Modelling of Harris Hawks optimization with deep learning-assisted microgrid energy management approach

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ABSTRACT

Microgrid (MG) is a potential decentralized energy distribution and generation technology that is resilient, reliable, and efficient. This small-scale power system is reliable and resilient since it connects to the grid or runs independently. Renewable energy is difficult to integrate into MG due to variable load and unreliable electricity. MG operation relies on an energy management system (EMS) to balance electricity demand and supply, reduce operational costs, and maximize renewable energy use. Intelligent control systems, optimization methods, and machine learning algorithms were used for MG EMS. The Harris Hawks optimization with deep learning-assisted microgrid energy management (HHODL-MGEM) technique is developed in this work. HHODL-MGEM comprises two main stages. In the first step, the HHODL-MGEM approach uses the Harris Hawks optimization or HHO algorithm to meet load power demands at a low cost while maintaining DC bus voltage and protecting the battery from overcharging and depletion. In the second step, long short-term memory (LSTM) networks can predict power costs. The HHODL-MGEM approach is evaluated using multiple methods. The experimental results showed that HHODL-MGEM outperforms other methods.

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1. INTRODUCTION

To smart and supportable states, an acceptance of clean power formation is increasing suddenly globally. The accessibility of distributed energy resources (DER) with renewable energy delivers a good solution; to find the energy and climate disaster so the novel technical improvements have produced a great decline in electricity bills [1]. As an outcome, smart grid methods were intended to substitute conventional power systems and deliver an eco-friendly atmosphere through intellectual distribution methods. The exact models in optimum energy resource switch are named multi-microgrids (MMG) that protect the deficiency of single microgrids (MGs), and enlarge the possible usage dependent upon cooperative energy organization and execution [2]. One of the most significant benefits of MMG is the capability to use DER and energy excess between MMG networks rather than generating all the essential energy individually. Furthermore, as an outcome of the cooperative device, it minimises the complete functioning price for MMG [3]. Also, the system operators be able to advance in additional features of the process due to cost decrease. For example, improve the safety and consistency of the power system [4]. Demand-side energy manufacture is the main for effectual energy organization among MMG power plants but, it is built on the method of operation that can able to arise as grid-connected mode or standalone MGs [5].

MGs can be either DC or AC, while the existing power grid in many locations is AC, many loads like computers, lighting methods, and battery chargers are DC. Likewise, renewable energy sources like energy storage systems, solar photovoltaic systems, and some others give DC powers [6]. The benefits and drawbacks of both kinds of methods and study into the similarities have been enlarged. The energy management system (EMS) besides executing energy balance in the MG also generally attempts to achieve other purposes [7]. These might be in reductions of operation prices, emissions, and losses between several other points that are based on the inspiration behind developing such a system. Numerous management methods also use a mixture of these intentions in a multi-objective method [8]. Deep learning (DL) techniques for predicting were assumed owing to the following purpose. When equated to classical machine learning (ML) models, the DL techniques do not level initial performance [9]. This indicates that with superior accessibility of data and enlarged computation power, the connection determined by the DL models will enhance and will not soak, unlike the standard techniques that after a definite threshold cannot able to boost the efficiency regardless of the number of data and availability of computation power [10].

This study develops a Harris Hawks optimization with deep learning-assisted microgrid energy management (HHODL-MGEM) approach. The HHODL-MGEM technique involves two major phases of operations. In the first stage, the HHODL-MGEM technique relies on the Harris Hawks optimization (HHO) algorithm which intends to satisfy the load power needs at a minimal cost with the guarantee of assuring steady DC bus voltage and safeguard battery over overcharging and depletion. Next, in the second stage, the long short-term memory (LSTM) model can be used to forecast electricity prices. The performance validation of the HHODL-MGEM method takes place under various measures.

2. RELATED WORKS

Li *et al.* [11] developed an edge-cloud-aided federated deep reinforcement learning (FDRL) technique. The MG process method first offered edge cloud computing state to enhance energy managing tactics with financial profits as an objective. Next, the federated duelling deep Q-network (DDQN) with new act search has been presented to solve the issue technique and it is exploited to project a new EMS in MG. Alam *et al.* [12] present an innovative technique for the EMS of a domestic MG combined with a battery ESS (BESS). The developed dynamic method incorporates a DL-based analytical method, bidirectional long short-term memory or BiLSTM, with an optimizer model for optimum energy distribution and planning of a BESS by defining the features of spread resource, BESS assets, and consumer’s life routine.

In research by Khan *et al*. [13], a hybrid method that combines multi-head attention (MHA)--based deep AE with an extreme gradient boosting (XGB) model has been introduced. This layer of edge computing simplifies data distribution over fog computing which certifies power balance among providers and users. Also, the structure includes numerous power consumption sectors and objects within smart cities like healthcare and transport in order to confirm effectual management. In a study by Qayyum *et al*. [14], an optimum power management method is presented for MG energy trade. This method includes recurrent neural networks (RNNs) forecast units to deliver valued visions to energy providers. Also, it contains three core optimizer modules optimizing energy trading costs, minimizing grid power consumption, and managing ESS power. The projected technique functions in an internet of thing (IoT)-orchestrated structure, using Raspberry Pi-based edge technique and IoT devices.

