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Hybrid Deep Learning Enabled Load Prediction for Energy Storage Systems

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Abstract: Recent economic growth and development have considerably raised energy consumption over the globe. Electric load prediction approaches become essential for effective planning, decision-making, and contract evaluation of the power systems. In order to achieve effective forecasting outcomes with minimum computation time, this study develops an improved whale optimization with deep learning enabled load prediction (IWO-DLELP) scheme for energy storage systems (ESS) in smart grid platform. The major intention of the IWO-DLELP technique is to effectually forecast the electric load in SG environment for designing proficient ESS. The proposed IWO-DLELP model initially undergoes pre-processing in two stages namely min-max normalization and feature selection. Besides, partition clustering approach is applied for the decomposition of data into distinct clusters with respect to distance and objective functions. Moreover, IWO with bidirectional gated recurrent unit (BiGRU) model is applied for the prediction of load and the hyperparameters are tuned by the use of IWO algorithm. The experiment analysis reported the enhanced results of the IWO-DLELP model over the recent methods interms of distinct evaluation measures.

Keywords: Load forecasting; smart grid; energy storage system; electricity load forecasting; artificial intelligence; clustering

1 Introduction

With an increased number of industries and rapid development of population, electricity grids become a complex process for managing the electricity demand for industrial and household purposes [1]. The increasing demand for electricity at certain times results in number of challenges such as failure of transformers, short circuits. To resolve this problem of communication of electrical energy through conventional grids, it is essential to forecast the consumption pattern of the customer to efficiently transport the electricity [2]. A smart grid (SG) could reasonably forecast the electricity demand and thus transfer the electrical energy based on the forecasted demands [3]. A SG through its smart prediction and sensing could resolve various problems of the conventional grids namely reduction of power usage, demand forecasting, reduce the risk of short circuits thus saving the loss of properties and lives [4]. SG has different stakeholders and it is linked to many other smart regions like smart buildings, smart vehicles, smart cities, smart power plants, and so on. In smart grid environments, there are several possibilities to save the energy cost of smart homes that are advanced from traditional homes by adapting three mechanisms, that is home automation, internal networks, and intelligent controls [5]. For instance, dynamic electricity prices are employed for reducing energy costs. It is significant to effectively handle the energy storage system (ESS). The ESS provides added value to enhance supply reliability and power quality [6]. With this regard, we consider need to forecast the ESS charge and energy consumption. Fig. 1 illustrates the process of ESS.

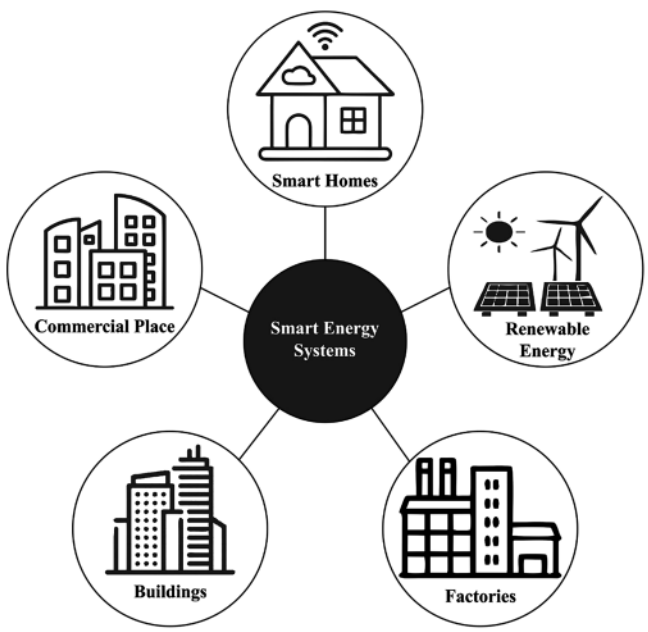

Figure 1: Energy storage systems

Despite the urgency and importance of making a transition from renewable energy (RE) to the smart grids, still it remains a challenge for developing an efficient and effective short-term load prediction because of this uncertainty, complexity, and variability of the RE resource [7]. Still, thorough information mining and data cleaning are inadequate for present prediction model in modelling future short-term load as noise could be hard to remove. Furthermore, uncertainty still exists and could not be explained well in machine learning (ML)-based prediction method, particularly for determining and parameter fine-tuning [8].

In addition to prediction precision, the robustness is often neglected in present research. The expansion of novel methods and advanced technologies with artificial intelligence to manage problems in the smart grid is indispensable. Especially, energy storage systems, distributed generation resources, and advanced control/operation are tackled in the SG. Generally, emerging an efficient and effective short-term load prediction method using higher accuracy and strength becomes a topmost priority for urban sustainability growth [9]. Artificial Intelligence (AI) is effectively employed for solving several industrial issues like neural networks (NN), fuzzy logic control, evolutionary computation, hybrid intelligent system, and so on. In recent times, deep learning (DL) network has gained considerable interest since they are capable of managing nonlinear problem [10].

