

Hybrid metaheuristic and DL approach for integrated solar and electric vehicle energy management in smart grid networks

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ABSTRACT

The increasing penetration of electric vehicles (EVs) and intermittent renewable generation has created challenges for accurate energy forecasting and stable smart-grid operation. Existing forecasting approaches often retain redundant variables or use manually selected model parameters, limiting their predictive reliability. This study developed a deep representation learning-based integrated solar and EV energy management (DRL-ISEVEM) framework to improve EV energy-consumption forecasting for smart-grid decision support. The input data were standardized using Z-score normalization. An improved whale optimization algorithm (IWOA) subsequently selected 17 informative variables from 19 candidate features, while a multivariate temporal convolutional network (M-TCN) captured nonlinear temporal dependencies and inter-variable relationships. A dung beetle optimizer (DBO) tuned the M-TCN hyperparameters by minimizing the validation error. Experimental evaluation on a benchmark EV energy-consumption dataset produced testing values of 0.001308 for mean squared error (MSE), 0.036168 for root mean squared error (RMSE), 0.029003 for mean absolute error (MAE), and 0.05438 for mean absolute percentage error (MAPE). The testing RMSE was only 1.46% higher than the training RMSE of 0.035648, indicating a small within-dataset generalization gap. These findings demonstrated that the sequential integration of feature selection (FS), temporal learning, and hyperparameter optimization provided accurate EV energy forecasts for smart-grid energy-planning applications.

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1. INTRODUCTION

Recently, classical vehicles have been replaced with electric vehicles (EVs) because of fuel gases and environmental pollution [1]. The adoption of EVs globally has accelerated significantly over the last few years thanks to improvements in battery technology, favorable government policies, the deployment of charging infrastructure, increased environmental awareness and general desire for greenhouse gas reduction and fuel

independence. EV and solar power batteries are vital to decrease the dependence on fossil fuels and signify the common development of the energy structure. Dual key inclines in energy usage that are expected for the upcoming future are the improvement in dispersed generation, like the advent of EV and solar energy as the impending means of transportation [2]. Conversely, photovoltaic (PV) solar energy-capturing struggles with daytime and cyclical differences, creating a need for energy storage technologies.

Furthermore, voltage and congestion problems are expected in the distributed network because of the rapid growth in renewable generation and the improved power demand for the fuelling of EVs [3]. To resolve the above issues, production of EVs employing PV energy would be a better solution, safeguarding a sustainable energy system. However, compared to modern EVs, they enhance the quality of the air by decreasing carbon emissions [4]. The major issues brought on by utilizing conventional vehicles will be addressed if EVs are successfully combined. Currently, the discernment of EVs has not exposed a significant impact on the grid's need for electricity. EVs will finally become more broadly employed and more inexpensive [5]. Consequently, they will have a huge effect on how the smart grid works and how much energy is required. To lessen the failures relevant to resource allocation and intelligent management systems, electricity flow across the smart grids is needed.

In the past years, the development of artificial intelligence (AI) and machine learning (ML) methods was related to enhancing the distribution grid and decreasing charging expenses [6]. The combination of ML and several sensors is considered a solution for forecasting grid stability and safeguarding adaptability to changing consumer requirements [7]. Some various ML algorithms, namely decision tree (DT), support vector machine (SVM), logistic regression (LR), and linear used to grid stability in dynamic states. ML methods, especially a group of data handling approaches are progressively popular for short-term load predicting in smart grids [8]. In spite of the long short-term memory (LSTM) model's high precision, its hardware requirements are superior to those of other methods. Furthermore, solar energy participates in decreasing greenhouse gas emissions, thereby contributing to mitigating worldwide temperature [9]. The solar energy sector has set a novel record in power generation, aimed at minimizing dependence on decreasing fossil fuel sources.

Although the use of EVs, and solar energy systems in the contemporary smart grids has been embraced, the dynamic interdependence between the energy production and consumption remains a major challenge. The generation of solar energy is highly fluctuating to the weather conditions and time-of-day variations, whereas the EV charging demand is unpredictable and will be determined by the user behavior and traveling patterns. Such data are usually non-linear, high-dimensional, and time-dependent and are often difficult to manage through traditional energy scheduling and optimization techniques. Also, most of the current ML methods have concentrated on prediction accuracy, and not on feature redundancy and the optimal selection of parameters, which can cause decreased efficiency and generalization power. Thus, a smart predictive model capable of modeling the temporal dependencies amid energy consumption and, at the same time, optimizing features and model parameters to enhance the stability and effectiveness of smart grid energy control is required.

This study presents a deep representation learning approach for integrated solar and EV energy management (DRL-ISEVEM) in smart grid networks. The first pre-processes the inputs using Z-score standardization to ensure data consistency. Next, an improved whale optimization algorithm (IWOA) has been implemented for feature selection (FS) to identify relevant features. A multivariate temporal convolution network (M-TCN) is exploited to predict energy consumption based on the preferred features. At last, a dung beetle optimizer (DBO) was implemented for hyperparameter tuning of the M-TCN to improve the prediction performance of the model. The comparative outcome shows the promising performance of the DRL-ISEVEM methodology on the recent techniques. Although ML and deep learning (DL) methods have made advancements in smart grid energy forecasting, most of the available methods do not either have an efficient feature optimization mechanism or are not able to adequately model the multifaceted temporal interaction in energy consumption data. Moreover, little research has been conducted on hybrid frameworks to apply metaheuristic optimization and deep temporal learning to predict energy in EV. In order to overcome these shortcomings, this paper suggests a hybrid DRL-ISEVEM architecture.

