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Research Article

Homogenized Point Mutual Information and Deep Quantum Reinforced Wind Power Prediction

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Accurate wind power prediction is very predominant for genuine and effective power systems with high wind power perception. Wind power prediction, as well as wind power generation resources, receives the electrical energy by converting wind into rotational energy of the blades and converting rotational energy into electrical energy by the generator. Wind energy increases with the cube of wind speed. There are numerous common and deep learning methods that have evolved to attain wind power prediction. Deep learning-based methods are referred to as straightforward, and robust, and have been utilized in the recent few years for wind power prediction with a certain level of success. However, due to the lack of an appropriate feature selection process and to minimize the effect of losses used for wind power prediction, a large amount of computation is necessitated when processing multi-input wind power data, therefore causing a negative influence on scalability and hence affecting wind power prediction time. To address these issues, in this work, a method called, Homogenized Point Mutual Information and Deep Quantum Reinforced (HPMI-QDR) wind power prediction are proposed. The HPMI-DQR method is split into two sections. In the first section, informative and relevant features required for robust wind power prediction using input wind turbine data are designed using Homogenized Point Mutual (HPM) Feature Selection model. With the relevant features selected, in the second section, the actual wind power prediction is made using the Deep Quantum Reinforced Learning model. To validate the proposed method, Wind Turbine SCADA Dataset is used for constructing and testing. Simulation of proposed method attains enhancement within wind power prediction accuracy as 13%, minimal wind power prediction time as 25%, as well as better wind energy generation as 20% and true positive rate as 25%, compared using conventional techniques. Moreover, a substantial improvement was also found in wind power prediction time with minimum error.

1. Introduction

With the certainty that the conventional fossil fuels are exhausting in an unalterable inclination, an excessive portion of renewable energy incorporation will be one of the essential features of the subsequent power system. Amidst all the complicated renewable energies, wind energy has fascinated noteworthy observations owing to the profuse and the cleanness. Wind energy is one of the strategies used to mitigate greenhouse gasses from human activities in the atmosphere. Wind energy capacity installed at the end of 2016 in Brazil was approximately 11 GW, with an estimate for 2020 will have around 18 GW of installed wind energy capacity, which will contribute to the country's energy security. EEMD-CSO-LSTMEFG was developed by [1] to predict the wind power as well as enhance prediction performance. Here, an improved long short-term memory network-enhanced forget-gate network (LSTMEFG) model, whose suitable metrics were optimized utilizing the Cuckoo Search Optimization algorithm (CSO), was utilized in forecasting the subseries data via Ensemble Empirical Mode Decomposition (EEMD).

With this, the forecasting accuracy was improved substantially. Despite improvement found in accuracy due to the optimization function being applied for wind power forecasting, however, with EEMD for forecasting subseries data, the time consumed in predicting was not focused. To address this issue, the Homogenized Point Mutual (HPM) Feature Selection model is used before the learning process and only with the informative and relevant feature obtained formed as input to the deep learning processing, therefore contributing to wind power prediction time. However, this scope of deep learning is a field of computer science to focuses on developing the performance of wind power prediction.

Wind power plays a significant part in secure transformation and power management. Hybrid scheme to short-term wind power forecasting including VMD, *K*-means clustering, as well as Long Short Term Memory (LSTM) was implemented by [2]. The Designed method of VMD-K means-LSTM split the raw wind power series within various layers involving distinct frequencies via VMD. Moreover, substantial improvement was found in terms of precision and reliability, prediction error was not focused on.

Second, *K*-means was utilized for breaking the data into an ensemble of features with homogeneous fluctuant levels of each layer, and finally, LSTM was applied for encapsulating the unsteady features of each component. With this, the forecasting reliability and precision were found to be improved. To address this issue, a Deep Quantum Reinforced Wind Power Prediction model is designed that, with the aid of quantum function, reduces the prediction error considerably.