This study develops an improved whale optimization with deep learning enabled load prediction (IWO-DLELP) scheme for ESS in smart grid platforms. The proposed IWO-DLELP model initially undergoes pre-processing in two stages namely min-max normalization and feature selection. Next, partition clustering approach is applied for the decomposition of data into distinct clusters with respect to distance and objective functions. In addition, IWO with bidirectional gated recurrent unit (BiGRU) model is employed to the prediction of load and the hyperparameters are tuned by the use of IWO algorithm. The simulation analysis of the IWO-DLELP model is performed and the outcomes are investigated under several aspects.

2 Related Works

Hong et al. [11] projected the short-term residential load forecasting (LF) structure that creates utilize of Spatio-temporal correlation present from appliance load data with DL. Several time series were conducted from the structure for describing consumed power performances and its internal Spatio-temporal connection. And this approach dependent upon deep neural network (DNN) and iterative ResBlock was presented for learning the correlation amongst distinct consumed power actions to short-term load forecasting (STLF). In [12], a DL approach was established for forecasting the current load accurately. The researchers presented a method that is dependent upon selective, extracting, and classifier of historic information. Grey Correlation based random forest (RF) and Mutual Information (MI) was carried out for feature selection (FS) and kernel principal component analysis (KPCA) was utilized to feature extracted and improved convolution neural network (CNN) was utilized to classifier.

Usman et al. [13] presented a DL based algorithm to forecast price and demand on big data utilizing deeper long short term memory (LSTM). Because of adaptive and automated feature learning of DNN, process of big data has simpler with LSTM as related to completely data driven techniques. The presented method was estimated utilizing a famous real electricity market information. In [14], a Bayesian DL was utilized for resolving this difficult problem. Especially, a novel multitasks probabilistic load forecasting (PLF) structure dependent upon Bayesian DL was presented for quantifying the shared uncertainty across various customer groups but accounting for its variances. Moreover, a clustering based pooling approach was planned for increasing the data diversity and volume of the structure.

In [15], a fast and accurate STLF technique was presented. The abstractive feature in the historical information was removed utilizing modified mutual information (MMI) approach. The factored conditional RBM (FCRBM) was allowed using learned for predicting the electrical load. At last, the presented genetic wind driven optimization (GWDO) technique was utilized for optimizing the efficiency. Syed et al. [16] presented a new hybrid clustering based DL technique to STLF at the distributing transformer level with improved scalability. It examines the gain from trained time and the efficiency with respect to accuracy if clustering based DL modeling was utilized to STLF. A k-Medoid based technique was utilized to cluster but the predict methods were created for various clusters of load profiles. In [17], STLF and mid-term LF (MTLF) are presented utilizing smart-metered data developed in real-life distributing grid with distinct typical and ML approaches. Data pre-processed was complete for transforming the raw data into suitable format by extracting the outliers existing from the data sets. The effective meteorological variable attained with correlation analysis together with past loaded was utilized for training the LF method.

3 The Proposed Model

In this study, a new IWO-DLELP algoithm has been presented to effectually forecast the electric load in SG environment for designing proficient ESS. The proposed IWO-DLELP model encompasses pre-processing, partition clustering, BiGRU based prediction, and IWO based hyper parameter tuning. For optimal tuning of the hyperparameters involved in the BiGRU, the IWO algorithm is utilized and it results in enhanced predictive performance. Fig. 2 depicts the working process of IWO-DLELP technique.

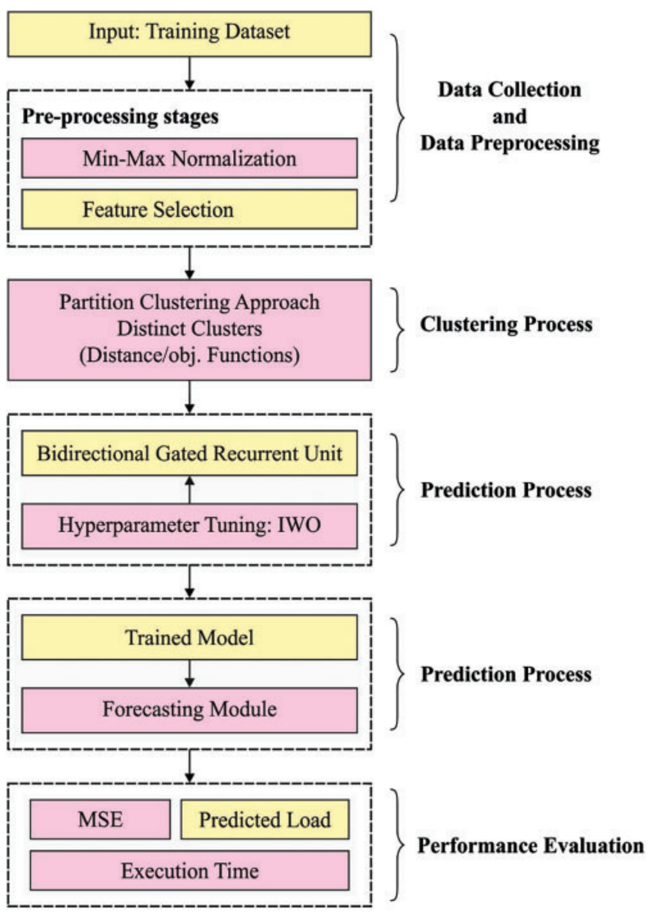

Figure 2: Overall process of IWO-DLELP technique

3.1 Data Pre-processing

Initially, the input dataset is pre-processed in two stages such as min-max normalization and feature selection. For incorporating the non-distorting scaler, mini-max normalization scale is utilized as defined in Eq. (1):