2. LITERATURE REVIEW

Though a number of ML and DL-based models have been developed in the context of energy management and prediction in the framework of smart grids, the vast majority of the existing methods give attention to the quality of prediction and ignore the issue of redundant features and optimization. Moreover, most of the models do not efficiently address complex time dependencies that exist in EV energy consumption data. These constraints can result into inefficient predictive performance and decreased model generalization. Thus, this paper suggests a combination of hybrid framework that promotes prediction accuracy and high resilience by combining metaheuristic optimization and deep temporal learning. This section provides a related works on EV energy management in smart grid networks. Li *et al.* [10] implemented a potentiality of solar

EVs to improve energy efficiency and provide for the power decarbonization and transportation field. The authors consider the merits of integrating PV systems and EVs, like decreased grid reliability and increased vehicle independence, and analyze approaches for maximizing the combination, comprising progressions in battery technology. Irfan *et al.* [11] addressed the residential application of a PV module with EV technology, emphasizing the advantages of employing bi-directional vehicle batteries along with top regions of PV systems. Furthermore, an innovative Q-learning-based-model (QLBM) method with the field of ML technique is utilized for dynamically improving the insight into the system. This new technique is developed for predicting optimum energy efficiency by focusing on the major inexpensive energy sources, thus lessening grid pressure and minimizing energy expenditures. Based Fukushima *et al.* [12], the critical engineering complexity and pioneering solutions for effectively incorporating EVs and intelligent grids, highlighting the elevating requirements for a robust and adaptable electrical grid with the global EVs. This research work contributes an advanced perception on overwhelming existing complexities by studying latest developments in advanced grid technology like AI and higher-capacity energy storage utilized for predictable load balancing and maintenance. Table 1 shows the comparison of existing studies.

Table 1. Comparison of existing studies on EV energy management and forecasting

Study	Method	Dataset/application	Key findings
Li <i>et al.</i> [10]	PV-EV integration analysis	Solar EV systems	Improved energy efficiency
Irfan <i>et al.</i> [11]	Q-learning model	Residential PV-EV systems	Reduced energy cost
Kumar <i>et al.</i> [13]	Smart grid optimization	Renewable energy grid	Improved load balancing
Wan <i>et al.</i> [14]	Temporal convolution network	Time-series forecasting	Accurate temporal modeling
Proposed DRL-ISEVEM	IWOA+M-TCN+DBO	EV energy dataset	Improved prediction accuracy

Vishnuram and Alagarsamy [15] developed numerous vehicle-grid integration (VGI) structures. This research analysis also examines the different categories of grid connectivity and the aspects relevant to them. This comprehensive analysis aims to give insights into the different aspects of integrating EVs into simulated power plants. It considers energy sustainability, technological developments, and the real-word implication outcomes for consumers. Kempton and Tomić [16] presented an hybrid electric vehicles (HEVs) and renewable energy sources (RES) interface, outcomes highlight the essential parts of complex grid management with demand-driven optimization. While there are capital expenditures, long-term performance, and potential profits focuses on the HEV changes economic viability in RES- incorporated smart grids. This research helps the environment and sustainable transportation purposes and aims to decrease climatic variations. Kumar *et al.* [13] presented a smart grid power generation and maintenance combined optimizer architecture with RES based on exploration of power generation. The operating expenses of traditional components, the costs of producing wind or solar power, and the expense of maintaining systems are the major issues in the main functions; the limitations are predominantly considered system limitations. The originality of this paper is that the hybridization of IWOA to select features, M-TCN to predict temporal energy and DBO to optimize hyperparameters is carried out, resulting in enhanced predictive performance. This framework has enabled smart grid environments to manage energy intelligently and effective integration of EVs and solar energy resources.

The key contributions of this paper are as follows:

- Design of a hybrid predictive model based on IWOA, M-TCN, and DBO.
- Using the proposed framework to model the patterns of energy demand at different operational conditions using an EV energy consumption data.
- Extensive experimental results comparing with a number of ML and DL models.
- Evidence that the suggested hybrid solution leads to an increase in the accuracy of predictions and the sustainable energy management of the smart grid.

3. PROPOSED METHOD

In this study, we have introduced a novel DRL-ISEVEM approach in smart grid networks. The main aim of this paper is to develop an efficient and accurate predictive system for energy management by integrating heuristic optimizer with DL approaches. It contains four different stages, such as data scaling, feature reduction, prediction, and parameter tuning, which are demonstrated in Figure 1. The proposed layout consisted of three operations which were scheduled in parallel. Firstly, IWOA implemented wrapper FS by using binary input masks and keeping variables which reduced the predictive error with penalisation on the number of variables. Second, M-TCN has been trained to learn multivariate temporal dependencies using dilated one-dimensional convolutions and residual connections, and has a long receptive field and

parallelizable training. Thirdly, with the goal of minimizing the mean squared error (MSE) of the model when validating, DBO only explored the hyperparameter space of the M-TCN: filter number, kernel size, dilation rate, dropout, learning rate, and batch size. It is therefore not the same optimization task that the two optimizers were trying to do: IWOA was reducing the input space, DBO was tuning the predictor. The sequence decomposition lowered the dimension of each search, and separated the effect of FS from of model fine-tuning. The big cost is additional optimization time outside of the online environment (called a deployment constraint).

