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Research article

Energy demand forecasting using convolutional neural network and modified war strategy optimization algorithm

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ABSTRACT

Predicting the electricity demand is a key responsibility for the energy industry and governments in order to provide an effective and dependable energy supply. Traditional projection techniques frequently rely on mathematical models, which are limited in their ability to recognize complex patterns and correlations in data. Machine learning has emerged as a viable tool for estimating electricity in the last decade. In this study, the Modified War Strategy Optimization-Based Convolutional Neural Network (MWSO-CNN) has been provided for electricity demand prediction. To increase the precision of electricity demand prediction, the MWSO-CNN approach integrates the benefits of the modified war strategy optimization technique and the convolutional neural network. To improve efficiency, the modified war strategy optimization technique is employed to adjust the hyperparameters of the CNN algorithm. The suggested MWSO-CNN approach is tested on a real-world electricity demand dataset, and the findings show that it outperforms many state-of-the-art machine learning techniques for predicting electricity demand. In general, the suggested MWSO-CNN approach could offer a successful and cost-effective strategy for predicting energy consumption, which will benefit both the energy business and society as a whole.

1. Introduction

Electricity demand is the quantity of electrical energy needed by consumer, companies, and industries to satisfy their energy demands [1]. It is an important aspect of managing and planning energy because it specifies how much energy must be created, transferred, and distributed at all times to meet demand. Population expansion, financial growth, climate change, and technology improvements may all have an impact on energy consumption [2]. There are three categories of energy demand: main electricity demand, final electricity demand, and useable electricity demand [3]. The entire energy necessary for the generation and conversion of energy sources into diverse types of energy, such as energy and fuel, is referred to as the main energy demand [4]. The energy utilized by end-users such as families, companies, and businesses is referred to as final energy demand [5]. The electricity that is actually utilized for productive reasons, such as heating, cooling, and lighting, is referred to as useful energy demand [6].

Electricity demand forecasting is an essential undertaking for energy firms and politicians because it allows them to efficiently manage and regulate energy supply [7]. Efficient demand for electricity prediction is required to guarantee that the appropriate

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quantity of energy is produced, transferred, and distributed at all times to fulfill demand. Predicting demand for electricity is projecting the quantity of energy needed to meet the demands of customers over a certain time period [8]. This may be accomplished using a variety of ways, including statistical modeling, machine learning algorithms, and simulation methods [9]. The accuracy of demand for electricity projections is determined by a variety of factors, including data quality and availability, the complicated nature of the electrical grid, and the amount of uncertainty related to future occurrences [10].

Accurate electricity demand prediction is critical for energy suppliers to effectively plan their operations [11]. Energies providers must guarantee that they have the resources needed to satisfy clients' energy demands, such as adequate generating capacity, transmission and distribution infrastructure, and fuel supply. Energy suppliers may improve their operations, save costs, and prevent overbuilding or underbuilding [12].

Traditional electricity demand projection is used techniques including time series analysis and regression analysis [13]. The nonlinear and complicated interactions in the information cannot be fully represented by these approaches, which can result in incorrect forecasts. Machine learning has become a powerful technique for predicting energy consumption in the past decade [14].

Machine learning algorithms can recognize complicated correlations and trends in data and create reliable forecasts. Convolutional Neural Networks (CNNs) have demonstrated successful outcomes in numerous disciplines, including image identification, natural language processing, and speech recognition, among others [15]. CNNs are a form of deep neural network that employs convolutional layers to extract features from input data and build complicated representations of the data [16].

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CNNs can be employed to assess historical energy consumption data and meteorological data to find trends and patterns that can be utilized to create reliable forecasts about the future need for electricity in the context of electricity demand estimation [20]. Creating a reliable and effective CNN-based model for electricity demand prediction, on the other hand, necessitates tackling many issues, such as selecting the best architecture and optimizing the model's hyperparameters. Scientists have suggested several techniques to optimize the CNN framework for electricity demand prediction in response to these problems [21].

Predicting electrical consumption is a challenging subject that necessitates the evaluation of enormous quantities of data as well as the application of powerful machine learning algorithms. Since its capacity to recognize temporal and spatial trends in data, convolutional neural networks (CNNs) have emerged as a viable option for electricity demand prediction [22]. Nevertheless, developing an effective CNN framework for electricity prediction is a difficult process since various aspects, such as the number of layers, the size of the filters, and the activation functions utilized in each layer, must be carefully considered [23]. In this post, we'll look into how metaheuristic algorithms may be used to improve CNN structure for electricity demand prediction.

Metaheuristic procedures are a type of optimization algorithm that searches a broad search space for the most suitable solution to a problem [24]. These algorithms are especially well-suited to handling complicated optimization issues that would be challenging or difficult to resolve with typical optimization approaches. Metaheuristic techniques are meant to intelligently and efficiently explore the search space, frequently employing probability or random methods to steer the search. Metaheuristic methods are an effective technique for improving CNN structures for anticipating energy consumption [25]. The application of metaheuristic techniques to improve CNN designs is projected to become more relevant as the demand for precise and effective demand for electricity forecasts grows [26]. Energy demand forecasting techniques based on artificial intelligence (AI) have grown in popularity in recent years. The following studies are a few that have been done on this subject [27].

Liang et al. [1] used a hunger games search optimization using artificial neural network framework to forecast the electricity consumption in eco-buildings. This research offers a unique computational system called Hunger Games Search-based Multiple Layers Perceptron Neural Network System to precisely determine the electrical power consumption of cooling and heating load processes. For related goals, three other benchmark intelligent models were also created. The outcomes showed that the suggested soft computing paradigm is the most reliable model for calculating the cooling load and heating load of the air conditioning systems. The relative compactness and glass area distribution factors, which are used to estimate the electrical power consumption of future buildings, were criticized for being superfluous.

Daniel et al. [2] utilized fuzzy optimization-based deep neural network recognition. The primary threat to network performance currently is data safety assaults to detect attacker nodes in wireless networks. Sensor node deployment in the open environment is vulnerable to numerous types of DoS attacks, such as black holes and wormhole assaults. To address these constraints, a deep neural network-based fuzzy imperialist competitive algorithm (DNN-FICA) that reliably identifies the existence of an attacker node in a wireless network is created. The program MATLAB is used to run the simulation, which takes into account performance parameters such as the identification rate, packet delivery ratio, electrical power consumption, network lifespan, end-to-end latency, communication overhead, efficiency, and residual electricity. The comparing findings were obtained, and the result evaluation revealed that the suggested DNN-FICA strategy outperformed the other examined methods in terms of overall efficacy.