In recent years the probable consequences of global warming across the planet have been analyzed by numerous researchers, motivating the utilization of renewable energy resources, to name a few being wind energy. Wind energy is considered to be one of the techniques utilized to reduce the greenhouse gasses from human activities in the atmosphere. For the victorious incorporation of wind energy into the power grid, precise predictions are required. Therefore, the tedium of information about the wind in a given location is paramount for the estimation of the wind power project.

Good method on Holt-Winters, Artificial Neural Networks, as well as Time-series model was presented in [3] for efficiently predicting wind speed to wind power generation. The hybrid methodology was utilized to measure the best fit for predicting wind speed. However, with involvement of high level dimensional patterns, a precise prediction method is essential. To overcome these problems, integration of the decision tree as well as support vector regression was achieved in [4] for reducing the runtime. Heterogeneous ensemble prediction was improved with high-dimensional patterns. However, prediction error was not reduced. Wind power prediction methods with deep learning were investigated in [5] for efficient technique of high-dimensional feature extraction as well as deep neural network. Moreover, deep neural network was not minimized to choose unrelated information to predict improved accuracy.

In recent few years, tangible and aggressive evolutions of the nation-wise wind markets have appeared. With the enormous fluctuation of weather conditions, measuring wind energy is still considered to be a major issue. The foremost objective in [6] was to design a multi-linear model estimating the correlation between daily sub-data (DSD) with the evaluated minimum and maximum power generation values and also taking into consideration the total power generation generated daily based on hourly main data (MWD) was designed. This accurate and reliable prediction was ensured. It is considered a laborious and time-consuming process to acquire accurate wind speed forecasting (WSF) owing to the sporadic and dynamic wind energy character.

In [7], a multi period-ahead WSF model based on variance, Stacked Denoising Auto Encoder (SDAE), and ensemble learning was proposed to although accuracy was improved. However, error involved was not focused. To address this issue, Artificial Neural Network was developed in [8] to produce acceptable predictions with minimum error. The related environmental and climatic conditions were introduced for discovering the wind power possible in the area. However, feature selection was not determined. Yet another method concentrating on prediction error using Adaptive Transfer Learning in Deep Neural Networks (ATL-DNN) was proposed in [9]. For straightforward and effortless power generation from the turbine, exact prediction of wind power is essential, nevertheless, owing to the oscillating wind behavior and unpredictability in the geographical characteristics and climatic conditions, precise wind power prediction is a critical task. Wind power was improved to predict the enhanced accuracy.

Deep Belief Network-based Meta-Regression Technique (DBN-MRT) was proposed in [10] for considering the error aspect with considerable extent. However, proposed technique was failed to reducing the time desirable for wind dataset. An extensive review of the recent forecasting methods together with their performance measure to address certain issues related to forecasting was investigated in [11]. However, most of the users are long run focused on forecasts of the generation of electricity rather than wind. Despite the generation of power depending on several factors apart from wind circumstances, the magnitude aspect is a pertinent yardstick to measure the influence of wind variability on production.

In [12], a mechanism for the generation to magnitude aspect for an extent of turbine classes was proposed. At present, a simulation method based on a single value is the favored selection for forecasting numerical wind speed. However, due to inevitable unpredictability it remains laborious in meeting the genuine requirements of both wind farms and grid systems. A method based on ensemble simulations of weather research and forecasting was constructed in [13] that utilized a Markov stochastic process, and an ordered weighted average strategy that integrated gray relationships with an evolutionary algorithm for dynamically forecasting numerical wind speed. However, the accuracy was not enough by using ensemble method.