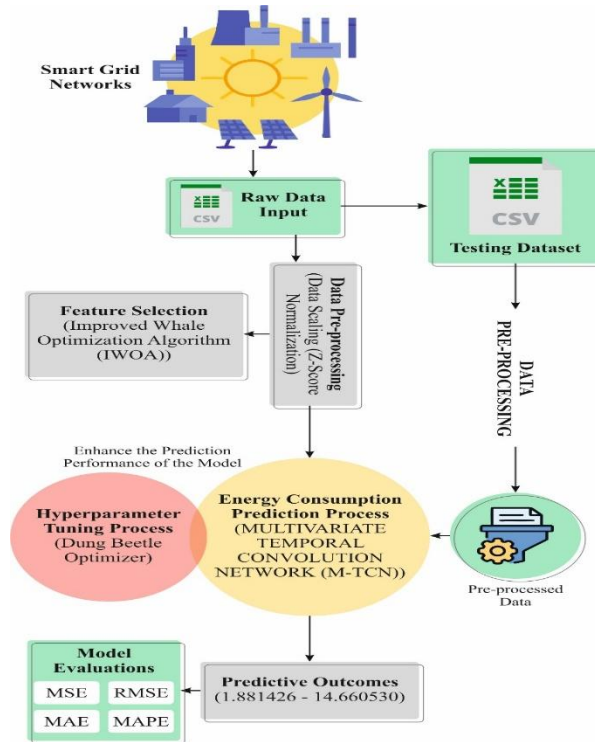


Figure 1. Overall process of DRL-ISEVEM approach

3.1. Stage I: data scaling

Initially, the proposed DRL-ISEVEM model undergoes pre-processing of the inputs utilizing Z-score standardization to make sure data consistency and model stability. For scaling the input data, the proposed model mainly employs a Z-score normalization model [17]. All features were rescaled for ensuring the mean and standard deviation (SD) are 1, before the standardization method has been employed. Its mathematical formulation is expressed (1):

$$X_{stand} = \frac{X - \text{mean}(X)}{\text{Standard Deviation}(X)} \quad (1)$$

The normalization of Z-score is beneficial for a range of optimization models. The dual foremost objectives are enhancing the efficacy of ML systems and diminishing bias in ML models.

3.2. Stage II: feature reduction method

In this stage, an IWOA is implemented for FS to identify relevant features while eliminating irrelevant ones. Even though the WOA has established robust performance in resolving numerous optimization issues, it undergoes certain restrictions when employed to intricate and higher-dimensional issues [18]. Particularly, WOA is susceptible to early convergence and might effortlessly become stuck in local goals when managing with a multimodal objective function. Furthermore, its speed of convergence can be sluggish in some situations, and the balance among exploitation and exploration is not at all times optimum, which controls its global search ability. In order to tackle these faults, an IWOA has been developed in this study. The developed IWOA enhances the global exploration capability and speed of convergence by integrating initialization of chaotic population, adaptive weight control, and a dimensional pinhole image reverse learning tactic. The foremost steps of IWOA are explained below:

- a. Population initialization depends upon enhanced tent map

The excellence of a preliminary population has a major impact on the speed of convergence and optimizer accuracy of swarm intelligence models. In the typical WOA, an initial population is produced at random, which might lead to an inadequate range and unequal spreading of the solution in the searching space. To overcome this restriction, an enhanced Tent chaotic mapping tactic is applied for initializing the population. Chaotic sequences display superior randomness and ergodicity when compared to only random initialization. Between numerous chaotic maps, the Tent map delivers higher consistency; however, it might undergo a short period. So, a random term of perturbation is presented for enhancing the chaotic behavior.

$$y_{i,j+1} = \begin{cases} \mu \times y_{i,j} + r/N, & y_{i,j} < 0.5 \\ \mu \times (1 - y_{i,j}) + r/N, & y_{i,j} \geq 0.5 \end{cases} \quad (2)$$

here N signifies the size, $j = 1, 2, \dots, d$ denotes the dimension of chaotic sequence, $r \in [0, 1]$ denotes a randomly produced number, and $\mu \in [0, 2]$ signifies the chaotic control parameter. Then, the chaotic variables are mapped to an actual search space by employing an inverse mapping:

$$x_{i,j} = lb_j + y_{i,j} \times (ub_j - lb_j) \quad (3)$$

whereas $[lb_j, ub_j]$ means the lower and upper bounds of j th dimension.

b. Dimensional pinhole image reverse learning

To further improve the global exploration ability and avert early convergence, a dimensional pinhole image reverse learning tactic has been presented. The conventional reverse learning model produces reverse solutions that depend upon fixed boundaries. Stimulated by the notion of pinhole imaging, the developed method achieves opposite learning in a dimension-wise manner. Let X_j^{best} signify the finest solution in j -th dimension, b_j and a_j denote the dynamic upper and lower bounds, correspondingly.

$$X_{best}^{'j} = \frac{(a_j + b_j)}{2} + \frac{(a_j + b_j)}{2n} - \frac{X_{best}^{'j}}{n} \quad (4)$$

when $n = 1$, the expression decreases to the traditional reverse learning formula:

$$X_{best}^{'j} = (a_j + b_j) - X_{best}^j \quad (5)$$

By employing this tactic on an elite individual kept in the present population and actively upgrading the search limits, the developed tactic efficiently enlarges the searching space and improves accuracy while decreasing the probability of dropping into local goals.