Liu et al. [3] employed machine learning to foresee the mechanical characteristics of a graphene/aluminum nanocomposite based on molecular dynamics modeling. The mechanical characteristics of graphene-reinforced aluminum (Gr/Al) nanocomposites were predicted using molecular dynamic (MD) modeling and machine learning (ML) approaches, and the Halpin-Tsai system was modified as a result. MD findings for Young's modulus and ultimate tensile strength of Gr/Al nanocomposites are obtained, taking into consideration the influences of graphene volume fraction, alignment angle, chirality, and environment temperature. The capacity to estimate Young's modulus and ultimate tensile strength is included in ML models. The Halpin-Tsai model was then adjusted using Young's modulus forecast using the MD and machine learning (ML) models.

Belge et al. [4] examined Optimization method using Path Planning and Tracking of Quadcopter for Payload Hold-Release Mission. This study examines how well an unmanned aerial vehicle (UAV) can plan and follow its journey in challenging geographic situations. To allow the UAV to carry out the payload hold-release task while avoiding challenges, it utilizes the hybrid metaheuristic optimization algorithm Harris hawk optimization (HHO)-grey wolf optimization (GWO). By contrasting the suggested method with metaheuristic swarms optimization methods such as particle swarm optimization (PSO) and GWO, its efficacy is evaluated. The suggested algorithm provides a quick and secure optimal path without becoming stuck in regional minima, according to experimental data, and the quadcopter follows the provided path with the least amount of electricity and time usage.

Sujan et al. [28] introduced a method to predict electricity demand by combining Convolutional Neural Networks and Echo State Networks in a hybrid model called CESN. The research utilized daily electricity demand data from four locations in Southeast Queensland, Australia to develop this innovative prediction model. The paper compared the performance of CESN with five other machine learning-based models, namely support vector regression, multilayer perceptron, extreme gradient boosting, deep neural network, and Light Gradient Boosting. The findings demonstrated that the proposed hybrid deep learning model surpasses the performance of the other models and achieves the highest prediction accuracy among them. Consequently, the study concluded that the proposed hybrid deep learning algorithm is a highly accurate method for forecasting electricity demand, surpassing existing state-of-the-art algorithms. However, it is important to acknowledge certain limitations of this work, such as the absence of external validation using data from different regions or countries, which may impact the generalizability of the proposed model. Furthermore, the study solely focuses on daily electricity demand data, and it would be worthwhile to explore the performance of the proposed model using data from other time scales, such as hourly or monthly data. Lastly, the paper lacks information regarding the computational requirements of the proposed model, potentially limiting its practical application in real-world scenarios.

Abdelkader et al. [5] investigated the combined Grey Wolf Optimization-Based Gaussian Process Regression Framework for Modeling the Deterioration Behavior of Highway Tunnel Components. For five highway tunnel components—cast-in-place tunnel liners, concrete interior walls, concrete portals, concrete ceiling slabs, and concrete slabs on grade—this research report suggests an integrated degradation prediction model. The model is verified against six well-known machine learning models and is made up of a combined version of Gaussian process regression and a grey wolf optimization method (GWO-GPR). Findings show that in the five tunnel elements, the created GWO-GPR approach greatly outperformed existing degradation forecasting approaches. Conclusion: The proposed degradation approach can help transportation authorities establish cost-effective and timely schedules for maintaining highway tunnels.

To achieve faster convergence rates with higher accuracy, modifying the weights throughout the training session of a convolutional neural network (CNN) is recommended. Additionally, the CNN has been enhanced with an improved metaheuristic algorithm called Modified War Strategy Algorithm. To meet the increasing demand for electricity and improve the efficiency and profitability of the energy system, highly adaptable electricity transmission networks must be constructed. Accurate estimation of client demand is crucial to prevent damage to electrical equipment and abuse of the energy system. Furthermore, the model needs to be capable of accurately predicting energy demand and assessing the feasibility and cost-effectiveness of new power generation facilities.

2. Convolutional neural networks

2.1. CNN layers

A CNN is made up of layers, each of which conducts a different sort of calculation on the incoming data. The following are the most typical types of layers in a CNN:

Convolutional layer that applies to the input data a collection of learnable filters to convolve with the input to generate a set of feature maps. The feature maps reflect the activation of a certain filter at a specific point in the input. *Pooling layer* that downsamples the feature maps created by the convolutional layer through performing a pooling operation to all local group of activations, such as max-pooling or average-pooling to reduce the dimensionality of the feature maps and makes the network more resistant to tiny changes in the input.

Activation layer is to take the output of the preceding layer and performs a non-linear activation function, such as ReLU. This contributes to the network's nonlinearity, which is required for simulating complicated interactions in the input data. The ReLU function is mathematically defined by equation (1):

$$F(x) = \max(0, x) = \frac{x + |x|}{2} \tag{1}$$

Batch normalization layer is the next layer that is used to normalize the activations of a layer by scaling and shifting them to a standard distribution. It aims to minimize the number of training epochs required to learn the network and enhance its performance by rescaling every scalar feature inside a mini-batch.

Dense layers (fully connected layers) connect every neuron from the previous layer to every neuron from the current layer, letting the network learn complicated nonlinear mappings between input and output.

Dropout layers are responsible for regularizing the CNNs. A dropout layer randomly picks a fraction of the neurons in the preceding layer and sets their outputs to zero with a particular probability, often around 0.5, throughout each training cycle.

2.2. Training stage

The process of training of a CNN involves identifying optimal weights for its convolutional and classifier components, in order to minimize the discrepancies between predicted outputs and the actual labels in the training dataset. Backpropagation is a widely employed technique for training neural networks, wherein the loss and optimization functions play crucial roles.

In this study, the loss function is referred to as the cost function. The difference between the actual output y and what was predicted by z is determined using a loss function known as cross-entropy (CE). The CE is mathematically determined as equation (2):

$$F_{CE} = -\sum_{j=0}^{N} y_j \log(z_j) \tag{2}$$

where, N describes the samples' number.

2.3. Transfer learning

Transfer learning is a deep learning approach, including CNNs, in which a previously trained model is utilized as a starting point for a new task. Transfer learning allows us to exploit the information and features learnt by a pre-trained model on a big dataset to enhance the performance and minimize the training time of a new model on a smaller dataset rather than training a new model from start.

The pre-trained model in transfer learning is often a big CNN that has been trained on a large dataset, such as ImageNet, to learn generic characteristics like edges, forms, and textures. This model's knowledge may be transferred to a new job by fine-tuning the model using a smaller dataset suited to the new task. This entails replacing the pre-trained model's final layers with new layers that are tailored to the new job, such as classification or regression layers, then training the new model on the smaller dataset.

Transfer learning gives a number of advantages for CNNs. First, it may greatly cut training time and increase new model performance, especially when the new dataset is tiny. Second, by exploiting the broad characteristics learnt by the pre-trained model, it can assist to prevent overfitting. Finally, it can help us tackle novel problems with limited data and processing resources, which is very useful in real-world applications.