Deepanraj *et al.* [15] proposed an intellectual wild geese algorithm with DL-driven short-term load forecasting (IWGADL-STLF) approach. This method employs an attention-based BiLSTM attention-fused bidirectional long and short-term memory (ABi-LSTM) system which includes the input parameter as a creation of commercial and domestic load profiles with MG as an output. In the proposed method, whole genome amplification (WGA) is used as a hyperparameter optimizer of ABi-LSTM technique. Kaewdornhan and Chatthaworn [16] developed a model-free data-driven system that helped the deep reinforcement learning (DRL) method. The deep neural networks (DNNs) technique is projected as a model-free data-driven to evaluate the power flow parameter of MG rather than the power loss factor (PLF). To make a particular optimization approach work, the majority of EMSs that have been published in the literature depend on using energy systems prediction. Energy management systems (EMS) for DC microgrids are presently getting more attention for the purpose of minimizing their size and associated costs. Various locations make use of microgrid technology, such as remote islands, military outposts, and university campuses. The development of improved steady-state energy management systems for microgrids is a major area of study [17]-[21]. Furthermore, the DRL is called a deep deterministic policy gradient (DDPG), which has been used as an optimizer algorithm. Furthermore, discovering suitable parameters of the DDPG is projected. Likewise, a lower-voltage distribution system was presented as MG.

3. THE PROPOSED METHOD

In this study, we have designed a novel HHODL-MGEM approach. The HHODL-MGEM technique involves two major phases of operations such as HHO algorithm and LSTM classifier. Figure 1 depicts the entire flow of HHODL-MGEM method.

3.1. Modeling of Harris Hawks optimization (HHO) algorithm

In the first stage, the HHODL-MGEM technique relies on the HHO algorithm. It intends to satisfy the load power needs at a minimal cost with the guarantee of assuring steady DC bus voltage and safeguard battery over depletion and overcharging. Alabool *et al.* introduced the HHO approach based on the capturing and hunting of prey of Harris Hawks in nature [22]. Two exploration and four exploitation approaches are the fundamental strategies in HHO algorithm.

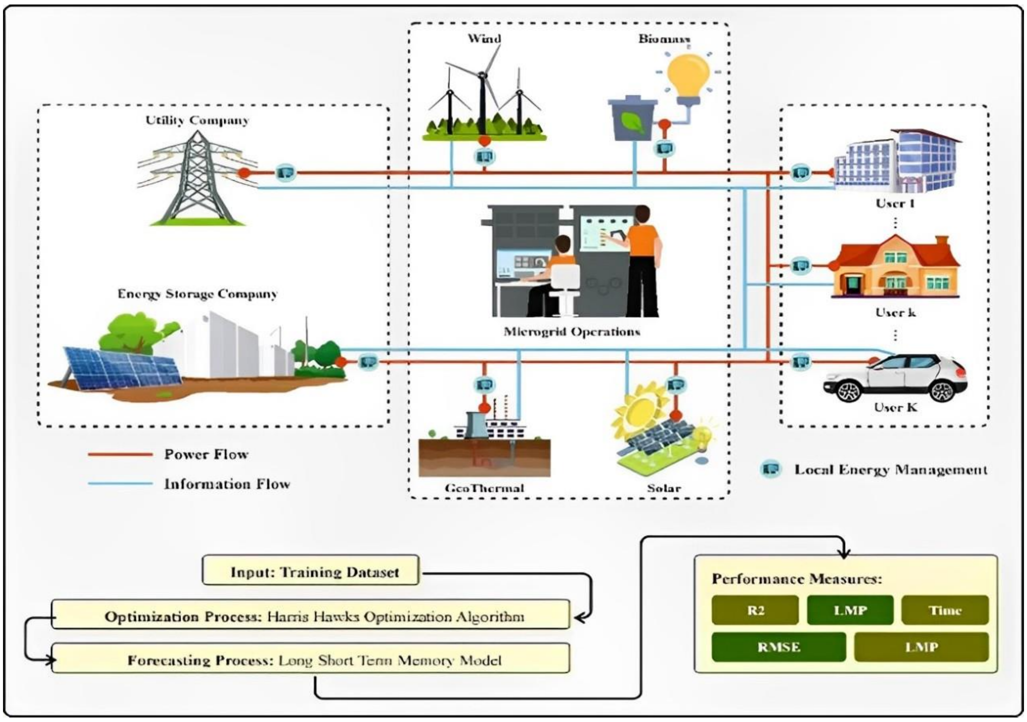


Figure 1. Overall flow of HHODL-MGEM method

3.1.1. HHO exploration strategies

HHO exploits two strategies to perch according to the value of q random parameter. The first technique is implemented when $q \geq 0.5$. The (1) and $q \geq 0.5$ then the second technique is used. In (1), $H(iter+1)$ denotes the Hawk's position in the following cycle, Prey's location is $iter$, $H_{prey}(iter)$, and the solutions' existing location is $H(iter)$., r_1, r_2, r_3, r_4, and q are all random values in the range of (0,1). The highest and lowest values are represented as $LoBo$ and $UpBo$, correspondingly. $H_{random}(iter)$ denotes the random solution and H_m is the average location of an existing swarm of solutions. Using (2), the location of the average hawk is evaluated:

$$H(iter+1) = \begin{cases} H_{random}(iter) - r_1 H_{random}(iter) - 2r_2 \mathrm{H(iter)} \\ , q \geq 0.5 \\ \left(H_{prey}(iter) - H_m(iter)\right) - r_3\left(LoBo + r_4(UpBo - LoBo)\right) \\ , q < 0.5 \end{cases} \quad (1)$$

$$H_m(iter) = \frac{1}{N}\sum_{i=1}^{N} H_i(iter) \quad (2)$$

Where the overall number of solutions is N, and the location of each solution in a given iteration is $H_i(iter)$. Before moving between the different exploitation stages, HHO alternates between the local and global search stages. Using (3), prey energy can be evaluated:

$$E = 2E_0\left(1 - \frac{iter}{\text{all}-iter}\right) \quad (3)$$

In (3), the power of the prey is E, all-iter indicates the overall count of cycles, and E_0 indicates the initial energy that changes randomly within $(-1,1)$ at all the cycles.