$$a_m^{'} = c + \frac{(a_m - \min(a))(q - p)}{(\max(a) - \min(a))} \tag{1}$$

where $a_m^{'}$ and a_m indicates new and actual attribute values, min(a) represents least value, and [p, q] is the scaling range. In order to elect optimal features, feature importance score gets determined by the use of permutation feature importance approaches. In addition, a top-down search enabled model named Sequential Backward Search (SBS) approach is applied for addressing the multi-collinearity among distinct features in contrast to individual feature technique [18].

3.2 Partition Clustering

At this stage, the decomposition of input data into different set of clusters was carried out using the partition clustering approach [18].

Partitional clustering methodology attempts to decompose the data (Rodriguez et al., 2019) according to an objective and distance function and it is utilized for measuring the quality of cluster attained whereas, distance function is utilized for identifying the similarity amongst data objects. An arithmetical explanation of the search problem is assumed that D characterizes the whole dataset, n denotes the data object number, and d indicates the feature number, that is, $D = \{x_1, x_2, \ldots, x_n\}$. Partitional clustering model tries to detect the optimal set of centers $C = C^1, C^2, \ldots, C^K$ that partition the data set D into K disjoint cluster.

$$F = \frac{1}{n}\sum_{i=1}^{n} \min d\left(C_j, x_i\right) \tag{2}$$

Whereas C_j indicates class j and $d(C, x)$ corresponding to the squared Euclidean distance among the point xi and the center of class C_j. *SI* method uses the objective function (2) to estimate the quality of solution.

3.3 BiGRU Based Load Prediction Model

The clustered data are processed by the BiGRU model to estimate the electricity load in the SG environment. The central component of gated recurrent neural network (GRNN) is the gated recurrent unit (GRU) that is a different from existing popular long- and short-term memory networks [19]. The iteration equation is as follows:

$$\begin{cases} z_t \sigma\left(\omega_z S_t + \lambda_z h_{t-1} + b_z\right) \\ r_t \sigma\left(\omega_r S_t + \lambda_r h_{t-1} + b_r\right) \\ \widetilde{h}_t\ tanh\left(\omega_h S_t + r_t \otimes \left(\lambda_h h_{t-1}\right) + b_h\right), \\ h_t\left(l - z_t\right) \otimes h_{t-1} + z_t \otimes \widetilde{h}_t \end{cases} \tag{3}$$

where $\otimes$ refers to the cross product function. Reset threshold r_t and upgrade threshold z_t control the data upgrade of all the hidden states. ω_* and λ_* signifies the co-efficient matrices. b_* implies the bias vector that is exploited for adaptably selecting and removing historical data which generates the existing semantics. BiGRU was utilized for extracting the condataual semantic data feature of data. The way one GRU has positive order way of the input order, and the other is reverse order way of the input order. If the feature extracting was executed on the input order, the GRUs from the 2 ways could not share the state. The state alteration rules of GRU follow the transition occurrence amongst the comparable states. But, at the similar moments, the output results of GRUs from the 2 ways were spliced as resultant of total BiGRU layer. This not only assumes the above semantic data, along with assumes the subsequent semantic data as follows:

$$e_i = \chi_a^T \tanh\left(\omega_a h_i + b\right), \tag{4}$$

where h_i refers to the hidden state outcome ω_a signifies the arbitrary initialized weight matrix, χ_a stands for the arbitrary initialized vector, and b represents the offset vector. Afterward, compute the weighted score θ as follows:

$$\theta = \frac{\exp\ (e_i)}{\sum_{k=1}^{L} \exp\ (e_i k)}. \tag{5}$$

Based on Eq. (6), the resultant vector c_i weight by dynamic adaptive weighted as:

$$c_i = \sum_{j=1}^{L} \theta \cdot h_j. \tag{6}$$

It is obvious that the attention model relates the target matrix with weighted matrix from the NN with a perception functions. Afterward, utilize the *softmax* function for regularizing it for obtaining the probability distribution.

3.4 IWO Based Hyperparameter Tuning

For ideal tuning of the hyper parameter involved in the BiGRU model, the IWO algorithm is utilized [20]. It employs two methods for exploration: the initial diversification technique chooses an arbitrary whale $\vec{x}_{\text{rand}}(t)$ from the present swarm to be the prey as follows:

$$a = 2 - t(2/Maxiteration);\ A = 2ar - a; C = 2r \tag{7}$$

$$\vec{D} = \left| C \cdot \vec{X}_{\text{rand}}(t) - \vec{X}(t) \right| \tag{8}$$