3. Modified War Strategy Optimizer

3.1. Modeling the war strategy algorithm (WSA)

There are 3 main groups in the war strategy including: King (K), Commander (C), and Soldiers. Both commander and king have the role of leader in the field of war whose motion will supervise the soldiers. Based on the combating power (cost function amount) of soldiers, each of them owns the equivalent chance of becoming Commander or King over each epoch. A probability also exists for the Commander or King to encounter hard contest from the soldiers of the competitor (Local Optimal). These rival soldiers own sufficient power for trapping the Leaders. To prevent such an incident, soldiers will be supervised regarding their collective motion strategies in addition to be guided by the situation of the Commander or King.

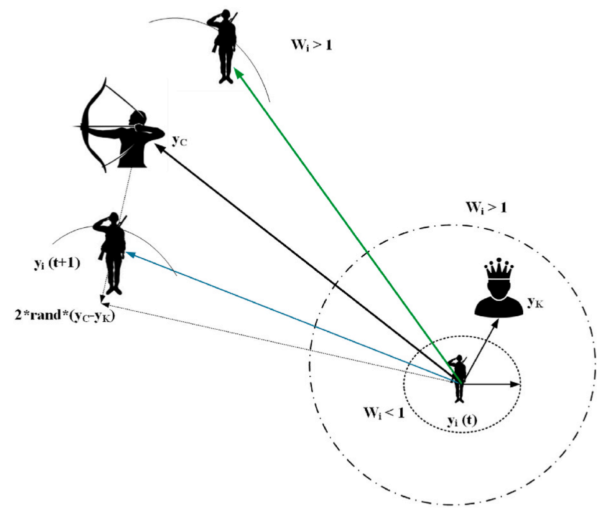

Fig. 1. Mechanism of renewing the attack model.

3.1.1. Attack tactic

2 war policies have been modeled in this paper. In the 1st strategy, each soldier does renew his own situation on the basis of the Commander and King situation. Fig. (1) demonstrates the mechanism of renewing the attack model. A beneficial situation is considered for the king to start a huge attack. Accordingly, the soldier who is endowed with the highest force of attack or cost has been considered the king. At the commence of the war, each soldier is going to have the identical weight and rank. Their rank does rise providing that they effectively execute the tactic. It is imperative to note that the soldiers' weight and rank is likely to be renewed on the basis of the tactic prosperity during the progresses of the war. When the war is going to be accomplished, the situations of the soldiers, Commander, and King become nearby because they reach the goal [equation (3)].

$$y_i(t+1) = y_i(t) + 2p(y_C - y_K) + rand(y_K \times W_i - y_i(t)) \tag{3}$$

Here, $y_i(t+1)$ and $y_i(t)$ demonstrate the new and the previous situation of the soldier. y_K and y_C demonstrate the king situation and the commander situation, and W_i is the weight.

In Fig. (1), the circles around the soldier illustrate the local points of $b = (y_K \times W_i - y_i(t))$ on the basis of the situation of the King. When $W_i > 1$, the b location is outside the situation of the king. Accordingly, the soldier's renewed situation is also outside the situation of the commander. The b location is going to be among the king situation and the existing situation of soldier when $W_i < 1$. The soldier's renewed situation is nearer in comparison to the previous item. The ending step of war occurs when $W_i \rightarrow 0$; hence, the renewed situation of soldier becomes adjacent to the situation of commander.

3.1.2. Renewing weight and rank

There is a correlation between renewing the situation of each individual and the relations of the king situation, the Commander location, and the soldiers' rank. Ranking of soldiers is influenced by their history of prosperity in the war which consequently overshadow the W_i factor. Ranking of every soldier implies the closeness of each soldier (search individual) to the goal (cost value). It is worth to mention that the factors of weight in other optimizers e.g., PSO, GWO, GSA, and WOA follow linearly variation, while in the offered optimizer, the weight experiences exponential variation as β factor. If the force of attack (cost) in the previous situation (F_{per}) is far greater than that of the new situation (F_{new}), the soldier dose take the previous situation [equation (4)].

$$y_i(t+1) = y_i(t) \times \left(F_{new} < F_{per}\right) + y_i(t+1) \times \left(F_{new} \geq F_{per}\right) \tag{4}$$

The soldiers' ranking (Ra_i) is going to be upgraded if they renew their situation in a successful way equation (5).

$$Ra_i = Ra_i \times \left(F_{new} < F_{per}\right) + (Ra_i + 1) \times \left(F_{new} \geq F_{per}\right) \tag{5}$$

With regard to the ranking, the new weighting can be determined as [equation (6)]:

$$W_i = W_i \times \left(1 - \frac{Ra_i}{Max\_iter}\right)^{\beta} \tag{6}$$

3.1.3. Policy of defense

The 2nd plan in renewing the situation is on the basis of the King, a randomly chosen soldier, and the Commander situation. The renewing of weight and ranking, however, does remain unchanged [equation (7)].

$$y_i(t+1) = y_i(t) + 2p(y_K - y_{ran}(t)) + rand \times W_i \times (y_C - y_i(t)) \tag{7}$$

This policy of war does search more and more areas in comparison to the previous policy when the situation of the randomly chosen soldier involves. Soldiers take giant footsteps in renewing their situation when larger amounts of W_i exist. When it comes to small values amounts of W_i the vice versa occurs.

3.1.4. Replacing the weak soldier

Over each epoch, the weak soldier with the worst value of cost function is identified. Several replacement tactics have been tested in this work. The easiest one is to substitute the weak soldier with the random one based on the below formula [equation (8)]:

$$y_W(t+1) = L_L + rand \times W_i \times (H_L - L_L) \tag{8}$$

The 2nd strategy is associated with substituting the weak soldier adjacent to the average of total army in the field as below formula. This strategy causes an improvement in the optimizer convergence [equation (9)].

$$y_W(t+1) = y_K - (1 - rand) \times (y_W(t) - median(y)) \tag{9}$$

3.1.5. Salient characters of the offered optimizer

a) The offered optimizer strikes an acceptable balance among the phases of exploitation and exploration.
b) There is a distinctive weight for every soldier (result) on the basis of their ranking.

c) The weight for every soldier has been renewed providing that the soldier makes an improvement in their cost value over the renewing stage. Hence, the renewing of the weight has been related to the particle situation correlated to the situation of Commander and King.
d) The variation of weights will be nonlinear. Over the early epochs, the weights variation is in large amounts. Over the last epochs, however, its variation is in small amounts. It causes a quicker merging to the global optimal.
e) The renewing of situation includes 2 steps. It does improve the capability of exploration regarding the global optimal result.
f) The offered optimizer is simple as much as it needs less and less calculations.

