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Industrial Cyber Blockchain Physical System for Microgrid in Data Based Predictive Analysis for Automatic Control Analysis

Chairil Faif Pasani[1*] and Euis Eti Rohaeti[2]

[1]Program of Mathematics Education, Faculty of Teacher Training and Education, Universitas Lambung Mangkurat Indonesia

[2]Program of Mathematics Education, Faculty of Education, Institut Keguruan Dan Ilmu Pendidikan Siliwangi Indonesia

[1]chfaifpasani@ulm.ac.id, [2]rohaeti_ikip@yahoo.com

https://orcid.org/0000-0001-7846-3302, https://orcid.org/0000-0002-0670-2594

Corresponding Author: Chairil Faif Pasani

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Abstract

As an efficient distributed renewable energy utilization model, a microgrid is predictable to realize the higher incorporation of the industrial cyber-physical system (CPS) that has gained significant interest in the academia and industry fields. Electric grid is now facing exceptional variations in generation and load as rising number of distributed energy resources (DERs), typically interfaced via power electronics converter, have been positioned, which possess multifaceted technical problems. In the context of electric grid, Blockchain (BC) was primarily developed for peer-to-peer energy trading through cryptocurrency. This paper presents a deep learning based predictive model for automated control analysis (DLBPM-ACS) in BC assisted industrial CPS environment. The presented DLBPM-ACS technique aims to forecast the short-term energy requirement for reducing the delivery cost of electrical energy for consumers. In addition, the presented DLBPM-ACS technique employs BC for effective energy utilization monitoring and trading control. Moreover, the presented DLBPM-ACS technique employs deep belief network (DBN) model for energy prediction process. Furthermore, the artificial ecosystem optimizer (AEO) algorithm is applied for optimal tuning of the hyperparameters related to the DBN approach. A wide range of simulations was conducted and the outcomes demonstrate the better outcomes of the DLBPM-ACS technique.

Keywords: Industrial CPS, Microgrids, Blockchain, Deep belief network, Prediction models

1. Introduction

Smart manufacturing addresses a high-level sort of manufacturing system in which the trade and examination of information continuously, through each type of the item lifecycles (counting the shop floor, store network, and venture) supports the development of the general proficiency, efficiency, and throughput of manufacturing processes through informed decision-production [1]. A CPPS is the intuitive and responsive foundation of a computerized manufacturing climate since it combines genuine world, unique CPS with cyber system through a correspondence calculation control circle, subsequently guaranteeing constant obtaining, trade, interaction, and input of information for effective and informed decision-production [2]. As opposed to the regular automation pyramid that happens in traditional manufacturing (progressive system of sensor-programmable rationale regulator procedure control-enhancement venture direction), CPS delivers more decentralized qualities that empower a huge number of instruments or machines on the shop floor to consistently convey and collaborate and with human administrators, fundamentally helped by the IIoT and information driven methods [3]. Figure. 1 depicts the overview of CPS.