A double prediction system using a non-linear and multi-objective evolutionary algorithm focusing on the accuracy of point prediction was proposed in [14]. A back propagation neural network was introduced to increase prediction accuracy. An interval prediction method was utilized to build dissimilar intervals based on the diverse data features through fuzzy clustering. But, designed method was failed to use a large dataset. The topic of forecasting short-term wind speed and wind power by integrating artificial neural networks (ANNs) and optimization techniques on wind speed and wind power data was designed in [15]. With this, the wind power forecasting accuracy was said to be improved in a significant manner. However, the wind power prediction time was improved. A comparative analysis of deep learning methods for predicting wind power was investigated in [16]. Response surface methodology (RSM) and artificial neural network (ANN) were discussed for accurate wind power prediction. However, the artificial neural network using prediction accuracy was improved.

Yet another method to enhance the accuracy rate using an adaptive neuro-fuzzy inference system based on the error factor for four different locations was analyzed in [17]. But, designed method was provided for better reliability and computational capability. A case study was tested with three training algorithms for predicting future wind power and was elaborated in [8]. However, the convergence factor was not analyzed. In [18], conjugate gradient descent was applied to the ANN model to improve prediction accuracy. Moreover, the wind power prediction was not wrongly identified.

A quantum particle swarm optimization (QPSO) was developed in [19] for handling the economic environmental (EED) issue. But, the accuracy was not improved. To overcome the issue, A hybrid model was introduced in [20] that depended on the quantum-behaved particle swarm optimization. However, the prediction time was not minimized. The deep learning neural network model was introduced in [21] for reducing the computational cost and time. But, designed technique was not selecting suitable features. A new neural-network prediction model named EALSTM-QR was designed in [22] for wind power prediction. However, designed method failed to improve the wind-power prediction accuracy by using novel machine-learning algorithm. Quantum deep reinforcement learning (QDRL) was introduced in [23] to offer dynamic control strategies online for obtaining enhanced control performance. But, the wind power prediction time was higher.

An efficient q-rung orthopedic fuzzy set was introduced in [24] depending on the Full Consistency Method and combined compromised solution method. But, the accuracy was not adequate. A novel hybrid approach combining Interval Rough Numbers (IRNs) into Best-Worst Method (BWM) and Measurement of Alternatives and Ranking according to Compromise Solution (MARCOS) was developed in [25]. The designed approach selects the best offshore wind farm site for precise analysis. Moreover, the time was enhanced. Type-2 neutrosophic number (T2NN) fuzzy-based multi-criteria decision-making (MCDM) model was presented in [26] to offer formulation flexibility and simple computation. But, the computation complexity was not reduced. A new Interval-valued Fuzzy-rough based Delphi Method was developed in [27] for discovering the significance of different criteria. However, the proposed technique failed to explain the site selection issue.

Short-term wind power prediction model (LCWGAN-GP) was discussed in [28] with higher prediction accuracy. But, the true positive rate was not measured. Extreme learning machine (ELM) algorithm was introduced in [29] for enhancing the prediction accuracy. Moreover, the time was not decreased. Two-step process approach was developed in [30] with historical wind speed data. But, the wind energy generation was not considered. Linear-quadratic regulator (LQR) algorithm was introduced in [31] an optimal control approach, which applies a state-space form to optimally design and control the system. But, designed approach was minimized the computational complexity.

A new smart battery design was introduced in [32] for space-resolved temperature matrix sensing. The low-order joint examination was utilized for measuring the heat creation rate, and higher capacity with aid of a thermal model-based approach. But, the accuracy was not enhanced. Knowledge-based, multi-physics-constrained fast charging approach was developed in [33] for lithium-ion batteries (LIB). Deep reinforcement learning was employed for addressing the LIB fast charging issue. However, the computational complexity was not reduced. Smart battery and management scheme was analyzed in [34] for sensor plan and combination. The designed scheme failed to consider the high design integrity as well as space limitation.

In this paper, a novel Homogenized Point Mutual Information and Deep Quantum Reinforced (HPMI-DQR) wind power prediction method is developed. The wind power prediction method is to consider the wind power output as early and as correctly as achievable. Wind power prediction minimizes the financial and technical risk of uncertainty of wind power production for all electricity market participants. To mitigate the impacts of time consumed in wind power prediction, the analysis of homogenization is applied to acquire a computationally efficient, informative and relevant feature selection model. However, Deep Quantum is adopted to perform deep learning to perform actual wind power prediction and eliminate the noise data. Finally, the 10 minutes time interval wind speed series have been employed to evaluate the proposed method. The novelty and contributions of this paper are as follows.