3.1.6. The phases of exploitation and exploration

The phases of exploitation and exploration have been 2 key principles for all metaheuristic optimizers. For making the optimizer more and more effective, an upright trade-off amid these two phases. In the proposed optimizer, the exploitation has been represented by attack tactic, while the exploration has been signified by defense tactic. There are also other key factors that overshadow these 2 phases and the performance of the offered optimizer. All these factors are illustrated as below:

1. The 'rand' parameter: This variable could accept random amounts from zero to one. 'rand' does decide about the movements of the soldier whether it is exploration or exploration oriented.
2. The $'p_r{}'$ parameter: This factor does assist the user to give flexibility of choosing a value which depends on the cost function. Based on the trials on diverse test functions, it is concluded that a small amount for p_r, ranging from zero to $\frac{1}{2}$, fits well for the unimodal functions. For the multimodal one, however, p_r between $\frac{1}{2}$ and 1 fits best.
3. The search individual motion in the y_{rand} direction: It causes the optimizer more and more explorative in searching the distinguished regions over the solution area for settling at the global optimal.
4 W_i: This factor overshadows the search individual direction towards the finest probable situation. This parameter causes a global movement of the search individuals for doing exploration. As a result, when the process of searching keep executing till the ultimate step, W_i causes the search individuals to become exploitative.

The assigned weight for every soldier have been adaptive and it varies over each epoch. Small value of weights is adapted by the soldier whose cost value is, while the high value of weights is for the soldier whose cost function value is low.

3.2. Modified War Strategy Optimizer

In this section, a modified version of the War Strategy Optimizer is presented, which incorporates Lévy flight (LF) and Chaos Map techniques. The LF is utilized to provide efficient exploration of search spaces, adaptability to changing landscapes, ease of implementation, and diversity of solutions, while the use of chaos maps helps to strike a balance between exploration and exploitation stages. These improvements have been implemented to enhance the convergence speed of the optimizer and overcome the issue of local optimum solution.

3.2.1. The lévy flight mechanism

Lévy flight is a kind of random walk with a mix of long and short moves. For metaheuristics, Levi-flight has several advantages that make it an attractive option for exploring complex search spaces. The advantage of Lévy flight is that it can explore the search space more efficiently compared to other random walk strategies. Levi flights allow the search process to quickly jump to distant regions of the search space, thus avoiding bogged down in local optimizations. This is especially useful in high-dimensional search spaces where traditional methods can struggle to find an optimal solution. Another advantage of Levi flights is that they can lead to more diverse solutions. By exploring different areas in the search space, Lévy Flight can uncover different solutions that may not be found by other search methods. This is especially important for multi-objective optimization problems where finding a diverse set of solutions is important.

Lévy Flight can also adapt to changing search environments. As the search progresses, Levy Flight can adjust the hop step size to reach better target regions of the search space that are likely to contain the best solution. Finally, Levi flights are relatively easy to implement and do not require extensive knowledge of the search space or problem domain. This makes it a popular choice for metaheuristic algorithms that should be applied to a wide range of problems.

The Lévy Flight works by using a random walk motion to control the local seek position, as shown equations 10–12.

$$Lévy\ (S) \approx S^{-1} \times S^{-\tau} \tag{10}$$

$$S = A \times |B|^{-1/\tau} \tag{11}$$

$$\sigma^2 = \left\{ \frac{\sin\ (\pi\tau/2)}{2^{(1+\tau)/2}} \times \frac{\Gamma(1+\tau)}{\tau\Gamma((1+\tau)/2)} \right\}^{\frac{2}{\tau}} \tag{12}$$

where, S designates step size, $\Gamma(.)$ signifies the Gamma function, and $A, B \sim N(0, \sigma^2)$. By assuming $\tau = 1.5$ [29], the heading to the best solution can be achieved as equation (13):

$$X_w(t+1) = X_i(t) + 2 \times \rho \times (K - X_{rand}(t)) + rand \times W_i \times (c - X_i(t)) \times Lf(\sigma) \tag{13}$$

3.2.2. Chaos map

Chaos mechanism uses pseudorandom values instead of random values to get faster results for the considered methods. This study uses sinusoidal map for this purpose. The advantages of using sine chart chaos charts with metaheuristics include enhanced exploration and exploitation capabilities. This algorithm can explore the search space better and avoid getting stuck in local optimizations. Additionally, the sine map-chaos map helps speed up metaheuristic convergence by generating more diverse and efficient search paths. This results in faster convergence to the global optimum and a more accurate solution. Sinusoidal Map-Chaos-Map has proven to be robust and effective in various optimization problems and can be used in combination with other meta-heuristics or as a standalone optimization algorithm. Finally, the sine chart chaos map is scalable and can easily handle large optimization problems. It can be applied to various optimization problems such as continuous optimization, discrete optimization, and combinatorial optimization problems. This map is applied to the replacement stage as equations 14 and 15:

$$X_w(t+1) = -(1-\theta) \times (X_w(t) - median\ (X) + K \tag{14}$$

$$\theta(t+1) = a\theta(t)^2 \sin(\pi\theta(t)), \tag{15}$$

Here, $\theta(t)$ represents the sinusoidal value for iteration t, a is a variable between 0 and 4,. Here, $\theta(0) = 0.5$.

3.3. Algorithm authentication

To evaluate the effectiveness of the suggested Modified War Strategy Optimizer, 10 benchmark functions were employed. The study focused on the first ten benchmark functions from the "CEC-BC-2017 test suite," which are widely used to assess the performance of optimization methods. In order to ensure a fair comparison with other algorithms, the decision variable bounds for the test functions are bounded in the range [−100, 100]. This approach allowed for consistent and uniform evaluation of the suggested algorithm and facilitated its comparison with other refined and tested algorithms.

The primary objective of this comparison was to assess the effectiveness of the proposed Modified War Strategy Optimizer and identify its advantages and disadvantages in comparison to other state-of-the-art algorithms, including Pelican Optimization Algorithm (POA) [30], Tunicate Swarm Algorithm (TSA) [31], and Gravitational Search Algorithm (GSA) [32]. The parameter values for all examined methods are provided in Table 1 for consistency and clarity in the comparison process. By comparing the performance of the Modified War Strategy Optimizer to other established and respected algorithms, the authors were able to provide a more comprehensive and accurate assessment of its effectiveness.

Random initialization in optimization methods can sometimes prevent them from producing a globally optimum solution. Instead, they may quickly converge to a suboptimal solution that is close to the ideal one. To address this issue, the authors performed 30 runs of each function to obtain more reliable results. Key metrics such as the average value (Avg) and standard deviation (StD) were calculated for easier analysis. The average value provides the mean results of the 30 runs, while the standard deviation helps assess the volatility of the findings.

To numerically compare the performance of the Modified a Modified War Strategy Optimizer to other optimization approaches, the authors presented the results in Table 2. By performing multiple simulations and calculating essential metrics, the authors were able to provide a more comprehensive and accurate assessment of the effectiveness of the proposed algorithm and its performance in comparison to other approaches.

Based on the results presented in Table 2, the proposed Modified a Modified War Strategy Optimizer demonstrated the highest level of efficiency in solving the CEC-BC-2017 test suite when compared to other algorithms. This finding suggests that the proposed algorithm outperforms the other approaches considered in the study. Moreover, the proposed algorithm also exhibited one of the lowest standard deviation (StD) values among the algorithms evaluated, indicating improved reliability in solving optimization problems over multiple runs. The lower StD value of the proposed algorithm, in comparison to more conventional approaches, suggests that it consistently produces reliable results across various assessments.