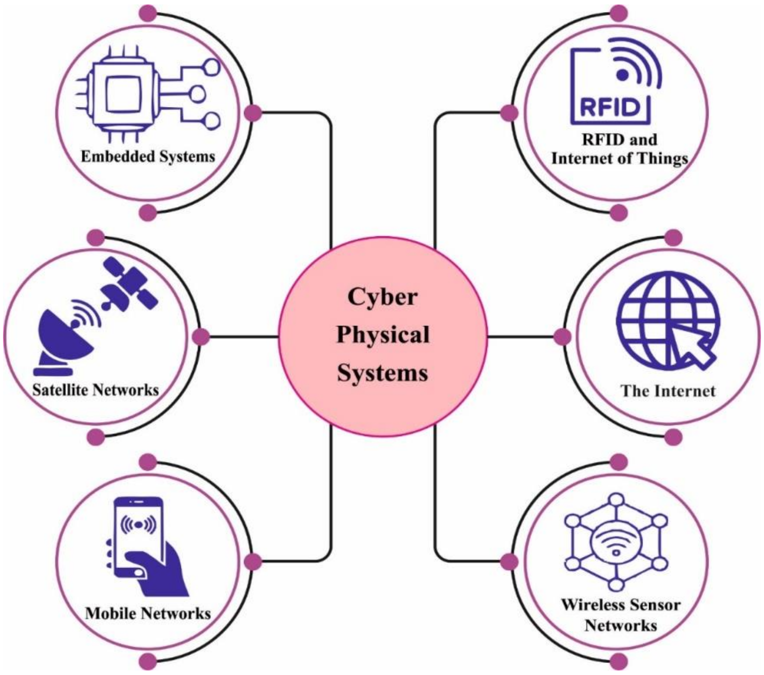

Figure 1. Overview of CPS

The CPS includes different information assortment and detecting gadgets that collaborate with the cyber system. The CPS information got from these gadgets, which investigations the information, performs calculations, and creates an impelling sign that is conveyed to the CPS over correspondence organizations [4]. These CPS should be appropriately coordinated to guarantee secure, protected, dependable, and persistent assistance accessibility. Hence, the correspondence networks are the foundation of the CPS and are additionally alluded to as cyber networks. CPS's potential applications spread over different areas, going from agribusiness to businesses, from diversion to basic data sharing, from fundamentally developed frameworks to assistive living, and a lot more [5]. Observation, independent vehicles, mechanized insulin conveyance siphons in medical care, home automation, brilliant lattice, and so on, are crucial applications in the CPS worldview. The CPS advances in a few spaces have been seriously investigated previously. The CPS advances in agribusiness the board, natural observing, modern automation, brilliant transportation, flight, strategic administration, smart network, telemedicine, medical care, and so on are very much investigated by specialists from the scholarly world and ventures [6]. The smart lattice is one such CPS, which is quickly advancing because of its unavoidable heterogeneous applications.

Customarily brought together fossil fuel-based energy systems have been confronting a few significant difficulties like significant distance transmission, fossil fuel by-products, climate contamination, and energy emergency. To construct a reasonable society by tending to these difficulties, use of sustainable power from different sources as well as working on the effectiveness of energy use are the two critical possible arrangements [7]. Lately, the smart framework idea which includes correspondence innovation, interconnected power systems, high level control innovation, and shrewd metering has been applied to work on the usage of environmentally friendly power sources and ease the energy emergency in some way or another. The idea of smart matrix has been presented as another vision of traditional power lattice which offers two-way energy and data trade to sort out an effective approach to conveying, making due, and coordinating green and sustainable power innovations [8].

Tragically, the brilliant framework makes it hard to upgrade the admittance to distributed and versatile energy resources at an enormous scope as well as assurance energy privacy and incorporate dissimilar means to deal with further develop the energy effectiveness and dependability. Nonetheless, the decentralized shrewd lattice system with an enormous number of parts and complex associations may likewise be a security, protection, and trust bad dream which requires new and imaginative innovations to address [9]. Then again, as an arising and promising innovation, Blockchain (BC) offers new chances to make decentralized systems. This BC innovation is decentralized, i.e., to oversee BC, no focal believed authority is expected; all things considered, different substances in the organization can do among themselves to make, keep up with, and store a chain of blocks. Each element can check that the chain request and information have not been altered. This decentralized system makes any system repetitive and versatile to system disappointment and cyber-chases down and addresses many issues of unified system. Albeit the BC is at first presented and populated as advanced monetary standards, due to having its fantastic properties, it is drawing in huge consideration in numerous other non-financial applications [10]. Simultaneously, past advanced monetary forms, BC is additionally advancing the acknowledgment of secure, privacy preserving, and confided in smart lattice improvements toward decentralization.

This paper presents a deep learning based predictive model for automated control analysis (DLBPM-ACS) in BC assisted industrial CPS environment. The presented DLBPM-ACS technique aims to forecast the short-term energy requirement for reducing the delivery cost of electrical energy for consumers. In addition, the presented DLBPM-ACS technique employs BC for effective energy utilization monitoring and trading control. Moreover, the presented DLBPM-ACS technique employs deep belief network (DBN) approach for energy prediction process. Furthermore, the artificial ecosystem optimizer (AEO) algorithm is applied for optimal tuning of the hyperparameters related to the DBN technique. A wide range of simulations was carried out and the results demonstrate the better outcomes of the DLBPM-ACS technique.