$$\vec{X}(t+1) = \vec{X}_{\text{rand}}(t) - A \cdot \vec{D} \tag{9}$$

Whereas r denotes an arbitrary value, r indicates the present iteration amount, Max Iteration signifies the maximal amount of iterations, a denotes a variable that has a reducing value; $||$ signifies the component-wise absolute value, $\vec{D}$ shows the distance among present swarm member $\vec{X}(t)$ and the arbitrary whale $\vec{x}_{\text{rand}}(t)$, C indicates a controlling coefficient, and $(\cdot)$ shows an component-wise multiplication:

$$\vec{D} = \left| C \cdot \overrightarrow{X^*}(t) - \vec{X}(t) \right| \tag{10}$$

$$\vec{X}(t+1) = \overrightarrow{X^*}(t) - A \cdot \vec{D} \tag{11}$$

Whereas $\overrightarrow{x^*}(t)$ indicates the optimum solution at iteration r and the parameter C, A are provided. WOA selects among the two divergence methodologies according to the accurate value of A variable.

For the intensification stage, WOA considering the optimal solution $\overrightarrow{X^*}$ (t) to be the prey and designs a spiral formula among the present whale $\vec{x}\,(t)$:

$$\vec{D} = \left|\overrightarrow{X^*}(t) - \vec{X}(t)\right| \tag{12}$$

$$\vec{X}(t+1) = \vec{D} \cdot e^{bl} \cdot \cos\,(2\pi l) + \overrightarrow{X^*}(t) \tag{13}$$

Whereas t denotes number of iterations, $\vec{D}$ indicates the distance among present swarm member and the optimal solution, b denotes a constant and l denotes an arbitrary value in the within $[-1, 1]$. WOA selects among the exploration and exploitation stages arbitrarily based on the value of p variable that has a value in the range.

$$\overline{x}(t+1) = \begin{cases} \overrightarrow{X^*}(t) - A \cdot \vec{D} & if\ p < 0.5 \\ \vec{D} \cdot e^{bl} \cdot \cos(2\pi l) + \overrightarrow{X^*}(\mathrm{t}) & if\ p \geq 0.5 \end{cases} \tag{14}$$

where p denotes an arbitrary value. Alternating the two stages ensures the balance among diversification and intensification methods, applying all the 50% of the time. Generally, the operation and structure of WOA are simpler that facilitate its improvement.

To optimize the efficiency of the conventional algorithm, the IWO approach is derived by the use of levy flight (LF) concept. LF was firstly established by the French mathematician in 1937 named Paul Levy [21].

$$Levy\,(\beta)\ \sim u = t^{-1-\beta},\ 0 < \beta \leq 2 \tag{15}$$

β indicates Levy index for altering the stability. The Levy arbitrary amount is evaluated by:

$$Levy\,(\beta) \sim \frac{\varphi \times \mu}{|\mathrm{v}|^{1/\beta}} \tag{16}$$

Algorithm 1: The WOA algorithm

1) Load the whale population $X_i (i = 1,\ 2,\ 3, \ldots,\ n)$.
2) Evaluate the fitness of a whale.
3) Fix X^* as optimum whale.
4) while ($t <$ *maximum number of iterations*) do
  for (*each search whale*) do
    Upgrade $a,\ A,\ C,\ l\,p$.
    if ($p < 0.5$) then
      if ($|A| < 1$) then
        The whale location is increased.
      else
        if ($|A| \geq 1$) then
            Decide the arbitrary whale X_{rand}
            The whale location is upgraded.
        End
    End

(Continued)

Algorithm 1: Continued

```
  else
      if (p ≥ 0.5) then
            Modify the whale location.
      end
  end
end
Validate if any searching agent exceeds the searching region.
Evaluate the fitness of a searching agent.
Upgrade X* once an optimal solution is accomplished.
t = t + 1
end
```

In which μ & v indicates regular distribution, Γ shows standard Gamma function, $\beta = 1.5$, & φ as follows:

$$\varphi = \left[\frac{\Gamma(1+\beta) \times \sin\left(\pi \times \frac{\beta}{2}\right)}{\Gamma\left(\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\frac{\beta-1}{2}}\right)} \right]^{\frac{1}{\beta}}. \tag{17}$$

For gaining a tradeoff amongst the exploitation and exploration capacities of metaheuristic model, LF approach is employed to upgrade searching agent position as follows:

$$X_i^{levy} = X_i + r \oplus levy(\beta) \tag{18}$$

In which X_i^{levy} indicates position of i th searching agent X_i after that upgrading and r indicate arbitrary vector in zero and one $\oplus$ designates dot product. The IWO algorithm computes an objective function with the minimization of mean square error (MSE), as defined in Eq. (19):

$$MSE = \frac{\sum_N^i |y_i - \hat{y}_i|^2}{N} \tag{19}$$

where y states the number of rounds, y_i indicates the experimental value, and $\hat{y}_i$ symbolizes forecasted values, correspondingly.

4 Experimental Validation

The experimental analysis of the IWO-DLELP method is performed using the historical hourly load dataset of 3 USA power grids, collected from openly accessible PJM electricity market. The three power grids are formula electric (FE) grid, Dayton grid, and East Kentucky Power Cooperative (EKPC) grid. The proposed is simulated using Python tool.