3.1.2. HHO exploitation strategies

There are four different exploitation strategies in the HHO. Consider that the possibility for the prey to successfully evade is $(r < 0.5)$ and that the possibility of prey being unsuccessful in evading is $(r \geq 0.5)$.

- SB: $r \geq 0.5$ and $E \geq 0.5$.

From the equations (4) and (5), where the difference between the prey and existing position in cycle iteration is $\Delta H(iter)$, r_5 is a random integer within $(0,1)$, and the random jumping strength of the prey is $J = 2(1 - r_5)$. The J value randomly changes within each cycle.

$$H(iter + 1) = \Delta(H(iter) - EJH_{prey}(iter) - H \quad (4)$$

$$\Delta H(iter) = H_{prey}(iter) - H(iter) \quad (5)$$

- HB: $r \geq 0.5$ and $E < 0.5$. In (6),

$$H(iter + 1) = H_{prey}(iter) - E\Delta H(iter) \quad (6)$$

- SB-PRD: $E \geq 0.5$ but $r < 0.5$. The Levy's flight ($LeF1$) is utilized in (7).

$$y = H_{prey}(iter) - EJH_{prey}(iter) - H(iter) \quad (7)$$

The $LeF1$is utilized as in (8).

$$Z = y + Size \times LeFl(Dim) \quad (8)$$

Where the dimensionality of the problem is Dim and $Size$ is a random vector by $1 \times Dim$ and the levy flight function is represented as $LeF1$ as (9).

$$LeFl(x) = 0.01 \times \frac{u \times \sigma}{U^{\frac{1}{\beta}}}, \sigma = \left(\frac{\Gamma(1+\beta) \times \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}}\right)^{\frac{1}{\beta}} \quad (9)$$

In (9), two random numbers within $(0,1)$ are u and u; this random variable takes value within [0,1]. Consider β as constant by allocating it a mathematical value of 1.5; in (10), y and Z are attained by (7) and (8).

$$H(iter + 1) = \begin{cases} y & if F(Y) < F \\ Z & if F(Z) < F \end{cases} \quad (10)$$

- HB-PRD

If $|E| < 0.5$ and $r < 0.5$, then (11) is employed:

$$H(iter + 1) = \begin{cases} y & if F(Y) < F \\ Z & if F(Z) < F \end{cases} \quad (11)$$

Where y and Z are calculated in (12) and (13).

$$y = H_{prey}(iter) - EJH_{prey}(iter) - H_m(iter) \quad (12)$$

$$Z = y + Size \times LeFl(Dim) \quad (13)$$

Where $H_m(iter)$ is calculated in (2).

The power shortage was supplemented by the BESS, the grid power, and the fuel cell, following the EMS if the power required exceeds the generated photovoltaic power [23]. The MG switched to the grid operational mode, with the maximum load being provided by the MG. This occurred when the operating costs closely related to utilizing the power resource were considerably greater or when the load power surpassed the capacity of the power resource. The main purpose is to reduce the costs closely related to the operation as shown in (14):

$$Cost = \sum_{t=1}^{T} (C_{FC}\big(P_{FC}(t) + C_{Bat}\big(P_{Bat}(t)\big) + P_{Grid}(t) \times EP(t)\Delta T\big) \quad (14)$$

where the electricity pricing in the market at t time is resented by the variable $EP(t)$. ΔT denotes the sample time. T characterizes the overall amount of power resources. N signifies the total time intervals, and the cost related to the i^{th} fuel cell (FC), battery energy storage system, and distributed generation (DG) are C_{FC}, C_{BESS}, and C_i correspondingly. The function encountered several shortcomings, like limited power equilibrium and power generation capacity. When the loss of the MG is omitted, then it is crucial for the power produced by the resource to be equivalent to the power expended by the load at t time. The analysis is shown in (15).

$$P_L = P_{PV} + P_{BESS} + P_{FC} + P_G \quad (15)$$

Based on the rules of the EMS, the MG is used to share BESS. However, few researchers encouraging an economic EMS failed to integrate SoC of the battery (state of charge) within the EMS. Thus, EMS should incorporate the SoC as a key element within the fitness function to alleviate the adverse effects of overcharging or excessive battery drain. From the (16), the variable $SoC(t)_{opt}$ indicates the optimum value of the SOC.

$$\begin{aligned} F_{Cost} &= \min \big(\textstyle\sum_{;=1}^{T} (C_{FC}(P_{FC}(t) \\ &+ C_{Bat}.P_{Bat}(\,)\Big(SoC(t) - SoC\big(t\big)_{opt})^2 + P_{Grid}(t) \times EP(t)\Delta T)\Big) \end{aligned} \quad (16)$$