2. Related Works

Kaur et al. [11] developed a novel variational autoencoder (VAE) based reduction dimension method for SG information to allow renewable energy generation predicting with better accuracy. The projected technique incorporates Bi-LSTM- DNN with variational inference, for generating an encoded demonstration of the higher dimension time sequence energy dataset. Further, the encoder dataset is exploited as lower dimension demonstration of the innovative information for energy forecasting applications that results in decreased computation cost and more precise prediction outcomes. Tariq et al. [12] presented a graphics-processing-unit-enabled adaptive robust state estimator. It encompasses nonlinear extended Kalman filter, DL algorithm, and LSTM, and is named LSTMKF. By using the SD IoT, it offers an online parametric state estimation.

The authors in [13] technologically advanced a Multi-directional LSTM (MLSTM) to forecast the steadiness of the smart grid networks. The outcomes attained are assessed against other widespread DL methodologies namely traditional LSTM, RNN, and Gated Recurrent Units (GRU). Jain et al. [14] present a new ML-based multi model predictive technique called intelligent energy CPS (iECPS) for smarter energy theft verification and detection. Moreover, the scheme has strength because verification from the user is taken into account as concluding validation for deciding further course of action. Furthermore, to effectively prevent and detect FDI attacks during data transmission from meters or sub-meters for the smart grids, de-watermarking and watermarking systems are developed.

Jain et al. [15] introduced a Fuzzy Logic-based Energy Management and TFP (FLEM-TFP) for CPS in ITS. The presented technique includes TFP and energy management. Also, an adaptive neuro-fuzzy inference system (ANFIS) method is exploited for computing the engine torque needed according to different outcomes. In [16], the NN is employed for estimating the state–action in the DQN and storing the specific state–action value rather than saving each state–action value.

3. The Proposed Model

This paper has developed a new DLBPM-ACS model in BC assisted industrial CPS environment. The presented DLBPM-ACS technique aims to forecast the short-term energy requirement for reducing the delivery cost of electrical energy for consumers. In addition, the presented DLBPM-ACS technique employs BC for effective energy utilization monitoring and trading control.

During the computation process, the dataset comprises several features and consists of dissimilar arithmetical values that rises the complications. Consequently, a normalization method is utilized to regularize data D^{hd} within [0,1] and to minimize the arithmetical complication. Different approaches are exploited for data normalization. In this work, the popular min-max normalization technique is utilized [17]. This technique plots a mathematical value, DV, of original data D^{hd} into DV_{norm} within th [0,1] as follows:

$$DV_{norm} = \frac{D^{hd} - DV_{\min}}{DV_{\max} - DV_{\min}} \times [new\_ \max - new\_ \min] + new\_ min \tag{1}$$

Now, DV_{norm}, D^{hd}, $DV_{\min}$, and DV_{max} indicates the regularized dataset, the original dataset, the minimal dataset, and the maximal dataset, correspondingly, whereas $new\_ \max$ and $new\_ \min$ shows the range of the transformed data values. Then, $new\_ \max = 1$ and $new\_ \min = 0$ is used.

3.1. DBN Based Prediction Model

At this stage, the presented DLBPM-ACS technique employs the DBN model for energy prediction process. DBN technique could generate the perfect model with highest throughput and efficacy [18]. In the present study, DBN is employed for modelling the new eye detection according to the EEG signal. DBN is a robust DL technique according to integration of RBM. Generative Stochastic NN (GSNN) is exploited for RBM so that there exists a connection for all the hidden layers (h) to the visible one (v) associated with the following RBM. Moreover, the RBM highest layer input is achieved from the RBM lowest layer output. Gibbs sampling is implemented due to the deficiency connections in the similar layers amongst nodes and units. Furthermore, there exists a deep architecture in DBN that generates a considerable method with RBM multilayers. For boosting the DBN model, the 1st and 2nd hidden states of the two R and Q hidden connections are taken into consideration. The feature selection and extraction from the input dataset are the benefits of applying DBN in the following:

$$P(v,h) = \frac{1}{z} \exp\left(-h^T W v - b^T h - c^T v\right), \tag{2}$$

In Eq. (2), the hidden units and binary visible are determined by v and h, correspondingly, and the balanced weights among them denote W, respective bias is considered as c and b variables, and lastly normalized constant is z and it is given in the following:

$$E(v,h) = h^T W v + b^T h + c^T v. \tag{3}$$

The logistic sigmoid function is described by the activator for j^{th} binary hidden units and are given below:

$$P(h_j = 1) = sigm\left(b_j + \sum_i v_i W_{ij}\right). \tag{4}$$

Log -probability gradient based on the visible unit is calculated through opposing convergence afterward k iterations to search the appropriate W parameter as follows:

$$\frac{\partial log P(v)}{\partial W_{ij}} \approx < v_i h_j > 0 - < v_i h_j > k. \tag{5}$$

In Eq. (5), afterward, m iteration based on the opposing divergence, $<.>m$ is taken into account as mean. Fig. 2 illustrates the infrastructure of DBN technique.

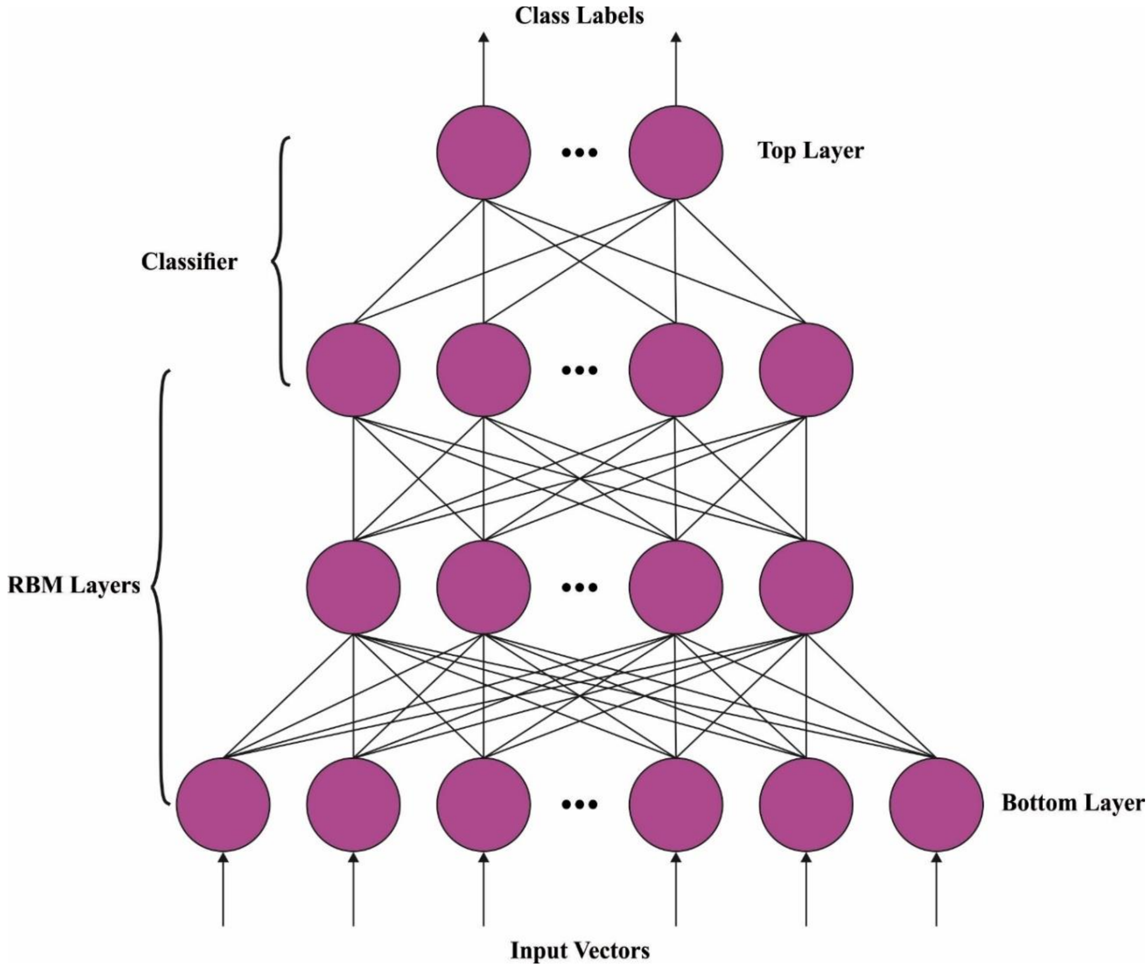

Figure 2. Framework of DBN

3.2. AEO Based Hyperparameter Tuning

Furthermore, the AEO algorithm is applied for optimal tuning of the hyperparameters related to the DBN model. AEO was approved and proposed as a stronger metacentric approach [19]. As per the energy flow of the ecosystem, AEO has been introduced. The elementary rules of the AEO depend on ecosystem operative of consumers, producers, and decomposers in the population. The better solution is defined by specifying the maximum energy level and it is mathematically expressed as follows:
I. initialize random population and it is accomplished by the following equation:

$$x_{i=1:n} = rand_n * (U_b - L_b) + L_b, \quad (6)$$

In Eq. (6), L_b and U_b indicates upper and lower bounds. n represents the population size.
I. Calculate the objective function according to the random population by defining the best population respective to the better values of the objective function.

$$F_{obj} = fit\ (x_i) \quad (7)$$

II. Defining the individual producer that is the first one x_1:

$$x_1(t+1) = (1-a) * x_n(t) + a * x_{rand}(t), \quad (8)$$

In Eq. (8), $a = (1 - t/T) * r_1$ and $x_{rand} = r * (ub - lb) + lb$. Furthermore, T symbolizes the overall number of iterations. r_l and r symbolize random numbers ranging from zero to one. Furthermore, x_{rand} represents an individual location. a signifies the straight weight coefficient. Lastly, x_n symbolizes a better individual solution.