Table 1 and Fig. 3 showcases the predictive outcomes of the IWO-DLELP model with existing models such as mutual information-based artificial neural network (MI-ANN), bi-level, ANN-based accurate and fast converging (AFC-ANN), and factored conditional restricted Boltzmann machine (FCRBM) under distinct hours on FE grid [22]. The experiment value indicates that the IWO-DLELP model has accomplished effectual results with the least difference among the actual and predicted values. For instance, on hour 1 with actual load of 671.8923 kW, the IWO-DLELP technique has obtained predicted value of 670.3248 kW whereas the FCRBM, AFC-ANN, Bi-level, and MI-ANN models have attained predicted values of 670.0814, 684.6426, 646.4398, and 652.2836 kW respectively. Besides, on hour 10 with actual load of 717.9577 kW, the IWO-DLELP technique has reached predicted value of 714.9781 kW whereas the FCRBM, AFC-ANN, Bi-level, and MI-ANN models have attained predicted values of 714.5973, 705.7591, 698.4807, and 720.5594 kW respectively.

Table 1: Actual and predicted values of IWO-DLELP model on FE grid

Hours	Actual (kW)	Predicted values				
		IWO-DLELP	FCRBM	AFC-ANN	Bi-level	MI-ANN
1	671.8923	670.3248	670.0814	684.6426	646.4398	652.2836
2	677.7923	680.9394	674.3200	659.7464	664.9966	629.4997
3	700.3192	698.7744	702.2352	717.1355	633.8909	727.1357
4	734.5654	738.1555	738.5565	725.9191	746.7706	758.8978
5	760.9115	755.7781	755.3893	744.3557	776.5063	741.9420
6	767.4346	769.7439	770.0551	756.7706	796.9988	796.4177
7	754.7077	751.9659	757.9168	728.5175	745.6620	752.3842
8	744.3962	746.0192	746.5117	713.3715	754.3015	740.8047
9	731.4692	729.5952	729.0985	700.5927	716.9274	736.8293
10	717.9577	714.9781	714.5973	705.7591	698.4807	720.5594
11	706.0231	707.8816	708.1387	701.0535	730.3990	760.7012
12	699.6500	695.8466	703.7537	710.2087	699.3351	686.2797
13	703.1462	707.3957	707.8183	730.0849	726.8572	709.0619
14	726.0346	728.7234	729.1591	706.4077	751.9937	710.5707
15	753.6077	758.6295	758.9644	754.3459	701.0167	741.5006
16	768.8000	765.5264	772.4617	784.2367	787.4651	766.1960
17	768.8538	773.9116	774.3989	739.5004	779.3322	721.7944
18	754.7423	751.5026	751.2915	720.2147	738.4580	762.0327
19	730.7462	727.3026	734.6504	740.3744	692.6104	754.7735
20	703.3885	701.2318	700.7822	716.9534	670.8546	742.8857
21	682.3577	679.2816	678.9207	759.4604	657.0928	763.9875
22	661.9192	666.1867	666.6637	676.7575	630.0183	683.6624
23	672.6923	674.5807	674.8346	681.8295	630.5106	675.6675
24	676.6923	673.7681	679.8514	684.9512	635.0780	678.9070

Table 2 and Fig. 4 demonstrates the overall predictive results of the IWO-DLELP model with recent techniques under diverse hours on Dayton grid. The results reported that the IWO-DLELP model has attained proficient results with the minimal variation amongst the actual and predicted values. For instance, on hour 1 with actual load of 175.3224 kW, the IWO-DLELP technique has gained predicted value of 172.5558 kW whereas the FCRBM, AFC-ANN, Bi-level, and MI-ANN models have achieved values of 178.5829, 168.5829, 171.5829, and 169.8923 kW respectively. In addition, on hour 10 with actual load of 215.6234 kW, the IWO-DLELP technique has attained predicted value of 714.9781 kW whereas the FCRBM, AFC-ANN, Bi-level, and MI-ANN models have provided predicted values of 215.9234, 217.4214, 216.4214, and 222.9577 kW respectively.