The fitness function (FF) considers the model's accuracy and the number of chosen attributes. Therefore, the following FF was applied for assessing an individual solution, as exposed (6):

$$Fitness = \alpha * ErrorRate + (1 - \alpha) * \frac{\#SF}{\#All_F} \quad (6)$$

here, *ErrorRate* indicates a proportion of erroneously classified to the quantity of classifications prepared, among 0 and 1; *ErrorRate* represents a classifier rate of error. *#All_F* denotes to a complete quantity of attributes in an original database. *#SF* signifies several chosen features. α is applied for controlling the significance of classifier quality.

3.3. Stage III: modeling of multivariate temporal convolution network

In this section, M-TCN is then utilized to predict energy consumption based on the chosen attributes. This study implements an M-TCN as the prediction method [18]. The main aim is to project a stable, flexible, and computationally effective structure that is capable of demonstrating intricate temporal dependencies amongst manifold correlated variables. The M-TCN method aids flexible input and output sequence lengths for accommodating the dissimilar prediction prospects and real-world application situations. By using residual learning mechanisms and 1D convolutional processes, the model improves extraction of feature ability and training consistency. Moreover, the structure of multi-variate permits the method to similarly learn time-based patterns from manifold input attributes, thus enhancing the accuracy of prediction for intricate time-series data. The following are complete details of the M-TCN model.

a. 1D convolutions

TCN employs causal convolution, whereas an output at t th time has been convolved with an element from t th time in the preceding layer. The causal convolutional is generally employed for assuming that every data point should have one-to-one causal relations in sequential order. It was mainly restricted by a time-series

absolute order and was ineffective for precise feature learning. Therefore, only a 1D convolution is implemented to evade this condition.

b. Dilated convolutions

This algorithm is employed in M-TCN model. Since the conventional convolution procedure is to pervert the sequence, which decreases the dimension of sequence and increases the receptive field simultaneously. Therefore, this algorithm might be well employed in a case of longer data dependence. Its mathematical formulation is expressed (7):

$$F(s) = (x *_{d} f)(s) = \sum_{i=0}^{k-1} f(i) \cdot x_{s-d \cdot i'} \quad (7)$$

whereas, d denotes a dilation factor and k means the size of the filter.

c. Residual block

The main purpose of ResNet is to form a shortcut for data dissemination in both layers of the back and front. Another method is to enlarge the size of convolutional kernel for a superior prediction. This model holds dual channels. Each has a non-linearity and dilated convolution, which utilizes the rectified linear unit (ReLU). The output is the quantity of outcomes of dual channel processes, which has a similar basic structure to residual block 1. To be further accurate, a dilated convolution with dissimilar factors of dilation and size of filter $k = 3$ are built for residual block. The filter of k bends over an input data X that is expressed (8)-(11):

$$ReLU(x) = \max(0, x) \quad (8)$$

$$h_{1k} = ReLU(W_k * X + b_k) \quad (9)$$

$$h_{2k} = ReLU(W_k * X + b_k) \quad (10)$$

$$h_k = h_{1k} + h_{2k} \quad (11)$$

here h_{1k} and h_{2k} denotes an outcome of channels 1 and 2, respectively. h_k represents an outcome of unit. $*$ indicates a convolutional process. A residual block covers a network that permits over a sequence of conversion functions $\mathcal{F}$:

$$o = (x + \mathcal{F}(x)) \quad (12)$$

d. Fully connected (FC) layer

This layer is mainly substituted by global average pooling (GAP) for superior accuracy. However, FC layers are vital in prediction task. So, an output z is formulated (13):

$$z = GAP(x_c) = \frac{1}{H \times W} \sum_{i=1}^H \sum_{j=1}^W x_c(i, j). \quad (13)$$

e. Multi-head model

The method is furthermore prolonged so that every input variable holds a dissimilar sub-model, called a multi-head model. Each input variable was described initially. Also, it learns the data with dissimilar attributes in sequence distinctly. Furthermore, the outputs are then united in sequence for producing a longer vector that is explained by FC layers beforehand the prediction is prepared.