3.2. LSTM based prediction

In the second stage, the LSTM model can be used to forecast electricity prices. Currently, RNNs are mostly dependent upon LSTM which has attained notable performance in dissimilar areas [24]. In LSTM, x^t refers to the input signal, h^t signifies the hidden layer (HL) and t denotes the time frame. At timeframe $t-1$, C^{t-1} signifies the memory cell state. $b^{\mathrm{f}}, b^i, b^c, b^o$ and w^f, w_i, w^o, w^c represents the biases and weights, correspondingly. $tanh$ and σ refer to the activation function. Figure 2 depicts the architecture of LSTM. At an initial stage, the LSTM computes the preceding data from the cell state C^{t-1} just by employing a forget gate as (17).

$$f^t = \sigma\big(w^f[h^{t-1}, x^t] + b^{\mathrm{f}}\big) \quad (17)$$

Here, f^t can be 0 or 1 to signify the entire block and transfer of the data. Next, the LSTM computes the future data that have to be kept by utilizing a dual-stage procedure. The 1st part controls the parameter to be employed over the (18).

$$i^t = \sigma(w^i[h^{t-1}, x^t] + b^i) \quad (18)$$

The 2nd part defines an optimum state value $\tilde{C}$ by employing the (19).

$$\tilde{C}^t = tanb(w^c[h^{t-1}, x^t] + b^c) \quad (19)$$

Then in 3rd part, the LSTM defines the existing state C^t by utilizing the given expression as (20).

$$C^t = f^t * C^{t-1} + i^t * \tilde{C}_t \quad (20)$$

the filtered form of the compressed cell state $tanh(C^t)$ indicates the output of HL h^t. The data must be kept and intended by employing the activation function of sigmoid o^t that is concluded as per the (21).

$$o^t = \sigma(w^o[h^{t-1}, x^t] + b^o) \quad (21)$$

Finally, the last HL output h^t was expressed as (22).

$$h^t = 0^t * tanh(C^t) \quad (22)$$

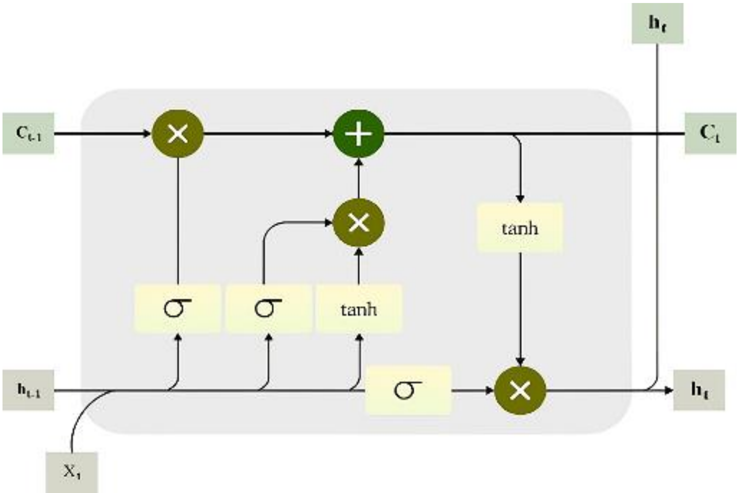


Figure 2. LSTM structure

4. EXPERIMENTAL VALIDATION

This section inspects the performance of the HHODL-MGEM technique with existing models. Table 1 presents a comparative result of the HHODL-MGEM technique with recent models on the training process [25]. Figure 3(a) shows that the HHODL-MGEM technique enhanced performance with a maximum R^2 of 96.35% whereas the artificial neural network (ANN), support vector regression (SVR), and online regularized extreme learning machine (OR-ELM) models obtain reduced R^2 values of 88.93%, 91.73%, and 95.68%, correspondingly. Also, Figure 3(b) illustrates that the HHODL-MGEM method improved performance with decreased mean absolute percentage error or MAPE of 1.71% while the ANN, SVR, and OR-ELM algorithms get higher MAPE values of 6.29%, 4.17%, and 2.05%. Meanwhile, Figure 3(c) displays that the HHODL-MGEM system has excellent performance with a minimized time of 0.590 s but the ANN, SVR, and OR-ELM algorithms obtain increased time values of 0.916 s, 4.862 s, and 0.802 s, respectively.

Table 2 demonstrates a comparative outcome of the HHODL-MGEM method with other algorithms during the testing process. Figure 4(a) showcases that the HHODL-MGEM system improved performance with increased R^2 of 94.98% while the ANN, SVR, and OR-ELM methods get decreased R^2 values of 87.41%, 90.83%, and 93.79%, respectively. Meanwhile, Figure 4(b) shows that the HHODL-MGEM techniques have better performance with lessened MAPE of 2.67% while the ANN, SVR, and OR-ELM algorithms get higher MAPE values of 8.47%, 6.88%, and 4.92%. Besides, Figure 4(c) shows that the HHODL-MGEM method has exceptional performance with a decreased time of 0.052s but the ANN, SVR, and OR-ELM systems provide improved time values of 0.065s, 0.903s, and 0.089s, correspondingly.