Table 1
Parameter set of the comparative algorithms.

Algorithm	Parameter	Value
Pelican Optimization Algorithm (POA) [30]	I	2
	R	0.6
	T	200
Tunicate Swarm Algorithm (TSA) [31]	Search agents	80
	P_{min}	1
	P_{max}	4
	Number of generations	200
Gravitational Search Algorithm (GSA) [32]	Search agents	80
	Gravitational constant	200
	Alpha coefficient	20
	Number of generations	200

Table 2
Comparison results of test functions' evaluation on the CEC-BC-2017 test suite.

Benchmark		MWSO	WSO [33]	POA [30]	TSA [31]	GSA [32]
F1	Avg	0.00	5.71	6.97	7.91	5.57
	StD	0.00	4.92	6.73	6.94	5.36
F2	Avg	3.53	5.68	6.45	6.69	5.48
	StD	3.19	5.40	5.83	6.47	5.37
F3	Avg	0.00	3.71e-9	5.89e-7	6.96e-8	6.47e-9
	StD	0.00	0.03	5.82e-6	6.33e-7	7.91e-8
F4	Avg	0.00	0.02	9.74e-5	8.93e-6	4.41e-7
	StD	0.03	0.03	6.05e-4	7.17e-5	7.44e-7
F5	Avg	0.00	5.57	6.67	7.91	5.15
	StD	0.00	4.91	5.23	7.35	4.47
F6	Avg	0.05	6.60	7.32	7.76	5.92
	StD	0.00	6.44	6.12	7.42	5.25
F7	Avg	0.00	7.72	7.86	8.12	7.58
	StD	0.72	7.38	7.47	7.64	6.93
F8	Avg	0.00	2.74	4.04	4.46	2.20
	StD	0.00	2.24	3.54	4.01	1.92
F9	Avg	0.00	0.83	2.17	3.38	0.02
	StD	0.00	0.59	0.89	2.03	0.00
F10	Avg	0.00	1.73	3.53	4.05	1.15
	StD	0.00	1.23	3.12	3.97	0.95

Therefore, this technique can be useful for our purpose. To forecast power demand, the utilization of CNN and Modified War Strategy Optimization Algorithm involves a series of steps:

1) The power demand data is inputted into a five-level CNN. The CNN is designed to learn and extract features from the bivariate sequence, ultimately producing a feature vector.
2) The feature vector is then fed into a Modified War Strategy Optimization (MWSO) algorithm. It adjusts the hyperparameters of the CNN, including the number and size of filters, activation functions, etc., with the aim of optimizing the prediction performance of the CNN.
3) Once the CNN is optimized, it is employed to predict the power demand for the subsequent time step based on historical and current data. The prediction is compared against the actual power demand, and the resulting error is calculated.
4) The prediction error is utilized to update the weights and biases of the CNN using a backpropagation algorithm. The CNN is trained iteratively until the prediction error is minimized or a predefined stopping criterion is met.

The primary advantage of this approach lies in its ability to combine the strengths of the CNN, which can effectively capture intricate patterns and correlations within the data, and the MWSO, which can fine-tune the CNN's hyperparameters. This combination ultimately leads to a high level of accuracy and efficiency in power demand prediction.

4. Proposed energy demand forecasting model

The proposed model is a novel technique to enhance the performance of CNN networks for energy demand forecasting by using ensemble learning. Ensemble learning is a method of combining multiple models to obtain a better prediction than any single model alone. The proposed model uses two pre-trained CNN networks, VGG16 and VGG19, as the base models for the ensemble. VGG16 and VGG19 are well-known CNN architectures that have achieved state-of-the-art results on various image recognition tasks. They consist of 16 and 19 layers, respectively, including convolutional, pooling, and fully connected layers. The proposed model leverages the pre-trained weights of these models, which have been trained on a large-scale image dataset, and fine-tunes them for the energy demand forecasting task. By combining two different CNN architectures, the proposed model can capture a larger variety of features and

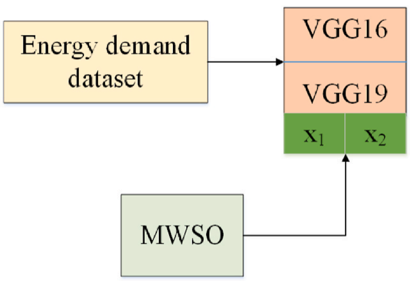

Fig. 2. Flowchart of the proposed model.

improve the overall network performance.

The proposed model consists of four steps: loading and optimizing the pre-trained models, training the models on the energy demand dataset, evaluating the models on the validation dataset, and ensembling the models on the test dataset. Fig. (2) shows the flowchart of the proposed model.

In the first step, the pre-trained VGG16 and VGG19 models are loaded and their hyperparameters are optimized using the Modified War Strategy Optimization (MWSO) method. The MWSO method is used to optimize the hyperparameters of the pre-trained models, such as the mini-batch size, the learning rate, the number of units in the fully connected layers, and the dropout ratio. The mini-batch size and the learning rate affect the speed and stability of the training process. The number of units in the fully connected layers and the dropout ratio affect the complexity and generalization ability of the models. As indicated in Table 3, the candidates were chosen to match the hyperparameters that needed to be improved.

The MWSO method can find the best combination of these hyperparameters that can maximize the prediction accuracy of the models.

The training set is used to train the models, the validation set is used to evaluate the models, and the test set is used to test the final prediction. The bivariate sequence is also normalized and reshaped to fit the input format of the pre-trained models. The pre-trained models are fine-tuned on the training set, which means that the weights of the convolutional layers are slightly updated, while the weights of the fully connected layers are retrained from scratch. The fine-tuning process can adapt the pre-trained models to the energy demand forecasting task, and transfer the knowledge learned from the image dataset to the energy demand dataset.

In the next step, the models are evaluated on the test dataset to verify their accuracy and select the best-performing models. The validation dataset is used to measure the prediction error of the models, using the cross-entropy (CE) as the evaluation metric. The lower the CE, the better the prediction performance. The models with the lowest MAE on the validation dataset are selected as the best-performing models for the ensemble. The best-performing models are ensembled to create the final prediction on the test dataset.

The proposed model is expected to achieve a high accuracy and efficiency in energy demand forecasting, by combining the advantages of the pre-trained CNN networks, the MWSO method, and the ensemble learning. The pre-trained CNN networks can extract high-level features from the bivariate sequence, and transfer the knowledge learned from the image dataset to the energy demand dataset. The MWSO method can optimize the hyperparameters of the pre-trained models, and enhance their performance for the energy demand forecasting task. The ensemble learning can combine the predictions of the different CNN architectures, and improve the overall network performance. The proposed model can provide a novel and effective solution for energy demand forecasting, which can benefit the energy industry and society as a whole.