3.4. Stage IV: parameter optimizer using dung beetle optimizer

Lastly, a DBO has been adopted for parameter tuning of M-TCN approach for enhancing the performance of prediction. It is originated from the dung beetles' (DBs) survival behavior naturally [19]. The algorithm plays a significant part in attaining global supremacy by pretending the systematic behavior of a dung ball via a DB and follows a drive by executing a behavior of dancing. Female DBs found a local search region by laying eggs and covering dung balls. Next, the young DBs mimic adults and therefore do a good exploration in a smaller region. Lastly, the behavior of competition occurs among individuals, accelerating the method to an optimum solution.

a. Population initialization

The DBO sets its population in a randomized method, where every DB's location corresponds to a latent solution. For the d dimensional, the location of i th DB is signified as $x_j = [x_{i,1}, x_{i,2}, \dots, x_{i,d}]$, and N dimension is represented as $X = [x_1, x_2, \dots, x_N]^T$, as exposed in (14):

$$X = \begin{bmatrix} x_{1,1} & \cdots & x_{1,d} \\ \vdots & \ddots & \vdots \\ x_{N,1} & \cdots & x_{N,d} \end{bmatrix} \quad (14)$$

b. Rolling stage

– Obstacle-free method

In a lack of difficulties, rolling DB pretends its normal complement by transmitting a ball of dung manifold times on its back and traveling with the aid of sunlight. This stage mainly concentrates on “covering a broader searching space with larger steps”. The location of the ball is upgraded according to (15):

$$x_i(t+1) = x_i(t) + \phi \cdot k \cdot x_i(t-1) + b\Delta x \quad (15)$$

here, $\phi = \pm 1$ is arbitrarily chosen for reflecting smaller defections, $\Delta x = |x_i(t) - X_w|$, X_w represents the worst individual location, and $X(t)$ upholds an endurance of a model.

– Obstacle method

When a DB meets a difficulty throughout rolling, it performs a behavior of dancing, thus by revolving on its dung ball and stopping briefly to rectify its pathway. The location upgrade regulation is described in (16):

$$x_i(t+1) = x_i(t) + \tan(\theta)|x_i(t) - x_i(t-1)| \quad (16)$$

here, $\tan(\theta)$ value takes on a typical range that yields from 0 defection $\theta = 0, \pi/2, \pi$ to great navigation.

– Behavior of reproduction

Female DBs will set beside a safer spawning region for their offspring at a definite distance. The model actively describes the lower and upper limits on the present local optimum location X^* that is exposed in (17):

$$\begin{aligned} Lb^* &= \max(X^* \times (1 - R), Lb) \\ Ub^* &= \min(X^* \times (1 + R), Ub) \end{aligned} \quad (17)$$

here, Lb, Ub mean the lower and upper bounds, respectively, as an iteration increases. A solitary spawn position is produced per iteration, as exposed in (18):

$$B_i(t+1) = X^* + b_1 \times (B_i(t) - Lb^*) + b_2 \times (B_i(t) - Ub^*) \quad (18)$$

whereas, $B(t)$ signifies the location information of i th spawn ball at t th iteration; b_1 and b_2 are binary independent randomly generated vectors.

– Foraging behavior

Some DBs permit the laying region to hunt on the ground, signifying the model's dissimilar and lesser step-size fine exploration. It also actively describes the foraging region on the global optimizer X^b , as exposed (19):

$$\begin{aligned} Lb^b &= \max(X^b \times (1 - R), Lb) \\ Ub^b &= \min(X^b \times (1 + R), Ub) \end{aligned} \quad (19)$$

here, Ub^b and Lb^b denotes the upper and lower bounds, correspondingly. The location of the smaller DB is upgraded by evaluating linear interpolation and normal perturbation, as exposed (20):

$$x_i(t+1) = x_i(t) + C_1 \times (x_i(t) - Lb^b) + C_2 \times (x_i(t) - Ub^b) \quad (20)$$

here, C_1 denotes a randomly produced numeral; C_2 refers to an arbitrary vector within an interval of (0,1).

– Behavior of stealing

In higher-density zones, few DBs try to “steal” balls of dung from others to rapidly obtain resources. This behavior looks like a jump-based location promotion that functions near convergence on the global greatest solution.

$$x_i(t+1) = X^b + S \times g \times \{|x_i(t) - X^*| + |x_i(t) - X^b|\} \quad (21)$$

here, g signifies the randomly produced vector size of $1 \times d$, and S means a constant.

In this work, the DBO was applied for determining the hyperparameter complex in the M-TCN model. The MSE is computed as an objective function, which is stated (22):

$$MSE = \frac{1}{T} \sum_{j=1}^L \sum_{i=1}^M (y_j^i - d_j^i)^2 \quad (22)$$

here, M and L signify the resulting value of layer and data, respectively. d_j^i and y_j^i means an appropriate and attained extent for j^{th} unit from the resulting layer in time t correspondingly.

Table 2 summarizes the optimal hyperparameter configuration utilized for training the M-TCN model. The architecture utilizes 3 temporal convolution layers with 62 filters per layer, a kernel size of 4, and a dilation rate of 5 to effectually gains temporal dependencies. Learning stability and regularization are confirmed by utilizing a dropout rate of 0.1, a learning rate of 0.001, and a batch size of 32. The model is trained for 50 epochs with a maximum of 100 iterations, whereas the DBO parameters are rolling beetle ratio (0.3), breeding probability (0.25), and foraging coefficient (1.2) to assist proficient hyperparameter optimization and convergence.