(i) To improve the wind power prediction accuracy with minimum time, the proposed HPMI-DQR method was introduced to utilizes a feature selection and prediction model

(ii) To achieve computational efficiency using homogenization function and low-frequency bias features are eradicated with minimum wind power prediction time by Proposed HPMI-DQR method uses a novel Homogenized Point Mutual (HPM) Feature Selection model.

(iii) To perform a feature selection model using a novel Homogenized Point Mutual (HPM) Feature Selection method. In this model, the innovation of the Point Mutual Information is obtained for selecting the computationally efficient informative and significant features.

(iv) To improve the wind power prediction accuracy by using proposed Deep Quantum Reinforced Wind Power Prediction algorithm is determined for robust wind power prediction.

(v) To find the relationship between State Space and Action Space by mapping which comprises wind power evaluation network and wind power action selection strategy by using novelty of Epsilon Greedy policy. Therefore, wind power prediction accuracy is developed.

(vi) Finally, experiments were conducted to estimate the proposed HPMI-DQR method along with conventional methods based on the different performance metrics. Meanwhile, performance assessment metrics such as wind power prediction time, accuracy, and true positive rate are utilized to explore and measure the execution of the proposed wind power prediction method.

The rest of the paper is organized as follows. In this section, a brief formulation for wind power prediction and works related to this area is reviewed. The analysis of the Homogenized Point Mutual Information and Deep Quantum Reinforced (HPMI-DQR) method is presented in Section 2. Experimental settings for simulation for performing HPMI-DQR method are briefed in Section 3. The numerical results with the aid of a table and graph are shown in Section 4. A conclusion is drawn in Section 5.

2. Methodology

The proposed Homogenized Point Mutual Information and Deep Quantum Reinforced (HPMI-DQR) method applies feature selection and prediction model to improve the wind power prediction accuracy using minimal time. HPMI-DQR method consists of two distinct phases. In the first phase, Homogenized Point Mutual (HPM) Feature Selection is used to select the relevant features. In the second phase, a Deep Quantum Reinforced (HPMI-DQR) method forecasts the final wind power based on the predictions made by the Homogenized Point Mutual (HPM) Feature Selection model. In order to predict robust wind power, Deep Quantum Reinforced Wind Power Prediction algorithm is employed for improving the wind power prediction accuracy.

In the proposed HPMI-DQR method, deep learning is utilized during the training of Homogenized Point Mutual (HPM) Feature Selection and Deep Quantum Reinforced Wind Power Prediction models. The block diagram of the proposed HPMI-DQR method in terms of relevant feature selection and wind power prediction is shown in Figure 1.

As shown in the above Figure 1, the block diagram of the HPMI-DQR method is split into two sections. In the first section, with wind turbine SCADA (Supervisory Control And Data Acquisition) data provided as input, informative and relevant features are selected. Next, with the resultant features selected and provided as input to the deep learning model, robust wind power prediction is made. The wind power prediction is employed for evaluating the expected production of one or more wind turbines and the proposed HPMI-DQR method has two existing methods such as EEMD-CSO-LSTMEFG [1], VMD-K means-LSTM [2], EALSTM-QR [22], and LCWGAN-GP [28] with the dataset of 10 minutes interval gap. From other methods and existing methods, a 10 minutes interval gap is applied. An elaborate description of the proposed HPMI-DQR method is provided in the forthcoming sections.