5. Dataset description

The dataset for this analysis has been acquired based on a report from 2022 entitled “UK Energy in Brief 2022” [34]. The input data was separated into subgroups for training, validation, and testing to guarantee a thorough investigation. This method allowed for a more complete study of the dataset, resulting in a more accurate and dependable assessment of the forecasting model.

The acquired dataset was deemed adequate for implementing the suggested optimized convolutional neural network-based forecasting model. This is because the dataset includes the necessary scheduling types, such as Short, Long, and Medium-Term Forecasting, which are essential for accurate energy demand forecasting. By leveraging the dataset’s diverse range of scheduling types, the proposed model was able to provide more robust and reliable energy demand predictions.

A 30-min precision day in advance forecast was used for this investigation since it was found to be more suited for the convolutional neural network model. Input, objective parameters, and the number of neurons in the hidden layer were all assigned prior to the experiment. The day, month, and year input variables were chosen for their relevance to energy demand forecasting. A hidden layer was found and used in the experiment to increase the accuracy and efficacy of network training. The model was able to capture more intricate interactions between the input factors and the objective variable by adding this layer, resulting in more accurate energy demand projections. Throughout the experiment, the variable related to power usage was selected as the goal variable. By focusing on this variable, the model was able to learn the patterns and trends of energy consumption, enabling it to provide accurate forecasts for future energy demand.

5.1. *Energy use during the summer*

Fig. (3) depicts an energy usage profile for weekdays throughout the summer season. This graph depicts the average value of energy consumed during the day. The graph depicts an hourly breakdown of the energy usage curve to offer a more precise picture of this trend. This breakdown may be used to detect the times of day when energy use is highest and lowest, as well as any trends or patterns in energy consumption. This data is useful for constructing reliable energy demand forecasting models because it allows researchers to

Table 3
Determining the decision variables during hyper-parameters optimization.

Decision variable	Hyper-parameter
x_1	Mini-batch size
x_2	Dropout ratio

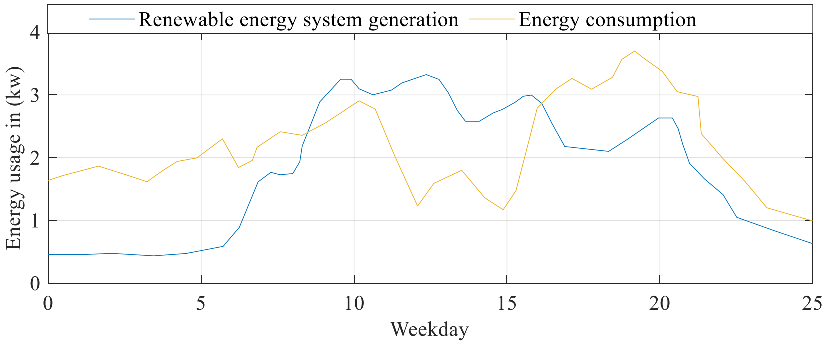

Fig. 3. Summer weekday energy consumption curve.

determine the elements that influence energy consumption and project future trends in energy consumption.

Fig. (3) and (4) provide valuable insights into the factors that influence energy demand during the summer season. Both figures highlight the heavy use of cooling equipment, such as air conditioners, which contribute significantly to overall energy consumption. This observation is particularly evident in Fig. (3), which shows the daily energy consumption curve for weekdays during the summer season. In addition to the heavy use of cooling equipment, Fig. (4) shows the pattern of energy consumption during holidays. By examining this graph on an hourly basis, it is possible to identify the periods of the day when energy consumption is highest and lowest. This information is critical for developing accurate energy demand forecasting models, as it enables researchers to identify the key factors that drive energy consumption and predict future trends in energy usage.

There is a significant pattern in energy usage throughout the summer season that is lower during vacation times than on working days. This is most likely due to lower energy consumption in the business and industrial sectors, as well as lower use of domestic appliances during holidays. In addition to this tendency, the longer bright days of summer can have a favorable effect on energy use. Solar panels, for example, are highly useful during this season since they can create more electricity owing to greater sunshine. This is an essential factor to include for energy demand forecasting models because it emphasizes the need of including renewable energy sources into the total energy mix.

5.2. *Energy use during the winter*

Fig. (5) depicts energy consumption patterns during the winter season, particularly during the workweek. The graph depicts the average amount of energy consumed throughout each hour of the day, giving an hourly picture of the energy consumption trend. This graph may be used to detect the times of day when energy use is the largest and smallest, as well as any trends or patterns in energy usage.

This figure's insights are especially useful for energy demand prediction models throughout the winter season. Understanding the elements that drive energy usage over this time period allows for the development of more accurate and dependable models that can assist energy conservation and efficiency policy choices.

Fig. (6) depicts the trend of electricity use over the winter holidays. The graph depicts the average amount of energy utilized during the day, offering an hourly picture of the power consumption trend. It is feasible to detect the times of day when energy use is highest and lowest by analyzing this graph on an hourly basis. Energy usage, on the other hand, could be lower during the middle of the day when people are out and about or engaged in leisure activities. This graph's insights are especially useful for constructing accurate energy demand-predicting models throughout the winter holiday season.

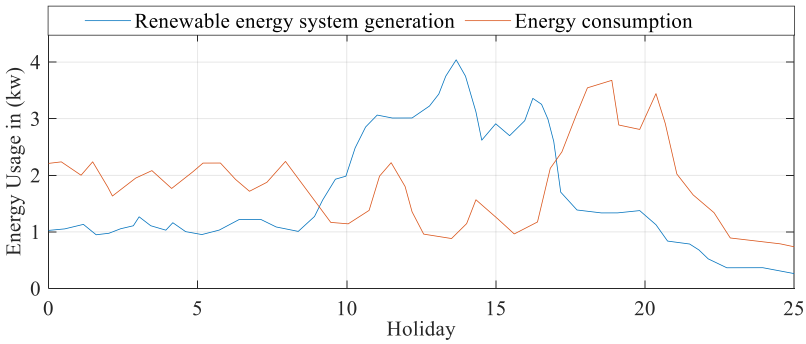

Fig. 4. Summer holiday energy consumption curve.

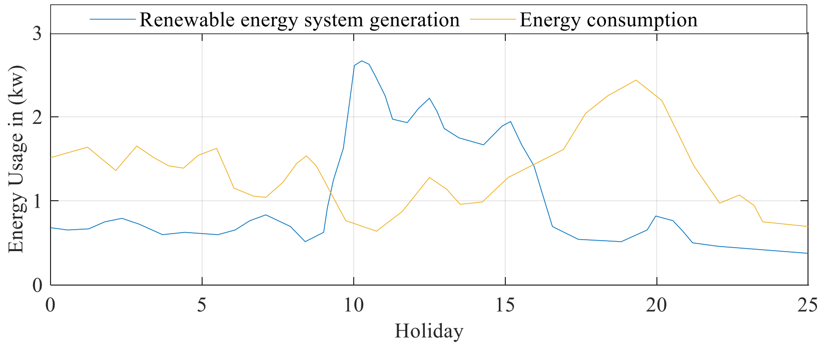

Fig. 5. Winter weekday energy consumption curve.