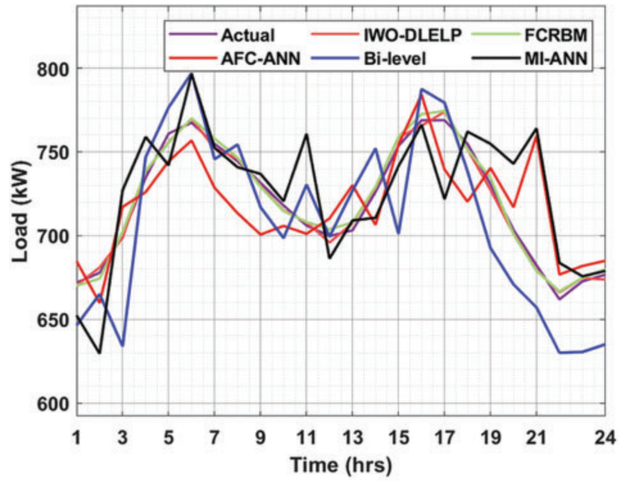

Figure 3: Actual and predicted values of IWO-DLELP model on FE grid

Table 2: Actual and predicted values of IWO-DLELP model on dayton grid

Hours	Actual (kW)	Predicted values				
		IWO-DLELP	FCRBM	AFC-ANN	Bi-level	MI-ANN
1	175.3224	172.5558	178.5829	168.5829	171.5829	169.8923
2	171.7990	169.0908	174.8321	165.4538	167.4538	165.7923
3	167.3052	174.6203	174.8754	166.7687	164.7687	162.3192
4	169.5134	163.9155	163.5234	162.1835	178.1835	162.5654
5	173.9342	166.8482	166.3543	183.1637	179.1637	180.9115
6	182.3425	187.0316	177.3824	178.2146	207.2146	198.4346
7	200.6273	186.2788	185.9854	211.4250	218.4250	208.7077
8	212.3932	226.3702	197.9234	218.0627	209.0627	221.3962
9	213.4532	217.1451	209.4321	213.8664	217.8664	215.4692
10	212.4507	215.6234	215.9234	217.4214	216.4214	222.9577
11	209.2531	216.4374	216.8374	220.5006	215.5006	220.0231
12	205.1459	209.4657	209.9321	221.0961	200.0961	217.6500
13	201.1462	206.3326	206.5612	197.6095	206.6095	198.6213
14	197.3546	208.4295	208.6578	210.6107	203.6107	209.1462
15	193.6077	203.9518	204.3196	203.3196	192.3196	200.0346
16	192.8345	191.1147	194.9134	187.5867	194.5867	189.6077
17	191.8538	190.9781	190.7534	202.6408	195.6408	200.8000
18	192.7023	195.5361	195.8034	203.0248	192.0248	201.8538
19	198.7462	194.7165	194.3480	203.3454	192.9239	201.7423
20	205.2805	208.0284	208.4567	185.9239	188.9967	187.7462
21	200.3075	197.3800	203.6512	181.9967	190.1795	189.3885
22	200.9032	188.4103	187.9234	210.1795	210.0057	213.3577
23	190.6533	187.9512	187.5915	203.2057	210.1417	200.9192
24	180.2476	182.4919	177.7435	175.5057	178.1530	170.6923

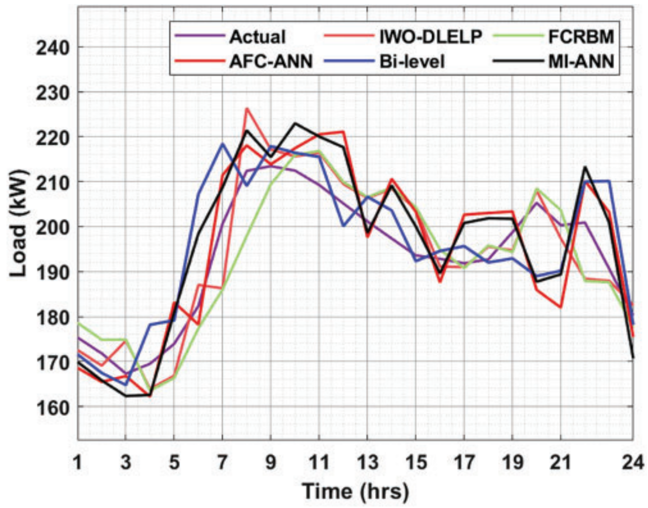

Figure 4: Actual and predicted values of IWO-DLELP model on dayton grid

Table 3 and Fig. 5 highlights the comprehensive prediction outcomes of the IWO-DLELP model with recent techniques under distinct hours on EKPC grid. The table values indicated that the IWO-DLELP model has reached proficient outcomes over the other methods with the minimal variation between the original and predicted values. For instance, on hour 1 with actual load of 132.8923 kW, the IWO-DLELP technique has gained predicted value of 134.9866 kW whereas the FCRBM, AFC-ANN, Bi-level, and MI-ANN models have depicted predicted values of 136.5019, 138.9234, 138.9234, and 139.8923 kW respectively. Meanwhile, on hour 10 with actual load of 150.4692 kW, the IWO-DLELP technique has exhibited predicted value of 151.6949 kW whereas the FCRBM, AFC-ANN, Bi-level, and MI-ANN models have demonstrated predicted values of 148.8664, 150.4214, 153.1423, and 150.4000 kW respectively.

Table 3: Actual and predicted values of IWO-DLELP model on EKPC grid

Hours	Actual (kW)	Predicted values				
		IWO-DLELP	FCRBM	AFC-ANN	Bi-level	MI-ANN
1	132.8923	134.9866	130.5829	136.5019	138.9234	139.8923
2	131.7923	129.7379	129.4538	123.3458	128.4832	127.7923
3	131.3192	132.5780	129.7687	123.6685	129.8723	127.3192
4	132.5654	130.4093	130.1835	145.1345	127.1358	139.5654
5	138.9115	141.2689	136.1637	147.1370	140.1378	142.9115
6	147.4346	149.1664	145.2146	153.1106	149.4634	151.4346
7	161.2115	157.9161	157.4474	168.4130	167.4013	168.2115
8	167.7077	163.7719	163.4250	170.2327	170.2723	173.7077
9	163.3962	161.3346	161.0627	175.6234	168.8602	170.3962
10	150.4692	151.6949	148.8664	150.4214	153.1423	150.4000
11	145.9577	143.7338	143.4214	157.0023	154.5602	153.9577
12	141.0231	142.2508	139.5006	140.3261	142.6101	140.0231