I. Afterward upgrading the producer, updating the consumer population must be carried out. A random value r was generated within zero and one to guarantee the exploration in the search space.
When $r < 1/3$, upgrade the consumer to herbivore mode:

$$x_i(t+1) = x_i(t) + C^*(x_i(t) - x_1(t)), i \in [2, \dots n], \tag{9}$$

When $1/3 \leq r \leq 2/3$, upgrade the consumer to omnivore mode:

$$x_i(t+1) = x_i(t) + C * (x_i(t) - x_1(t)), j = \ randi([2i - 1])\ , i \in [3, n], \tag{10}$$

When $r > 2/3$, upgrade the consumer to carnivore mode:

$$x_i(t+1) = x_i(t) + C^*(r_{2^*}(x_i(t) - x_1(t)) + (1 - r_2)^* \\ (x_i(t) - x_j(t))), i \in [3, \dots, n], \tag{11}$$

Now, C indicates the consumption factor according to Levi's flight function. C is arithmetically modelled in the following:

$$C = \frac{1}{2} * \frac{v_1}{v_2}, \tag{12}$$

In Eq. (12), $v_1 \sim N(O, 1)$, $v_2 \sim N(0,1)$ and $N(O, 1)$ indicate a normal distribution function.
I. Evaluating the value of objective function considered updating the better individual solution respective to the best value of the objective function.

$$F_{obj} = fit(x_i). \tag{13}$$

II. Update the decomposer location as follows:

$$x_i(t+1) = x_n(t) + D^*\big(e^* x_n(t) - h^* x_i(t)\big) i = 1, \dots, n, \tag{14}$$

In Eq. (14), $D = 3 * u, u \sim N(O, 1)$ represents the decomposition factor. $e = r_3 * randi([1\ 2]) - 1$ and $h = 2 * r_3 - 1$ weight coefficients

I. Calculate the fitness of individual and update the better solution found so far X_{best}.

Algorithm 1: Pseudocode of AEO
Arbitrarily initialize variables in ecosystem X_i (solutions) and calculate the fitness t_i , and X_{best},= an optimal solution initiated so far. While the ending criteria are not met do For individual X_1, upgrade the solution. For individual $X_i (i = 2, \dots, n)$, If $rand < \ 1/3$, upgrade the solution, Else If $\frac{1}{3} \leq rand \leq \ 2/3$, upgrade the solution Else upgrade the solution, End If. End If. Calculate the fitness of individual. Upgrade the optimum solution X_{best}. · Upgrade the place of individual. Compute the fitness of individual. Upgrade an optimal solution X_{best}, End While. Return $Xbest$.