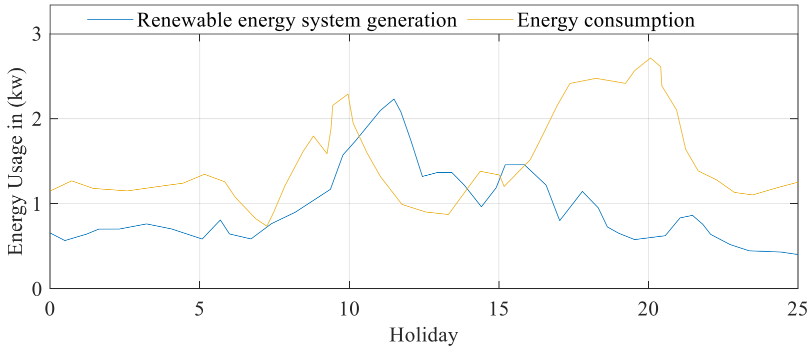

Fig. 6. Winter holiday energy consumption curve.

Fig. (5) and (6) give useful information on energy use patterns during the winter season. These graphs show that electricity consumption during the winter season is slightly greater than during the summer season, especially at night when heating equipment is utilized. This is most likely due to increasing energy consumption in the household and business sectors during the winter months. Furthermore, it is crucial to note that the electricity provided by renewable energy sources is often lower in the winter than in the summer. This is because the winter months have less sunshine and fewer daylight hours.

6. Simulation results

This section displays and discusses the findings achieved using the proposed method. The fitness of candidate solutions was determined after any iteration of MWSO based on the rate of loss acquired from the particles in the validation set after K number of CNN training iterations. After extensive testing, it was shown that when the number of training iterations is less than three, CNN's convergence capability is poor. When the training iterations quantity exceeds six, the MWSO training procedure requires an exponential amount of time. As a result, the value of K was set to six, implying that for each OLPSO iteration, a total of six CNN training epochs were performed to compute the fitness of individual solutions. Following the termination of the MWSO algorithm, the suggested hyperparameters were provided in Table 4.

The deep transfer learning that we outlined before was trained using the MATLAB R2017b programming language. All studies were carried out on a Tesla K80 GPU running Ubuntu with Google Collaboratory Linux (CNN with VGG-16 and VGG-19).

It is estimated that there would be a maximum of 200 iterations and 80 individuals. Using the proposed CNN models improves the accuracy of energy forecasts. The forecasted power from the suggested VGG approach is utilized to satisfy consumer energy demand and to better understand how consumers use energy. The proposed improved VGG/MWSO approach (the best of VGG-16 and VGG-19) is compared to various techniques in the literature, including the genetic algorithm enhanced adaptive deep neural network (GA/CNN) [35], hybrid LSTM (hLSTM) [36], and CNN-LSTM neural networks [37].

Table 4
Optimal values of the hyperparameters achieved by MWSO.

Model	Dropout ratio	Minibatch size
VGG 16	0.34	43
VGG 19	0.46	88

6.1. Daily energy demand prediction

Fig. (7) depicts a typical day's anticipated energy use and customer power consumption patterns during the time. A time frame is being set up to gather the customer's goal and input data at 20-min intervals, enabling very effective neural network training. Fig. (7) depicts the results of evaluating expected and real energy demand.

Fig. (7) shows the power demand forecasting for the suggested VGG/MWSO compared with alternative methods, such as, GA/CNN [35], hLSTM [36], and CNN-LSTM [37]. The daily energy consumption forecasting comparison demonstrated that, notwithstanding the fact that all techniques provide an acceptable outcomes, the suggested VGG/MWSO method delivers the best satisfying results in energy demand forecasting, that is proved by observing its proximity to the consumed profile.

6.2. Monthly energy demand prediction

Fig. (8) depicts the predicted energy consumption trends for a typical month, as well as the associated customer power consumption patterns. In order to allow successful neural network training, a time schedule for obtaining consumer input data and goals is set. The data gathered during this time period is critical for constructing a model that appropriately reflects the consumers' energy use trends. The neural network may be trained by examining data patterns to discover the important elements that impact energy use and to generate more accurate forecasts of future energy use.

Furthermore, the data gathering time frame allows the neural network to be trained on a wide range of data, including peak and off-peak consumption times, weekdays, weekends, and holidays. This enables the network to learn patterns and trends in consumer energy use and generate accurate forecasts for various circumstances.

According to Fig. (8), the proposed VGG/MWSO approach has a low error rate when compared to other comparable algorithms. It is also demonstrated that the proposed VGG/MWSO estimates short-term energy usage with great accuracy.

6.3. Annual energy demand prediction

Fig. (9) depicts a typical annual forecasting energy use and customer power consumption patterns during the time. A time frame is being set up to gather the customer's goal and input data, enabling very effective neural network training.

6.4. Comparing optimization results

The convergence values of the proposed optimization methodology were compared to those of the other studied methods for both short- and long-term power forecasting. Figs (10) and (11) illustrate the outcomes.

The study's findings show that the VGG/MWSO approach surpassed other comparable methods in terms of cost values, obtaining much lower values than the other methods studied. This conclusion shows that the VGG/MWSO method, which delivers more accurate and trustworthy findings, may be a more useful way for short-term energy prediction. Furthermore, the study reveals that the VGG/MWSO method may be a better solution for medium-term power and long-term energy projection. This conclusion is based on the VGG/MWSO method's superior convergence results for both short-term power forecasting and long-term energy prediction.

The VGG/MWSO method's effectiveness can be ascribed to its capacity to include a wide range of input data and efficiently train the neural network to recognize patterns and trends in energy use. The neural network's weights are improved using the VGG/MWSO approach to provide more accurate and dependable predictions, which makes it a valuable tool for demand forecasting. Table 5 illustrates the comparison results of the MSE values among studied methods.

Table 5 demonstrates that in the short-term forecasting situation, the VGG/MWSO approach indicated in the study delivers the most precise outcomes, with a minimal mean squared error (MSE) of 0.5. When compared to the real data, these findings are quite satisfying, as they show the lowest MSE across all types of forecasts.