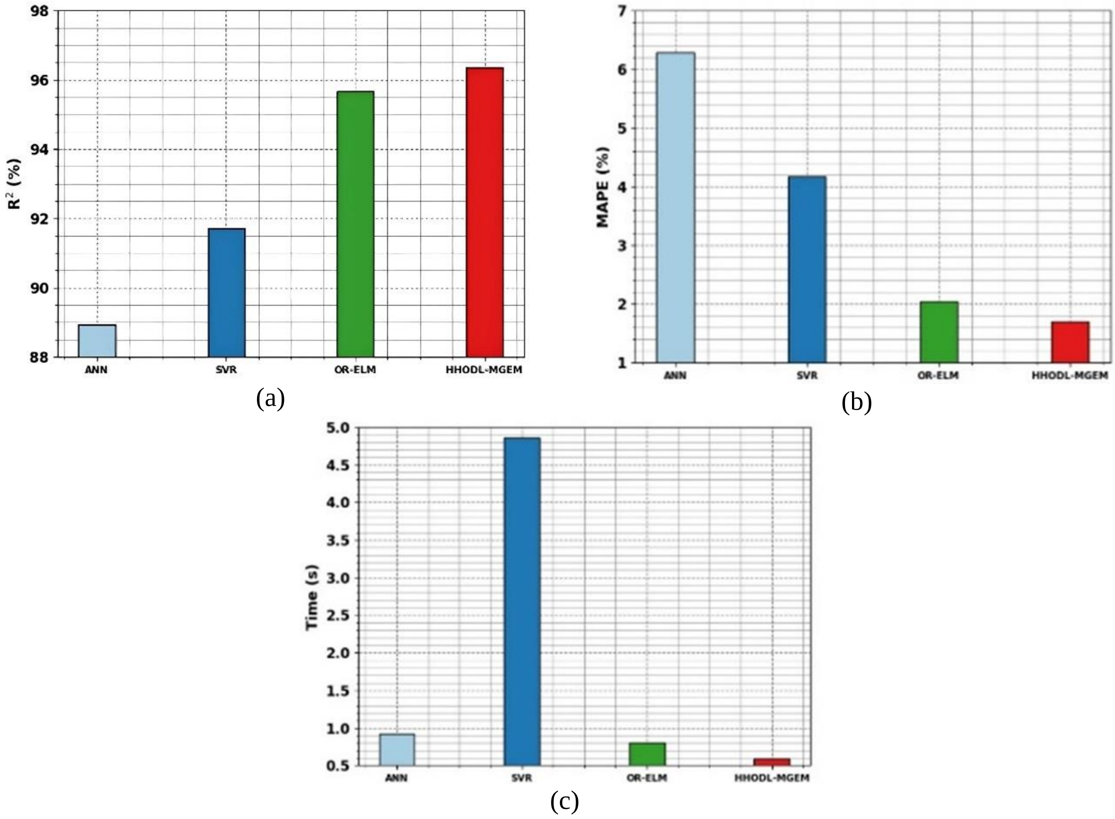
Table 3 and Figure 5 portray a comparative root mean square error (RMSE) result of the HHODL-MGEM technique under varying k-folds. With 1-fold, the HHODL-MGEM technique offers reduced RMSE of 6.709 while the OR-ELM, SVR, and ANN methods attain increased RMSE of 7.503, 7.289, and 8.113, correspondingly. Also, based on 3-fold, the HHODL-MGEM system gives decreased RMSE of 2.100 although the OR-ELM, SVR, and ANN techniques accomplish boosted RMSE of 2.772, 3.199, and 3.901. In line with 5-fold, the HHODL-MGEM system provides a diminished RMSE of 1.398 however, the OR-ELM, SVR, and ANN algorithms get increased RMSE of 2.345, 2.833, and 2.802. Meanwhile, based on 7-fold, the HHODL-MGEM system obtains minimized RMSE of 0.971 while the OR-ELM, SVR, and ANN approaches achieve higher RMSE of 1.826, 2.314, and 2.680. Moreover, with 9-fold, the HHODL-MGEM method offers a reduced RMSE of 0.849 while the OR-ELM, SVR, and ANN methods gain raised RMSE of 1.948, 2.345, and 2.711. Finally, based on 10-fold, the HHODL-MGEM technique gives decreased RMSE of 0.818 whereas the OR-ELM, SVR, and ANN models attain increased RMSE of 1.917, 2.161, and 2.528, correspondingly.

Table 1. Comparative results of the HHODL-MGEM model with other approaches under the training process

Forecast model	R^2	MAPE (%)	Time (s)
ANN	88.93	6.29	0.916
SVR	91.73	4.17	4.862
OR-ELM	95.68	2.05	0.802
HHODL-MGEM	96.35	1.71	0.590