2.1. Homogenized Point Mutual (HPM) Feature Selection Model. Homogenized Point Mutual (HPM) Feature Selection model forecasts the last wind power based on predictions made by proposed method. The wind power prediction using this novelty of HPM feature selection model. Feature selection technique is developed to choose a compact set of input features for the wind power prediction model. To overcome the nonstationarity of wind power series and improve the prediction accuracy. Proposed HPMI-DQR method used to dataset contains a group of data for 10 minutes intervals from wind turbines, SCADA Systems that is working and generating power in Turkey. The datasets include information about the measurement of power and also the meteorological forecast related to components of wind. Date/time (DT), LV Active Power (LVAP), Wind Speed (WS), Theoretical Power Curve (TPC), and Wind Direction (WD) of wind are included as features. The forecast is released by the Turkey center once every 10 minutes interval gap. To select a more informative and relevant feature set among the five feature sets, Homogenized Point Mutual Information (PMI) is used. Figure 2 shows the block diagram of the Homogenized Point Mutual (HPM) Feature Selection model.

As shown in the above Figure 2, the feature set of average PMI value of possible events between the weather forecast and power are selected (i.e., informative relevant feature set), while the remaining feature sets are discarded. The prevailing weather forecasts are hence dependent on succeeding weather forecasts and power measurements. So, to explore the dependency of power measurement on the previously predicted powers and associated feature set, the average of all possible events along with associated features are provided as input features to the proposed method. Mathematically feature set matrix "$FS(t) = (DT\ , LVAP, WS, TPC, W\ D)$" for wind power forecast is expressed as given below.

$$FS(t) = \begin{bmatrix} DT(t-1) & DT(t-2) & \dots & DT(t-24) \\ LVAP(t-1) & LVAP(t-2) & \dots & LVAP(t-24) \\ WS(t-1) & WS(t-2) & \dots & WS(t-24) \\ TPC(t-1) & TPC(t-1) & \dots & TPC(t-1) \\ W\ D(t-1) & W\ D(t-2) & \dots & W\ D(t-24) \end{bmatrix}. \quad (1)$$

From the above equation (1), "DT" represents the prediction of Date/time (DT), "$LVAP$" indicates the LV Active Power, "WS" denotes the Wind Speed, "TPC" symbolizes the Theoretical Power Curve, and "$W\ D$" signifies the Wind Direction at 10 minutes intervals whereas "$t-1, t-2, \dots, t-24$" refers to the wind prediction forecast at the initial time.

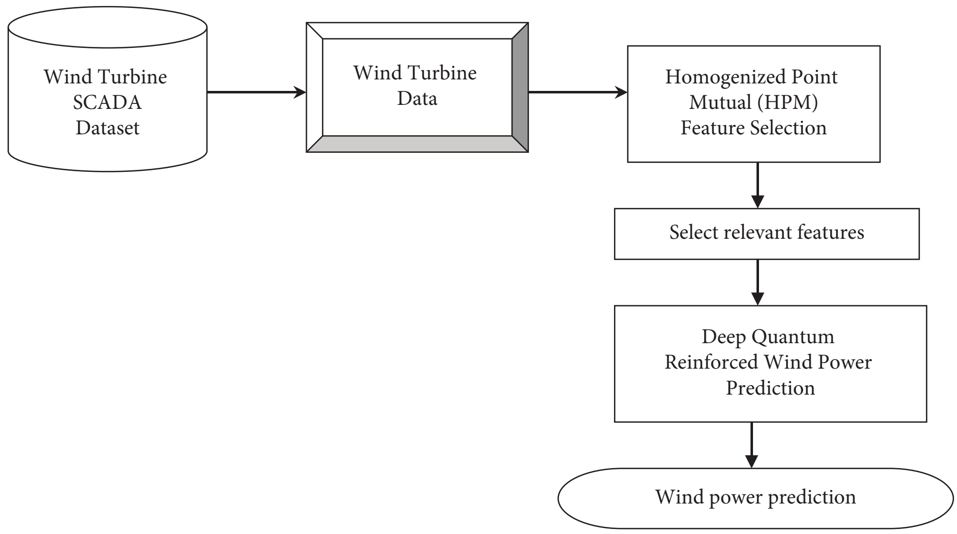

Figure 1: Block diagram of HPMI-DQR method.