7. Conclusions

The demand for electricity refers to the quantity of electrical power that is needed by consumers, businesses, and industries to fulfill their electricity requirements. Predicting energy consumption is a crucial responsibility for both energy companies and governments, as it enables them to effectively control and manage the energy supply. In this study, a Modified War Strategy Optimization (MWSO)-Based Convolutional Neural Network (CNN) was employed to accurately forecast electricity demand. By combining MWSO with CNNs, a robust technique was developed that can handle complex and nonlinear interactions between input data and extract valuable features from it. The findings revealed that the CNNs aided in extracting significant characteristics from the input data, thereby enhancing the predictive capabilities of the model. Additionally, the suggested MWSO algorithm offered a more efficient and successful approach to optimizing the model's parameters, resulting in improved forecast accuracy. To evaluate the proposed method, it was tested on a real-world energy demand dataset and compared with other state-of-the-art methods such as GA/CNN, hLSTM, and CNN-LSTM. The proposed method exhibited the ability to predict energy demand for a typical day, month, and year with a minimal error rate and a close proximity to the actual energy demand. Furthermore, the proposed method outperformed the other methods in terms of cost values and mean squared error (MSE) values. These results highlight the potential of the proposed method for practical applications in the electricity market, as it can provide reliable and timely information for energy planning and management. In order to extend the application of the suggested method to alternative energy sources, such as renewable energy, and diverse energy markets, such as

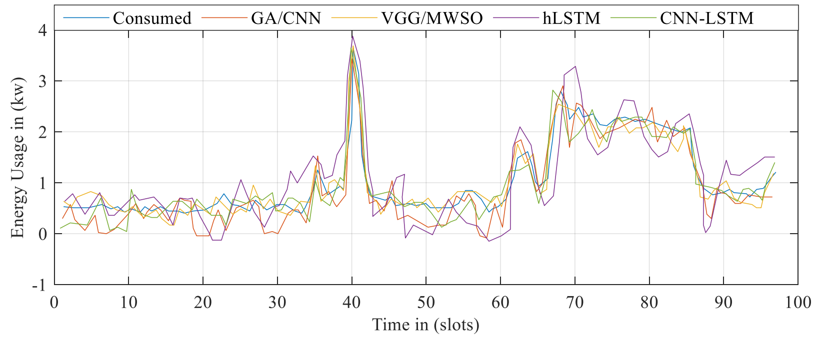

Fig. 7. Energy usage forecasting for a normal day.

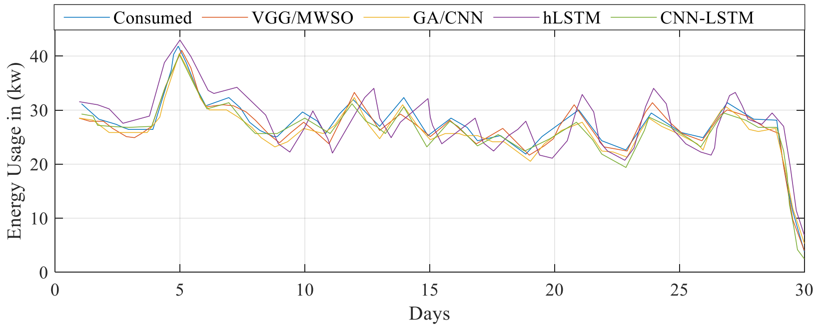

Fig. 8. Energy usage forecasting for a normal month.

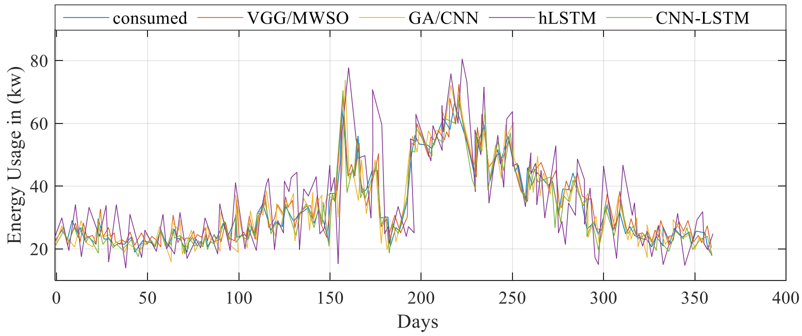

Fig. 9. Energy usage forecasting for a normal year.

smart grids, it is imperative to modify the input data and customize the CNN models to suit the unique attributes and complexities of these particular scenarios.

Data availability statement

Research data are not shared.

CRediT authorship contribution statement

Huanhuan Hu: Software, Resources, Formal analysis, Data curation, Conceptualization. **Shufen Gong:** Writing – review & editing, Software, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Bahman Taheri:** Writing – review & editing, Writing – original draft, Software, Resources, Methodology, Formal analysis, Data curation, Conceptualization.

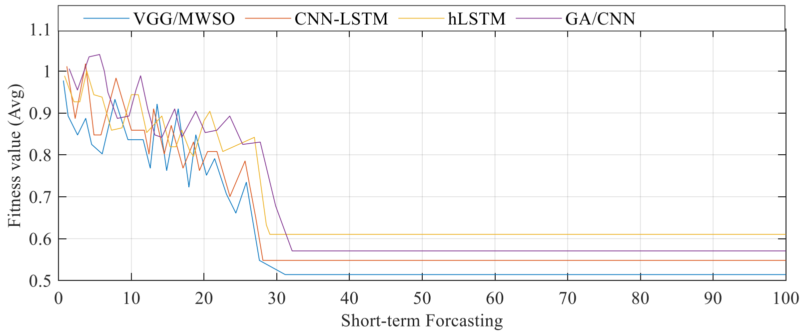

Fig. 10. Optimization convergence values for the proposed VGG/MWSO toward studied methods in short-term energy projection.

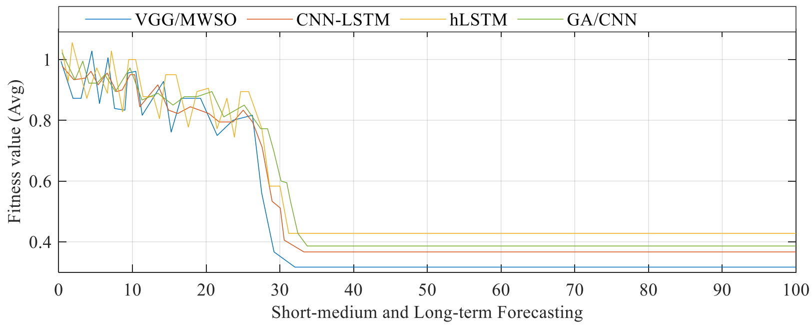

Fig. 11. Optimization convergence values for the proposed VGG/MWSO toward studied methods in Long, medium, and short-term energy projection.

Table 5
Comparison results of MSE values among studied methods.

Method	Prediction type	MSE	Method	Prediction type	MSE
hLSTM [36]	Short-term	0.82	CNN-LSTM [37]	Short-term	0.72
	Medium-term	0.73		Medium-term	0.73
	Long-term	0.74		Long-term	0.77
GA/CNN [35]	Short-term	0.62	VGG/MWSO	Short-term	0.50
	Medium-term	0.66		Medium-term	0.54
	Long-term	0.69		Long-term	0.55

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.

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