Table 2. Hyperparameter table

Component	Hyperparameter	Optimal value
M-TCN architecture	Number of temporal convolution layers	3
	Number of filters per layer	62
	Kernel size	4
	Rate of dilation	5
	Rate of dropout	0.1
	Rate of learning	0.001
	Size of batch	32
Training parameters	No. of epochs	50
	Maximum iterations	100
	Rolling beetle ratio	0.3
	Breeding probability	0.25
DBO	Foraging coefficient	1.2

4. EXPERIMENTAL VALIDATION

The performance evaluation of the DRL-ISEVEM technique can be tested using benchmark EV Energy Consumption Dataset from Kaggle repository [20]. The EV Energy Consumption Dataset is established to support research on energy efficiency in new energy vehicles (NEVs), mainly EVs. This dataset acquires real-world driving behavior, road environments, weather factors, and vehicle features for predicting energy consumption in kWh (Kilowatt-hour). This dataset is useful for ML-based energy optimization, facilitating increased EV sustainability and resource management in transportation. The total number of features is 19, and 17 features are selected.

Figure 2 denotes the correlation matrix of the relationships among vehicle dynamics, battery parameters, environmental factors, and energy consumption. Energy consumption displays a strong positive correlation with speed and distance travelled, representing their dominant implications on power utility, whereas voltage and battery condition show slight correlations. Most alternative attributes exhibit lower correlations, signifying minimized multicollinearity and independent contributions to the prediction method.

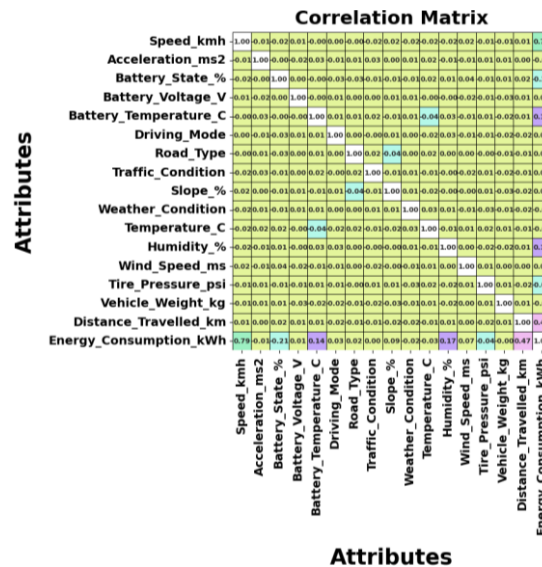


Figure 2. Correlation matrix

Figure 3 portrays the difference in energy consumption across distinct vehicle IDs, presenting an extensive range of values for all vehicles. No clear pattern is noticeable in terms of vehicle ID, demonstrating that energy consumption is not directly reliant on the identifier itself. This dispersion implies that operational and environmental factors play a more important role in affecting energy consumption.

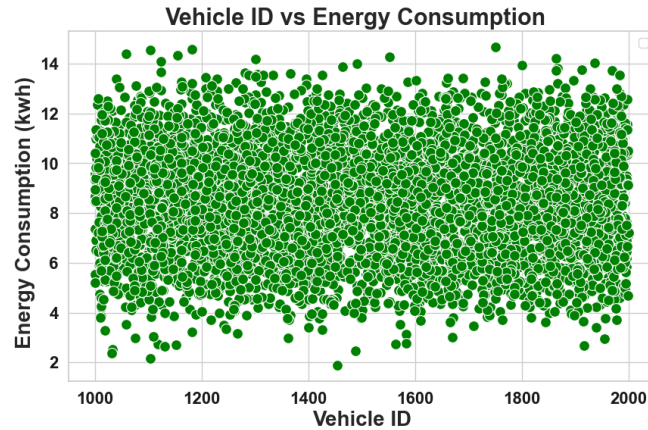


Figure 3. Vehicle IDs vs energy consumption

In Table 3, the overall results of the DRL-ISEVEM technique are clearly depicted under training and testing sets. With training set, the DRL-ISEVEM technique gains MSE of 0.001271, root mean squared error (RMSE) of 0.035648, mean absolute error (MAE) of 0.028469, and mean absolute percentage error (MAPE) of 0.053941. Also, on testing set, the DRL-ISEVEM system obtains MSE of 0.001308, RMSE of 0.036168, MAE of 0.029003, and MAPE of 0.05438. The increased performance of the DRAI-ISEVEM model can be explained by the synergy between the optimization of features, the modeling over time and the tuning of hyperparameters. This is because the IWOA algorithm is very effective in eliminating redundant features so that the prediction model can concentrate on the most significant variables that affect energy consumption. Meanwhile, M-TCN architecture records the temporal relationship of driving behavior and environmental conditions that play a significant role in effective energy prediction. Lastly, the DBO optimizer is better in the choice of parameters, i.e., it can converge much faster and its generalization is better.

Table 3. Overall outcome of DRL-ISEVEM method

Metrics	Training set	Testing set
MSE	0.001271	0.001308
RMSE	0.035648	0.036168
MAE	0.028469	0.029003
MAPE	0.053941	0.05438

Figure 4 exemplifies the comparison among actual and predicted normalized values with training and testing sets at Figures 4(a) epoch 20, (b) epochs 30, (c) epochs 40, and (d) epochs 50. As the number of epochs rises, the predicted curves gradually align more closely with the definite values, representing enhanced learning and convergence. The testing outcomes indicate minimized fluctuations at higher epochs, considering higher generalization performance. In general, epoch 50 reveals the more consistent and correct prediction behavior across both splits.

