Data Validation	**Data Quality Assurance**	Validate the quality and accuracy of input data sources used in building energy consumption models. This includes energy bills, meter readings, building characteristics, weather data, and occupant behavior data.
	Cross-Validation Techniques	Employ cross-validation techniques to assess the performance of energy consumption models and ensure their robustness. Split the dataset into training and testing subsets to evaluate the model's predictive accuracy and generalization ability.
	Sensitivity Analysis	Conduct sensitivity analysis to examine the impact of variations in input parameters and assumptions on model outputs. Identify key factors that influence energy consumption and quantify their uncertainties.
	Comparison with Field Measurements	Validate model predictions against field measurements of energy consumption in residential buildings. Compare simulated energy usage with actual meter readings to assess the model's accuracy and identify discrepancies.
	Feedback Loop	Establish a feedback loop between model predictions and observed data to continuously improve the accuracy of energy consumption models. Incorporate new data sources and refine model parameters based on real-world observations.

are assessed based on the accuracy criteria cited. It is worth noting that the testing data are not initially provided to the networks. Thus, the findings in this section demonstrate the trained models' ability to forecast energy consumption under hypothetical scenarios. The testing outcomes are illustrated in Figs. 8b–10b, accompanied by histogram charts that display the frequency of calculated error values.

4.4. Taylor diagrams

Taylor diagrams, introduced by Taylor in 2001 [95], offer a graphical representation of the degree of conformity between observations and a pattern or set of patterns. The correlation, centered root-mean-square difference, and standard deviations that measure the degree of similarity between two patterns are used for this purpose. These diagrams are particularly advantageous when evaluating complex models with multiple aspects or comparing the performance of various models, as seen in IPCC [96].

The Taylor diagram, presented in Fig. 11, depicts the application of the current database to summarize the comparative proficiency of various models in reproducing the spatial arrangement of average annual precipitation. The statistical analysis was carried out for four models, and a label was assigned to each model. The position of each label on the plot illustrates the degree to which that model's simulated precipitation pattern corresponds with the observations. The pattern correlation values between observations and HBO-MLP, MVO-MLP, and WOA-MLP are approximately 0.97, 0.98, and 0.99, respectively.

5. Discussion

Interpreting the results in the context of the study's objectives, where MVO ranks highest, followed by WOA and then HBO, provides insights into the strengths and weaknesses of each method and factors influencing their performance.

MVO demonstrated the highest ranking in the evaluation, indicating its effectiveness in optimizing the neural network model for energy consumption prediction. MVO's ability to balance exploration of the solution space and exploitation of promising regions likely contributed to its competitive performance. MVO's robustness in handling complex optimization problems might have enabled it to adapt well to predicting energy consumption in the residential sector. While MVO performed well overall, its exploration capabilities might be limited compared to other algorithms, affecting its ability to find the global optimum in highly complex and nonlinear problem spaces. The performance of MVO could be sensitive to its parameter settings, requiring careful tuning for optimal results. MVO's scalability to larger datasets or more complex models might be a concern, especially if computational resources are limited.

WOA achieved the second-highest ranking among the evaluated methods, indicating its competence in optimizing the neural network model for energy consumption prediction. WOA's ability to perform global search might have facilitated exploration of the solution space, enabling it to find reasonably good solutions. Compared to more complex algorithms, WOA's simplicity and ease of implementation might make it a practical choice for specific applications. WOA might converge slower than other algorithms, affecting its efficiency in finding optimal solutions, especially in time-sensitive applications. WOA might suffer from premature convergence, so it is essential to settle on suboptimal solutions before thoroughly exploring the search space. WOA's exploration capabilities might be limited, particularly in high-dimensional or complex optimization problems, potentially hindering its ability to find the global optimum.

Despite ranking last in the evaluation, HBO still demonstrated competitive performance, especially regarding R^2 scores, indicating its consistency and stability in optimizing the neural network model. HBO's suitability for various optimization tasks beyond energy consumption prediction might make it a versatile choice for different applications. HBO's adaptability to different problem domains and data characteristics might enable it to perform well under diverse conditions. HBO's exploration capabilities might be limited compared to other algorithms, potentially causing it to get trapped in local optima and hindering its ability to find globally optimal solutions. HBO might be susceptible to stagnation, where it struggles to escape local optima, particularly in highly nonlinear or multimodal optimization problems. HBO's performance could be sensitive to its parameter settings, requiring fine-tuning for optimal results, which might increase the computational burden. Variations in algorithm design, including exploration-exploitation trade-offs and search mechanisms, likely influenced the algorithms' performance. The choice of algorithm parameters, such as population size, mutation rates, and convergence criteria, could significantly impact performance. The dataset's complexity, size, and noise level might have affected how well each algorithm adapted to the task of energy consumption prediction. Differences in convergence criteria and stopping conditions might have influenced the algorithms' ability to converge to optimal solutions. Variations in computational resources, including processing power and memory, could have affected the algorithms' performance and scalability. The evaluation results provide valuable insights into the strengths, weaknesses, and performance factors of MVO, WOA, and HBO in predicting building energy consumption. Understanding these factors can guide the selection and optimization of algorithms for similar tasks in the future, contributing to advancements in energy forecasting and optimization techniques.

Incorporating energy economics and data validation is crucial when building models to estimate energy consumption in the residential sector. By integrating energy economics principles and robust data validation techniques into the modeling process, researchers and practitioners can develop more accurate and reliable estimates of energy consumption in the residential sector. This contributes to informed decision-making, policy development, and energy efficiency initiatives aimed at reducing energy consumption and carbon emissions in residential buildings. Table 7 shows how these elements can be integrated into the process.

6. Conclusions

This study delves into energy consumption prediction in the residential sector by employing evolutionary algorithms in conjunction with conventional neural networks. The primary aim was to evaluate the efficacy of three distinct evolutionary algorithms—Heap-Based Optimizer (HBO), Multiverse Optimizer (MVO), and Whale Optimization Algorithm (WOA)—in this predictive task. Through rigorous experimentation and analysis, the study sought to provide insights into the performance of these algorithms and their potential utility in enhancing energy consumption forecasting accuracy.

The study underscores the significance of evolutionary algorithms in augmenting conventional neural networks for energy consumption prediction in the residential sector. MVO and WOA emerged as promising candidates for optimizing predictive models, with MVO demonstrating a slight edge in overall performance for both RMSE (48.55082 in training and 68.44517 in testing) and R^2 (0.99184 in training and 0.98236 in testing). These findings underscore the nuanced interplay between algorithm selection and predictive accuracy, emphasizing the need for tailored approaches in energy forecasting tasks. Moving forward, future research avenues may explore hybrid methodologies or parameter optimization techniques to further enhance the predictive capabilities of evolutionary algorithms in this domain. Ultimately, this study contributes valuable insights to the energy forecasting field, with potential implications for informed decision-making and sustainable energy management practices in residential settings.

CRediT authorship contribution statement

Guimei Wang: Writing – original draft, Validation, Data curation, Conceptualization. **Azfarizal Mukhtar:** Writing – original draft, Supervision, Investigation. **Hossein Moayedi:** Writing – review & editing, Validation, Supervision. **Nima Khalilpoor:** Writing – review & editing, Validation. **Quynh Tt:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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