(Continued)

Table 3: Continued

Hours	Actual (kW)	Predicted values				
		IWO-DLELP	FCRBM	AFC-ANN	Bi-level	MI-ANN
13	138.6500	140.9271	136.0961	146.9501	144.1295	146.6500
14	136.1462	141.3745	130.6095	130.6107	132.6071	130.1462
15	130.0346	128.9351	128.6107	130.3602	134.3106	136.0346
16	130.6077	128.8003	128.3196	127.5671	128.5027	123.6077
17	130.8000	130.9168	130.5867	124.6418	130.4082	124.8903
18	133.8538	132.0544	131.6408	143.3485	137.1348	139.8038
19	137.7423	135.5053	135.0248	146.3541	139.3924	141.0233
20	142.7462	140.7647	140.3454	137.9339	139.2267	137.7053
21	152.3885	151.3986	150.9239	149.9557	149.1534	147.3885
22	151.3577	152.3215	149.9967	156.9520	153.2357	157.3577
23	136.9192	139.2480	134.1795	135.1257	140.1017	139.9192
24	132.6923	130.4298	130.0057	133.5231	138.1530	139.6053

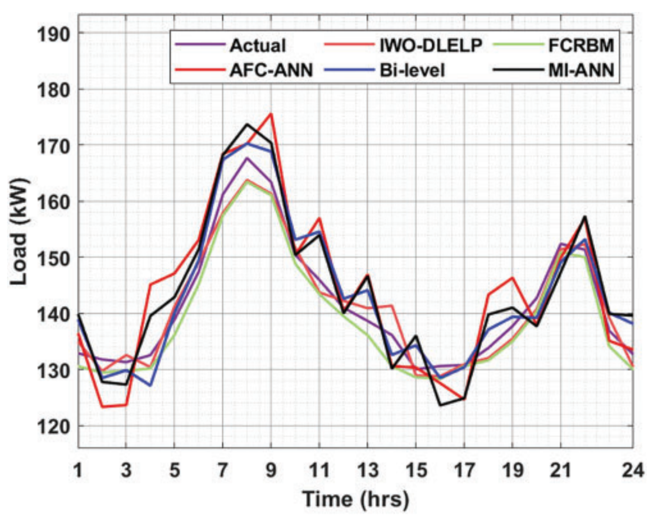

Figure 5: Actual and predicted values of IWO-DLELP model on EKPC grid

A comparative MSE inspection of the IWO-DLELP with recent methods is made under distinct hours in Fig. 6 on FE grid. The results indicated that the IWO-DLELP model has accomplished proficient results with the minimal MSE values under several hours. For instance, with 1 h, the IWO-DLELP model has obtained lower MSE of 1.5675 whereas the FCRBM, AFC-ANN, Bi-level, and MI-ANN techniques have attained higher MSE of 1.8109, 12.7503, 25.4525, and 19.6087 respectively. At the same time, with 15 h, the IWO-DLELP model has obtained lesser MSE of 5.0218 whereas the FCRBM, AFC-ANN, Bi-level, and MI-ANN techniques have attained higher MSE of 5.3567, 0.7382, 52.5910, and 12.1071 correspondingly. Along with that, within 24 h, the IWO-DLELP approach has reached lower MSE of 2.9242 whereas the FCRBM, AFC-ANN, Bi-level, and MI-ANN algorithms have attained higher MSE of 3.1591, 8.2589, 41.6143, and 2.2147 correspondingly.