In Figure 5, the loss curves show the convergence behavior of the model across training and testing sets employing MSE, RMSE, MAE, and MAPE metrics. All metrics indicate a sharp reduction during the initial epochs, accompanied by a constant plateau, demonstrating effective learning and rapid convergence. The close arrangement among training and testing curves suggests minimum overfitting and better generalization performance. Generally, the results confirm the constancy and robustness of the DRL-ISEVEM technique through epochs.

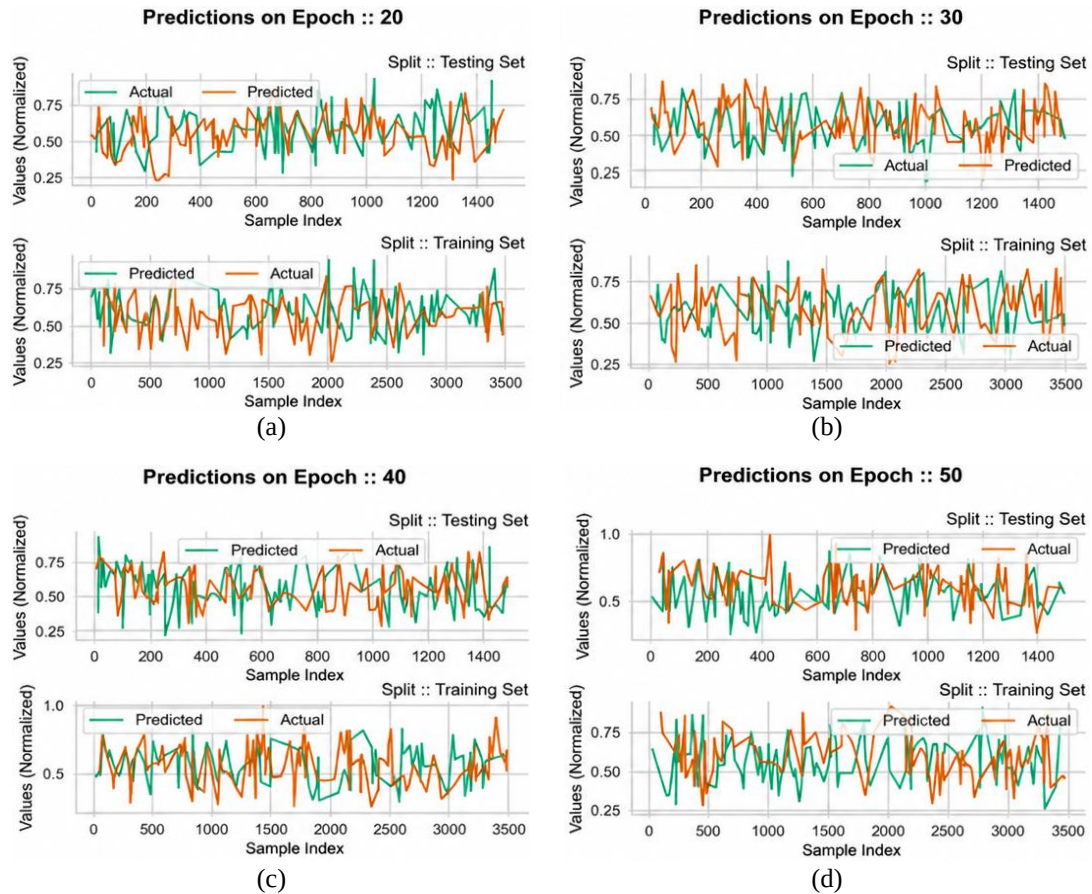


Figure 4. Actual and predicted normalized EV energy consumption at successive training stages: (a) epoch 20, (b) epoch 30, (c) epoch 40, and (d) epoch 50