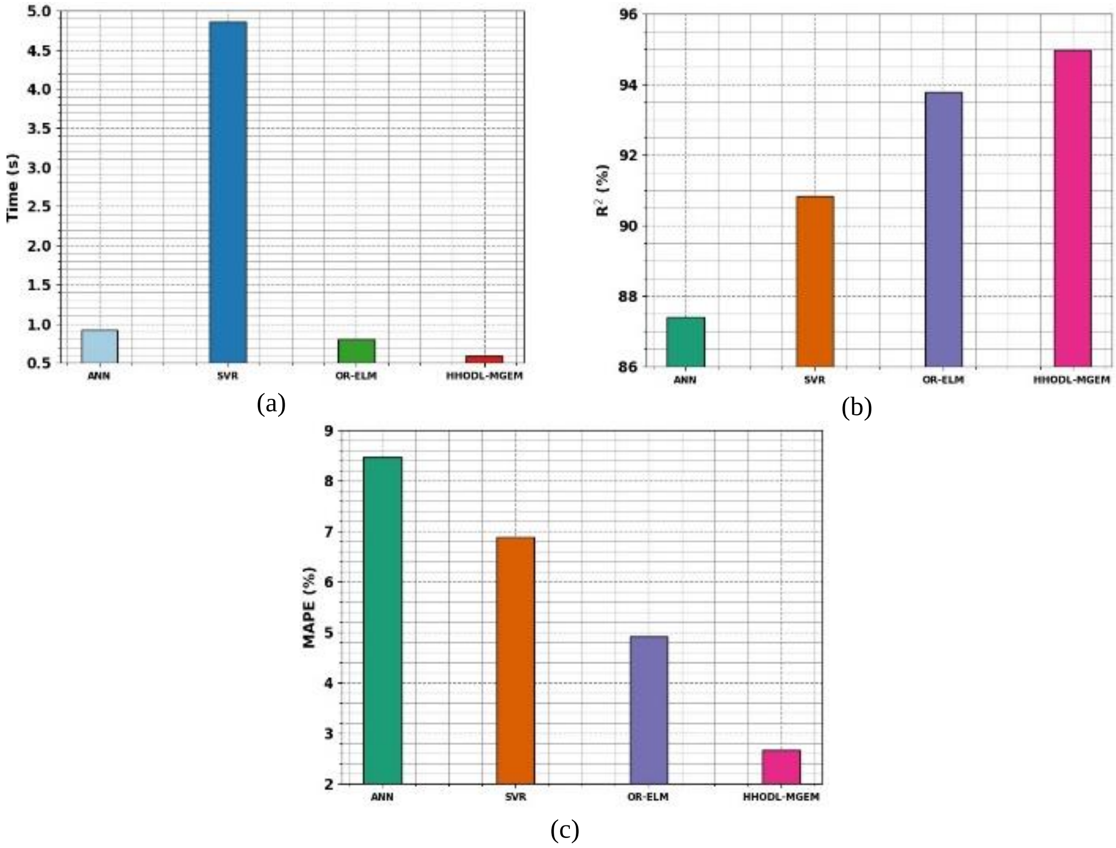
Table 2. Comparative outcome of HHODL-MGEM system with other methods under testing process

Forecast model	R^2	MAPE (%)	Time (s)
ANN	87.41	8.47	0.065
SVR	90.83	6.88	0.903
OR-ELM	93.79	4.92	0.089
HHODL-MGEM	94.98	2.67	0.052



(a) (b) (c)

Figure 3. Training process: (a) R2, (b) MAPE, and (c) time



(a) (b) (c)

Figure 4. Testing process: (a) time, (b) R2, and (c) MAPE

Finally, the predictive outcomes of the HHODL-MGEM technique are compared with recent systems and reported in Table 4 and Figure 6. Based on 14 hours and actual price of 2.503 cents/KWh, the HHODL-MGEM technique predicted the closer value of 2.643 whereas the OR-ELM, SVR, and ANN models provide the predicted values of 2.223, 2.457, and 2.036, correspondingly. Additionally, based on 48 hours and actual price of 2.714 cents/KWh, the HHODL-MGEM system forecast the reasonable value of 2.947 while the OR-ELM, SVR, and ANN techniques offer the predicted values of 3.228, 2.527, and 3.929. Followed by, 96 hours and actual price of 2.643 cents/KWh, the HHODL-MGEM method predictable the closer value of 2.807 although the OR-ELM, SVR, and ANN systems provide the predicted values of 2.480, 2.667, and 3.345. Furthermore, based on 144 hours and actual price of 3.648 cents/KWh, the HHODL-MGEM system predicted the considerable value of 3.859 then, the OR-ELM, SVR, and ANN techniques offers the predicted values of 3.461, 2.620, and 2.947. At last, based on 168 hours and actual price of 2.246 cents/KWh, the HHODL-MGEM algorithm predicted the closer value of 2.363 but, the OR-ELM, SVR, and ANN methods achieves the predicted values of 2.340, 2.457, and 3.017, respectively. Thus, the HHODL-MGEM technique can be applied for effectual management of MGs.

Table 3. RMSE outcome of HHODL-MGEM method with recent algorithms under various k-folds

RMSE (Cents/KWh):10-folds cross-validation for RMSE				
k-folds	HHODL-MGEM	OR-ELM	SVR	ANN
1	6.709	7.503	7.289	8.113
2	3.901	4.084	4.390	4.969
3	2.100	2.772	3.199	3.901
4	1.795	2.528	2.833	3.077
5	1.398	2.345	2.833	2.802
6	1.307	2.161	2.436	2.589
7	0.971	1.826	2.314	2.680
8	1.063	1.917	2.161	2.589
9	0.849	1.948	2.345	2.711
10	0.818	1.917	2.161	2.528

Table 4. Local marginal pricing (LMP) outcome of HHODL-MGEM model with other methods under various hours