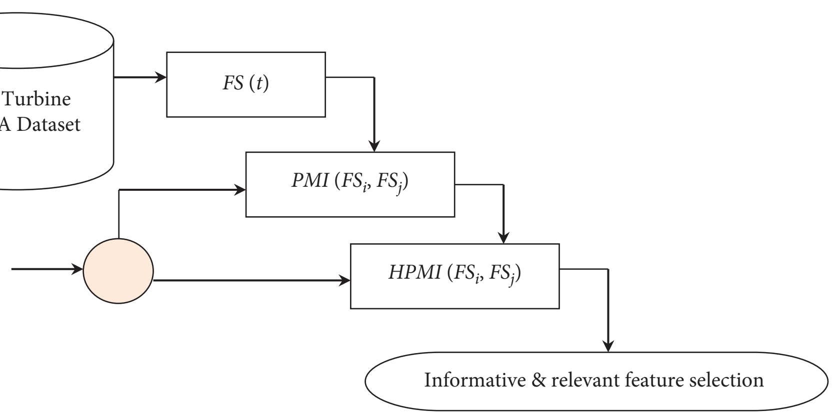

Figure 2: Block diagram of homogenized point mutual (HPM) feature selection.

Next, informative and relevant features are selected using an irrelevancy and redundancy filter that measures the association between the probability of their co-occurrence provided with joint and individual distributions exploiting the concept of Point Mutual Information (PMI). This PMI is mathematically formulated as given below

$$
\begin{aligned}
PMI\left(FS_i, FS_j\right) &= \text{loglog}\frac{\text{Prob}\left(FS_i, FS_j\right)}{\text{Prob}\left(FS_i\right)\text{Prob}\left(FS_j\right)} \\
&= \text{loglog}\frac{Prob\left(FS_i|FS_j\right)}{Prob\left(FS_i\right)} \\
&= \text{loglog}\frac{Prob\left(FS_j|FS_i\right)}{Prob\left(FS_j\right)}.
\end{aligned}
\tag{2}
$$

From the above equations (2), a pair of outcomes "FS_i" and "FS_j" belonging to discrete random variables "$FS_i = DT$" and "$FS_j = LVAP$" quantifies the discrepancy between joint distribution as in (2) individual distribution as in (2). Also to minimize a known sensitivity for low-frequency features homogenized PMI is applied. This low-frequency feature homogenization using HPMI is mathematically expressed as given below.

$$
HPMI\left(FS_i, FS_j\right) = \frac{\text{loglog}Prob\left(FS_i, FS_j\right)/Prob\left(FS_i\right)Prob\left(FS_j\right)}{-\text{loglog}\left(Prob\left(FS_i, FS_j\right)\right)}.
\tag{3}
$$

From the above equation (3), the wind direction value of "$HPMI$" is computed. If two feature sets only occur together "$HPMI\left(FS_i, FS_j\right) = 1$," then, the features are said to be relevant "RF." If the two feature sets are distributed as expected under independence "$HPMI\left(FS_i, FS_j\right) = 0$," then, the features are said to be not relevant "NR." Finally, if two feature sets take place independently "$HPMI\left(FS_i, FS_j\right) = -1$," then, the features are said to be less relevant "LR." With these resultant values, informative and relevant features are acquired. The pseudo-code representation of Homogenized Point Mutual (HPM) Feature Selection is given below.

As given in the above Homogenized Point Mutual (HPM) Feature Selection Algorithm 1, the objective remains in retrieving the informative and relevant feature in a computationally efficient manner. To achieve this objective the first feature set for wind power prediction is formulated. Next, relevant and information features are selected using the Point Mutual function. Finally, computationally efficiency is attained by performing perfect association using the homogenization function. With this, certain less frequency bias features are removed, therefore contributing to wind power prediction time.