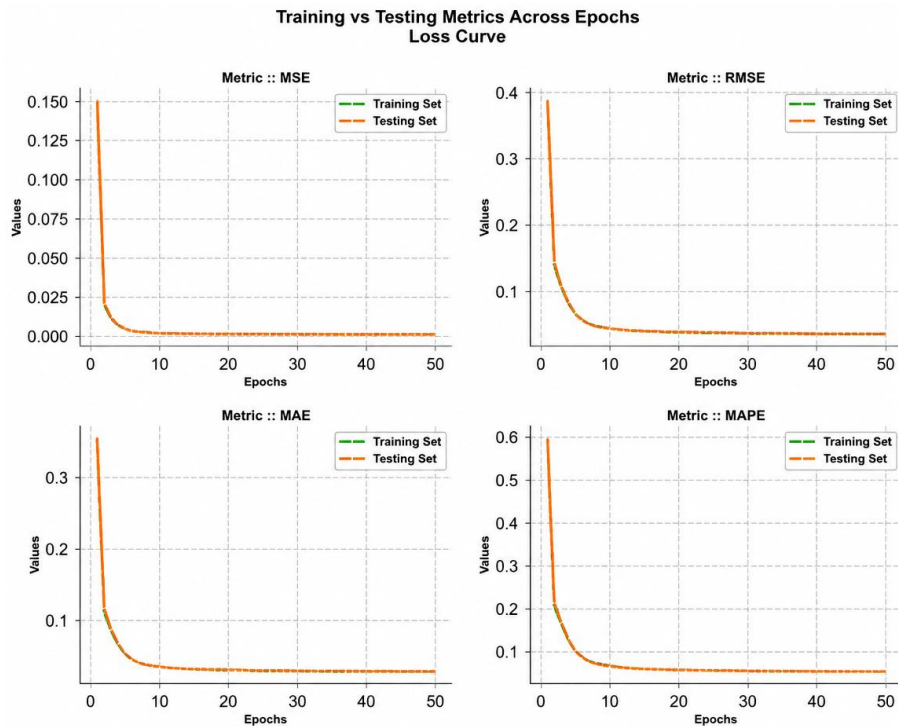


Figure 5. Loss curve of DRL-ISEVEM approach

In Table 4, an extensive comparison outcome of the DRL-ISEVEM model is noticeably proved [21]–[25]. These experimental outcomes specify that the SVR system has revealed ineffective performance. Furthermore, the extreme gradient boosting (XGB), multilayer perceptron (MLP), and gated recurrent unit (GRU) algorithms have shown somewhat reduced results. Whilst the LSTM, DT, and RF algorithms have displayed marginally closer results. But, the DRL-ISEVEM model surpasses the other techniques with lesser RMSE of 0.0356, MAE of 0.0285, and MAPE of 0.0539.

Table 4. Comparative outcome of DRL-ISEVEM approach with existing methods

Algorithm	RMSE	MAE	MAPE
XGB	0.4373	54.6055	57.0548
RF	0.1181	34.6301	56.7060
MLP	0.2448	51.9831	203.1225
SVR	1.2344	42.4560	318.6580
DT	0.1570	0.1820	0.1710
GRU	0.1910	0.1750	0.1570
LSTM	0.1710	0.1890	0.1960
DRL-ISEVEM	0.0356	0.0285	0.0539

Also, the test results that were kept out were very near to the test results obtained from training, namely 0.000037, 0.000520, 0.000534 and 0.000439 for MSE, RMSE, MAE, and MAPE respectively. The relative RMSE increase of 1.46% suggests that the model maintained its predictive abilities for the unseen samples in the same dataset. This performance is due to three complementary mechanisms. IWOA reduced 2 of the 19 potential variables, which eliminated unnecessary variation prior to learning; dilated residual convolutions were used to effectively capture both long and short ranges; M-TCN was configured with three layers, 62 filters, a kernel size of 4 and a dilation rate of 5; and a dropout of 0.1 was used. However, this superiority should be viewed in the context of a common split/preprocessing pipeline, target scale and tuning budget. The baseline table has therefore been reviewed to ensure that all the methods share the same test target and metric definitions that have been normalised. More statistical significance and external generalization needs to be established. Table 4 provides all assessment measures that are computed using normalized data so that inter-comparison of baseline models and the proposed DRL-ISEVEM method can be held consistently. Thus, the DRL-ISEVEM technique can be effectively used to improve EV resource management and enhance sustainability in transportation systems.

There are three key reasons why DRA-ISEVEM performs better than the other models. First, the IWOA-based attribute selection makes the model more efficient in learning as redundancy is eliminated. Second, the M-TCN structure is efficient in recording time-dependence in the EV energy consumption patterns. Lastly, the method of optimizing hyperparameters using DBO enhances the convergence of the model and eliminates overfitting. All these lead to the enhanced accuracy of the prediction that is experienced in the experimental results. The experimental evidence confirms that the combination of metaheuristic optimization and deep temporal learning outperform the deep temporal learning in performance when it comes to making predictions. The IWOA method of FS saves time and storage by eliminating redundancy in the data set so that the model can concentrate on the most applicable variables influencing energy consumption. The M-tcn model also accounts complex of time relationships in the driving of behavior and environmental conditions whereas the DBO maximizes the model parameters to maximize convergence stability.

5. CONCLUSION

In this paper, a sequential model of IWOA-M-TCN-DBO for prediction of normalized energy consumption of EVs in smart grid has been developed. It achieved MSE, RMSE, MAE, and MAPE of 0.001308, 0.036168, 0.029003, and 0.05438, respectively on the held-out test set, where test RMSE was 1.46% higher than the training RMSE, suggesting a small within-dataset generalization gap. The framework can split the input selection from the temporal modelling and hyperparameter tuning to deliver prediction information for charging coordination, load planning and demand-response decisions. The evaluation employed a single public EV dataset and normalised targets, however, it did not evaluate multi-regional data, live PV generation, distribution network constraints and end-to-end real time scheduling. There is also an added computational cost for the two stages of the metaheuristics, which limits the use of the system for practical purposes depending on the frequency of retraining and hardware available. Based on this evidence, the present contribution is in favor of an energy-forecasting contribution and not grid-control performance. Future work will include reporting denormalized kWh errors and runtime costs, as well as conducting ablation and statistical testing,

validation of the model with measured multi-site PV–EV–grid data and integration of the forecasts with constrained charging and demand-response controllers.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization

M : **M**ethodology

So : **S**oftware

Va : **V**alidation

Fo : **F**ormal analysis

I : **I**nterpretation

R : **R**esources

D : **D**ata Curation

O : **O**riginal Draft

E : **E**diting

Vi : **V**isualization

Su : **S**upervision

P : **P**roject administration

Fu : **F**unding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data supporting the findings of this study are available from the corresponding author, [JS] upon reasonable request.

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