LMP (Cents/KWh)					
Hours	Actual real price	HHODL-MGEM	OR-ELM	SVR	ANN
0	2.480	2.690	2.270	2.784	2.340
14	2.503	2.643	2.223	2.457	2.036
48	2.714	2.947	3.228	2.527	3.929
72	3.999	4.139	3.905	3.999	2.643
96	2.643	2.807	2.480	2.667	3.345
120	2.433	2.550	2.667	2.363	2.760
144	3.648	3.859	3.461	2.620	2.947
168	2.246	2.363	2.340	2.457	3.017

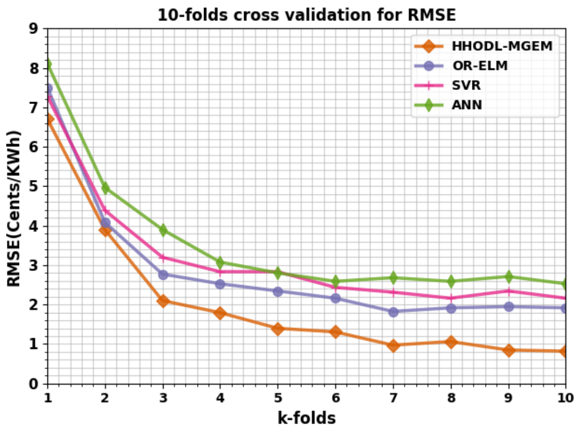


Figure 5. RMSE outcome of HHODL-MGEM technique under various k-folds

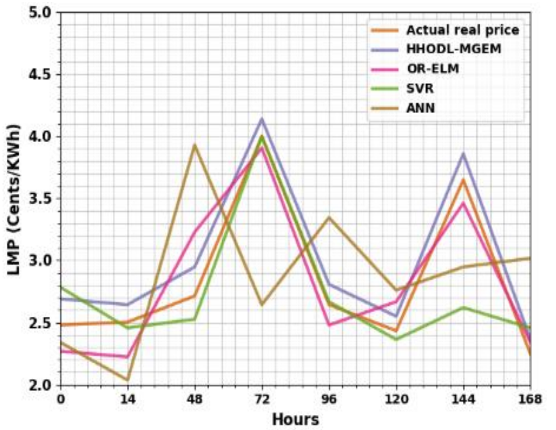


Figure 6. LMP outcome of HHODL-MGEM system under various hours

5. CONCLUSION

In this study, we have designed a novel HHODL-MGEM approach. The HHODL-MGEM technique involves two major phases of operations. In the first stage, the HHODL-MGEM technique relies on the HHO algorithm which intends to satisfy the load power needs at a minimal cost with the guarantee of assuring steady DC bus voltage and safeguard battery over overcharging and depletion. Next, in the second stage, the LSTM model can be used to forecast electricity prices. The performance analysis of the HHODL-MGEM technique takes place under various measures. The experimental values highlighted that the HHODL-MGEM method obtains optimal performance over other approaches.

REFERENCES

[1] B. Chen, J. Wang, X. Lu, C. Chen, and S. Zhao, "Networked microgrids for grid resilience, robustness, and efficiency: a review," *IEEE Trans Smart Grid*, vol. 12, no. 1, pp. 18–32, Jan. 2021, doi: 10.1109/TSG.2020.3010570.

[2] S. Wang, X. Zhang, L. Wu, and S. Sun, "New metrics for assessing the performance of multi-microgrid systems in stand-alone mode," *International Journal of Electrical Power & Energy Systems*, vol. 98, pp. 382–388, Jun. 2018, doi: 10.1016/j.ijepes.2017.12.002.

[3] M. Ahmed, L. Meegahapola, A. Vahidnia, and M. Datta, "Stability and control aspects of microgrid architectures a comprehensive review," *IEEE Access*, vol. 8, pp. 144730–144766, 2020, doi: 10.1109/ACCESS.2020.3014977.

[4] S. E. Ahmadi, N. Rezaei, and H. Khayyam, "Energy management system of networked microgrids through optimal reliability-oriented day-ahead self-healing scheduling," *Sustainable Energy, Grids and Networks*, vol. 23, p. 100387, Sep. 2020, doi: 10.1016/j.segan.2020.100387.

[5] F. S. Gazijahani, S. N. Ravadanegh, and J. Salehi, "Stochastic multi-objective model for optimal energy exchange optimization of networked microgrids with presence of renewable generation under risk-based strategies," *ISA Trans*, vol. 73, pp. 100–111, Feb. 2018, doi: 10.1016/j.isatra.2017.12.004.

[6] H. Fu and X.-P. Zhang, "Market equilibrium in active distribution system with μ VPPs: A coevolutionary approach," *IEEE Access*, vol. 5, pp. 8194–8204, 2017, doi: 10.1109/ACCESS.2017.2691316.

[7] A. A. Anderson and S. Suryanarayanan, "Review of energy management and planning of islanded microgrids," *CSEE Journal of Power and Energy Systems*, vol. 6, no. 2, pp. 329–343, 2020, doi: 10.17775/CSEEJPES.2019.01080.

[8] X. Liu, B. Gao, Z. Zhu, and Y. Tang, "Non-cooperative and cooperative optimisation of battery energy storage system for energy management in multi-microgrid," *IET Generation, Transmission & Distribution*, vol. 12, no. 10, pp. 2369–2377, May 2018, doi: 10.1049/iet-gtd.2017.0401.

[9] P. A. Østergaard, N. Duic, Y. Noorollahi, H. Mikulcic, and S. Kalogirou, "Sustainable development using renewable energy technology," *Renew Energy*, vol. 146, pp. 2430–2437, Feb. 2020, doi: 10.1016/j.renene.2019.08.094.