4. Results Analysis

The performance validation of the DLBPM-ACS system under distinct aspects is given in this section. Table 1 offers a comparative MSE study of the DLBPM-ACS method with recent techniques. Fig. 3 indicates the MSE examination of the DLBPM-ACS approach with existing algorithms on training data. The figure implied that the MLP and ANN models have reported poor outcomes with maximum MSE of 3.310 and 3.120 respectively. Eventually, the NBC model gained moderately reduced MSE of 2.850. Following by, the GB and LDA models have shown reasonable MSE of 1.310 and 1.000 respectively. But the DLBPM-ACS model has showcased minimal MSE of 0.910.

Table 1. MSE analysis of DLBPM-ACS approach with recent algorithms

	Mean Squared Error		
Methods	**Training Data**	**Testing Data**	**Validation Data**
DLBPM-ACS	0.910	0.930	0.900
MLP	3.310	0.380	2.190
GB Algorithm	1.310	3.390	0.300
LDA Model	1.000	3.900	0.740
NBC Algorithm	2.850	2.950	2.480
ANN Model	3.120	2.360	1.200

Figure. 4 specifies the MSE inspection of the DLBPM-ACS with existing approaches to testing data. The figure implied that the MLP and ANN models have described poor results with maximum MSE of 0.380 and 2.360 correspondingly. Eventually, the NBC model has shown moderately reduced MSE of 2.950. Then, the GB and LDA models have gained reasonable MSE of 3.390 and 3.900 correspondingly. But the DLBPM-ACS method has demonstrated minimal MSE of 0.930.

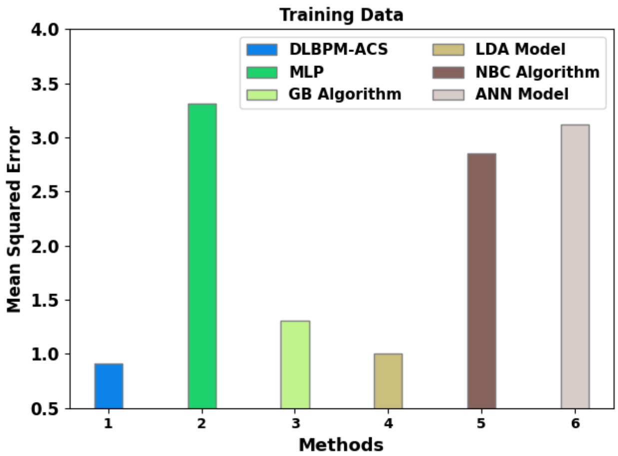

Figure 3. MSE analysis of DLBPM-ACS approach under training data

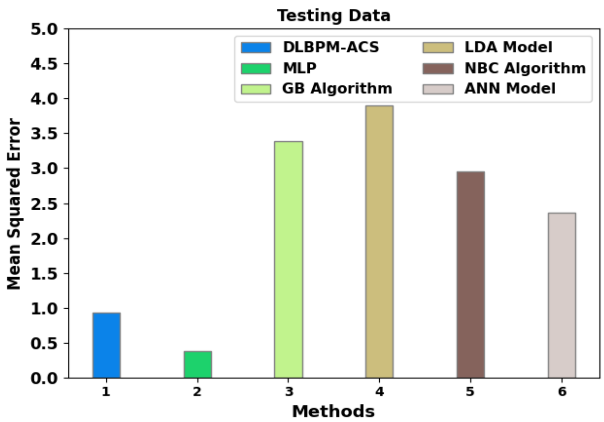

Figure 4. MSE analysis of DLBPM-ACS approach under testing data

Figure. 5 illustrates the MSE inspection of the DLBPM-ACS methodology with existing models on validation data. The figure implied that the MLP and ANN approaches have reported poor outcomes with maximum MSE of 2.190 and 1.200 correspondingly. Finally, the NBC model has shown moderately reduced MSE of 2.850. Then, the GB and LDA techniques have gained reasonable MSE of 0.300 and 0.740. But the DLBPM-ACS model has showcased minimal MSE of 0.900.