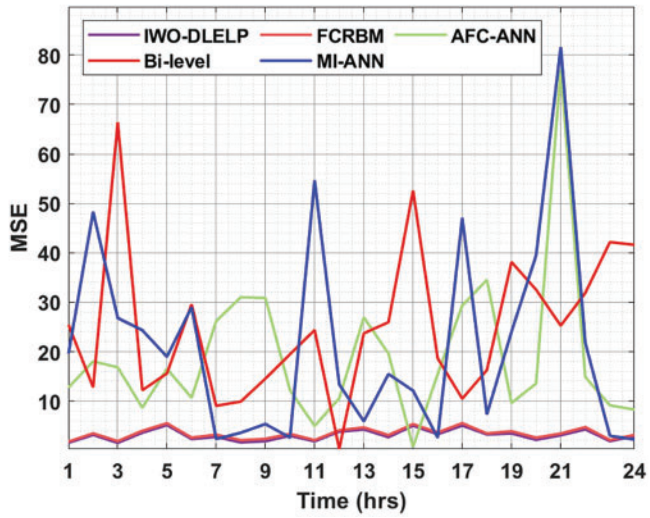

Figure 6: MSE analysis of IWO-DLELP technique under FE grid dataset

A brief MSE inspection of the IWO-DLELP with recent methods is made under distinct hours in Fig. 7 on Dayton grid. The outcomes exposed that the IWO-DLELP model has accomplished proficient results with the lesser MSE values under different hours. For instance, with 1 h, the IWO-DLELP algorithm has reached lower MSE of 2.7666 whereas the FCRBM, AFC-ANN, Bi-level, and MI-ANN techniques have attained higher MSE of 3.2605, 6.7395, 3.7395, and 5.4301 correspondingly. Followed by, with 15 h, the IWO-DLELP model has obtained lesser MSE of 10.3441 whereas the FCRBM, AFC-ANN, Bi-level, and MI-ANN techniques have attained higher MSE of 10.7119, 9.7119, 1.2881, and 6.4269 correspondingly. Next, within 24 h, the IWO-DLELP technique has obtained reduced MSE of 2.2443 whereas the FCRBM, AFC-ANN, Bi-level, and MI-ANN methods have attained higher MSE of 2.5041, 4.7419, 2.0946, and 9.5553 respectively.

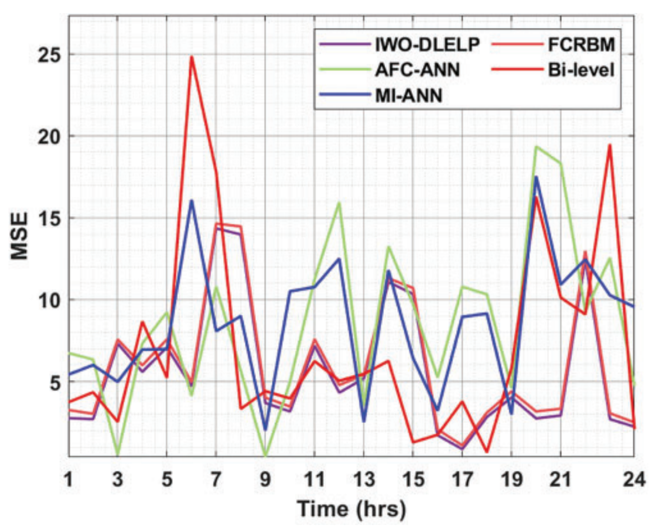

Figure 7: MSE analysis of IWO-DLELP technique under Dayton grid dataset

A detailed MSE inspection of the IWO-DLELP with recent methods is made under distinct hours in Fig. 8 on EKPC dataset. The results indicated that the IWO-DLELP model has accomplished proficient results with the minimal MSE values in several hours. For instance, with 1 h, the IWO-DLELP approach has obtained lower MSE of 2.0943 whereas the FCRBM, AFC-ANN, Bi-level, and MI-ANN techniques have reached higher MSE of 2.3094, 3.6096, 6.0311, and 7.0000 correspondingly. Simultaneously, with 15 h, the IWO-DLELP model has obtained lower MSE of 1.0995 whereas the FCRBM, AFC-ANN, Bi-level, and MI-ANN techniques have attained maximum MSE of 1.4239, 0.3256, 4.2760, and 6.0000 respectively. Lastly, within 24 h, the IWO-DLELP methodology has obtained decreased MSE of 2.2625 whereas the FCRBM, AFC-ANN, Bi-level, and MI-ANN approaches have attained maximum MSE of 2.6866, 0.8308, 5.4607, and 6.9130 correspondingly. After examining the results and discussion, it is ensured that the IWO-DLELP model has accomplished superior results over the other methods.

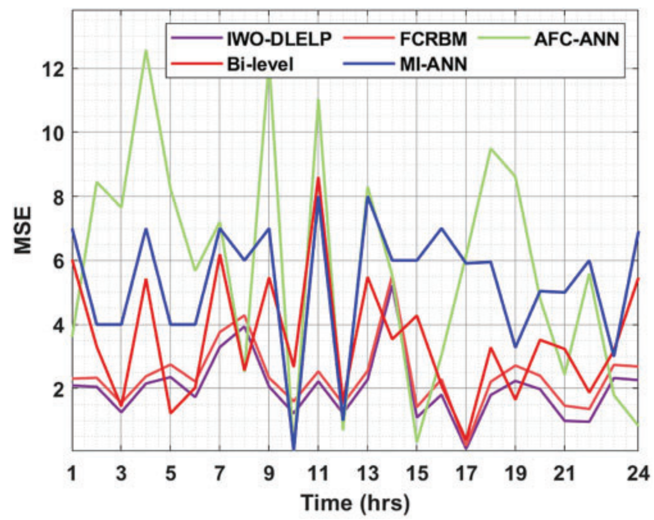

Figure 8: MSE analysis of IWO-DLELP technique under EKPC dataset

5 Conclusion

In this study, a new IWO-DLELP technique has been presented to effectually forecast the electric load in SG environment for designing proficient ESS. The proposed IWO-DLELP model encompasses pre-processing, partition clustering, BiGRU based prediction, and IWO based hyperparameter tuning. The simulation analysis of the IWO-DLELP model is performed and the results are inspected under several aspects. The comparison study reported the enhanced outcomes of the IWO-DLELP model over the recent methods interms of distinct evaluation measures. Therefore, the IWO-DLELP technique can be utilized for the promising load prediction performance in the SG environment. In future, metaheuristics based feature selection models can be derived to enhance the predictive performance.

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