[10] L. Yin, T. Yu, B. Yang, and X. Zhang, "Adaptive deep dynamic programming for integrated frequency control of multi-area multi-microgrid systems," *Neurocomputing*, vol. 344, pp. 49–60, Jun. 2019, doi: 10.1016/j.neucom.2018.06.092.

[11] H. Li, Y. Yang, Y. Liu, and W. Pei, "Federated dueling DQN based microgrid energy management strategy in edge-cloud computing environment," *Sustainable Energy, Grids and Networks*, vol. 38, p. 101329, Jun. 2024, doi: 10.1016/j.segan.2024.101329.

[12] Md. M. Alam, Md. H. Rahman, Md. F. Ahmed, M. Z. Chowdhury, and Y. M. Jang, "Deep learning based optimal energy management for photovoltaic and battery energy storage integrated home micro-grid system," *Sci Rep*, vol. 12, no. 1, p. 15133, Sep. 2022, doi: 10.1038/s41598-022-19147-y.

[13] N. Khan, S. U. Khan, F. U. M. Ullah, M. Y. Lee, and S. W. Baik, "AI-assisted hybrid approach for energy management in IoT-based smart microgrid," *IEEE Internet Things J*, vol. 10, no. 21, pp. 18861–18875, Nov. 2023, doi: 10.1109/JIOT.2023.3293800.

[14] F. Qayyum, H. Jamil, N. Iqbal, and D.-H. Kim, "IoT-orchestrated optimal nanogrid energy management: Improving energy trading performance and efficiency via virtual operations," *International Journal of Electrical Power & Energy Systems*, vol. 155, p. 109668, Jan. 2024, doi: 10.1016/j.ijepes.2023.109668.

[15] B. Deepanraj, N. Senthilkumar, T. Jarin, A. E. Gurel, L. S. Sundar, and A. V. Anand, "Intelligent wild geese algorithm with deep learning driven short term load forecasting for sustainable energy management in microgrids," *Sustainable Computing: Informatics and Systems*, vol. 36, p. 100813, Dec. 2022, doi: 10.1016/j.suscom.2022.100813.

[16] N. Kaewdornhan and R. Chatthaworn, "Model-free data-driven approach assisted deep reinforcement learning for optimal energy management in microgrid," *Energy Reports*, vol. 9, pp. 850–858, Oct. 2023, doi: 10.1016/j.egyr.2023.05.130.

[17] F. Yang, X. Feng, and Z. Li, "Advanced microgrid energy management system for future sustainable and resilient power grid," *IEEE Trans Ind Appl*, vol. 55, no. 6, pp. 7251–7260, Nov. 2019, doi: 10.1109/TIA.2019.2912133.

[18] S. Leonori, M. Paschero, F. M. F. Mascioli, and A. Rizzi, "Optimization strategies for microgrid energy management systems by genetic algorithms," *Appl Soft Comput*, vol. 86, p. 105903, Jan. 2020, doi: 10.1016/j.asoc.2019.105903.

[19] S. Ali, Z. Zheng, M. Aillerie, J.-P. Sawicki, M.-C. Péra, and D. Hissel, "A review of DC microgrid energy management systems dedicated to residential applications," *Energies (Basel)*, vol. 14, no. 14, p. 4308, Jul. 2021, doi: 10.3390/en14144308.

[20] A. Kowalczyk, A. Wlodarczyk, and J. Tarnawski, "Microgrid energy management system," in *2016 21st International Conference on Methods and Models in Automation and Robotics (MMAR)*, IEEE, Aug. 2016, pp. 157–162. doi: 10.1109/MMAR.2016.7575125.

[21] S. Leonori, A. Martino, F. M. Frattale Mascioli, and A. Rizzi, "Microgrid energy management systems design by computational intelligence techniques," *Appl Energy*, vol. 277, p. 115524, Nov. 2020, doi: 10.1016/j.apenergy.2020.115524.

[22] H. M. Alabool, D. Alarabiat, L. Abualigah, and A. A. Heidari, "Harris Hawks optimization: a comprehensive review of recent variants and applications," *Neural Comput Appl*, vol. 33, no. 15, pp. 8939–8980, Aug. 2021, doi: 10.1007/s00521-021-05720-5.

[23] H. Zhang, Y. Ma, K. Yuan, M. Khayatnezhad, and N. Ghadimi, "Efficient design of energy microgrid management system: A promoted Remora optimization algorithm-based approach," *Heliyon*, vol. 10, no. 1, p. e23394, Jan. 2024, doi: 10.1016/j.heliyon.2023.e23394.

[24] D. Thakur, S. Biswas, E. S. L. Ho, and S. Chattopadhyay, "ConvAE-LSTM: convolutional autoencoder long short-term memory network for smartphone-based human activity recognition," *IEEE Access*, vol. 10, pp. 4137–4156, 2022, doi: 10.1109/ACCESS.2022.3140373.

[25] I. Brahmia, J. Wang, H. Xu, H. Wang, and L. D. O. Turci, "Robust data predictive control framework for smart multi-microgrid energy dispatch considering electricity market uncertainty," *IEEE Access*, vol. 9, pp. 32390–32404, 2021, doi: 10.1109/ACCESS.2021.3060315.

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