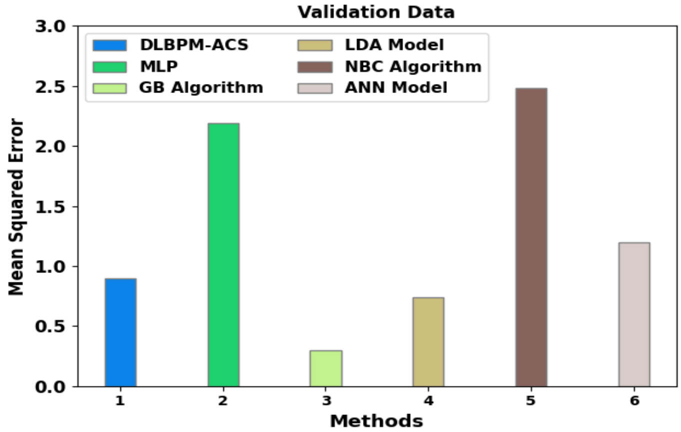

Figure 5. MSE analysis of DLBPM-ACS approach under validation data

Table 2 offers a comparative RMSE examination of the DLBPM-ACS model with other models. The obtained values inferred that the DLBPM-ACS model has reached least values of RMSE. For instance, on training data, the DLBPM-ACS model has attained lower RMSE of 0.954 whereas the MLP, GB, LDA, NBC, and ANN models have achieved increased RMSE of 1.819, 1.145, 1, 1.688, and 1.766. At the same time, on testing data, the DLBPM-ACS model has accomplished lesser RMSE of 0.964 while the MLP, GB, LDA, NBC, and ANN models have attained improved RMSE of 0.616, 1.841, 1.975, 1.718, and 1.536.

Table 2 RMSE analysis of DLBPM-ACS approach with recent algorithms

	Root Mean Square Error		
Methods	**Training Data**	**Testing Data**	**Validation Data**
DLBPM-ACS	0.954	0.964	0.949
MLP	1.819	0.616	1.480
GB Algorithm	1.145	1.841	0.548
LDA Model	1.000	1.975	0.860
NBC Algorithm	1.688	1.718	1.575
ANN Model	1.766	1.536	1.095

Table 3 offers a comparative MAPE inspection of the DLBPM-ACS model with other models. The acquired values inferred that the DLBPM-ACS model has attained lower values of MAPE. For example, on training data, the DLBPM-ACS model has achieved least MAPE of 9.587 whereas the MLP, GB, LDA, NBC, and ANN models have reached improved MAPE of 34.561, 13.831, 10.870, 28.521, and 31.211. Simultaneously, on testing data, the DLBPM-ACS model has achieved lesser MAPE of 9.192 while the MLP, GB, LDA, NBC, and ANN models have attained improved MAPE of 4.359, 34.291, 39.704, 30.837, and 24.954.

Table 3 MAPE analysis of DLBPM-ACS approach with recent algorithms

	Mean Absolute Percentage Error		
Methods	**Training Data**	**Testing Data**	**Validation Data**
DLBPM-ACS	9.587	9.192	9.184
MLP	34.561	4.359	22.339
GB Algorithm	13.831	34.291	2.978

LDA Model	10.870	39.704	7.802
NBC Algorithm	28.521	30.837	24.995
ANN Model	31.211	24.954	12.452

5. Conclusion

This paper has developed a new DLBPM-ACS model in BC assisted industrial CPS environment. The presented DLBPM-ACS technique aims to forecast the short-term energy requirement for reducing the delivery cost of electrical energy for consumers. In addition, the presented DLBPM-ACS technique employs BC for effective energy utilization monitoring and trading control. Moreover, the presented DLBPM-ACS technique employs the DBN model for energy prediction process. Furthermore, the AEO algorithm is applied for optimal tuning of the hyperparameters related to the DBN model. A wide range of simulations was conducted and the results demonstrate the better outcomes of the DLBPM-ACS technique.

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Authors' contributions
All authors contributed toward data analysis, drafting, and revising the paper and agreed to be responsible for all the aspects of this work.
Declaration of Conflicts of Interests
Authors declare that they have no conflict of interest.

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