2.2. Deep Quantum Reinforced Wind Power Prediction Model. In second step remains in designing a robust wind power predict with minimum error, a novelty of Deep Quantum Reinforced Wind Power Prediction algorithm is employed for improving the wind power prediction accuracy. The wind power prediction is one of paramount energy growths of country's economy are purely dependent on wind power due to its clean nature and pollution-free environment. To improve the profits, scheduling of the economy in a more robust manner and dispatching the same considerable demand for wind power prediction with less error is necessary.

In this work, a Deep Reinforcement Learning model is designed. In our work, DRL is applied to the problem of wind power prediction where the LV Active Power (LVAP) is transferred through an array of quantum dots when the array is affected by losses that arise from the interaction of dots with the surrounding environment, therefore resulting in prediction error. The existing quantum deep reinforcement learning algorithm was developed in [23] for avoiding optimization processes. But, the prediction error was not minimized. To address this issue, Quantum Deep Reinforcement Learning (QDRL) model is proposed to minimize the error during wind power prediction. The two logical gates are used. Figure 3 shows the block diagram of the Quantum Deep Reinforcement Learning model.

As shown in the above Figure 3, state space, environment, action space, input neurons, hidden layer, and output neurons form the elements for wind power prediction. The environment, state space and action space form as input to the input neurons and the prediction made forms the output neurons. Finally, in the hidden layer the actual wind power prediction made using Quantum Deep Reinforcement Learning is performed.

From the figure, to start with the Quantum Deep Reinforcement Learning (QDRL) environment, "E" is denoted by a rectilinear order of quantum controlled by two logical gates represented by "$\beta_{12}(t)$" and "$\beta_{23}(t)$" at the time "t" respectively. These two logical gates monitor the three features selected (i.e., relevant features) and therefore at each timestamp, the QDRL environment is said to be modeled by a "3 ∗ 3" density matrix that is employed as an input state space observation. The state-space of the wind from a wind turbine's SCADA system that is working and generating power in Turkey is selected from the Homogenized Point Mutual (HPM) Feature Selection algorithm and this is mathematically expressed as given below.

$$SS = \{S|S_t = WS(t), TPC(t), W\ D(t)\}. \tag{4}$$

From the above equation (4), "SS" represents the state space, "S_t" symbolizes the current state at instant "t," "WS" denotes the wind speed, "TPC" indicates the theoretical power curve at the time "t", and "$W\ D(t)$" symbolizes the wind direction "$W\ D$" respectively at the time "t." It's corresponding "3 ∗ 3" density matrix is shown below.

$$SS = \left\{ \alpha(t) = \begin{bmatrix} \alpha_{11} & \alpha_{12} & \alpha_{13} \\ \alpha_{21} & \alpha_{22} & \alpha_{23} \\ \alpha_{31} & \alpha_{32} & \alpha_{33} \end{bmatrix}, \beta_{12}(t), \beta_{23}(t) \right\}. \tag{5}$$

From the above equation (5), "$(\alpha_{11}, \alpha_{12}, \alpha_{13})$" represents the wind speed state space, "$(\alpha_{21}, \alpha_{22}, \alpha_{23})$" denotes the theoretical power curve state space, and "$(\alpha_{31}, \alpha_{32}, \alpha_{33})$" represents the wind direction state-space respectively and "$\beta_{12}(t)$" and "$\beta_{23}(t)$" is indicated two logical gates represented at the time "t." Next, in the wind power generation, the action space "AS" comprises "n" discrete quantities of the TVAP generated by the turbine for that moment and is mathematically expressed as given below.

$$AS = \{\beta_{12}(t)[a_1, a_2, \ldots, a_n], \beta_{23}(t)[a_1, a_2, \ldots, a_n]\}. \tag{6}$$

From the above action space equation (6), action space is denoted as the "AS," and the relationship between State Space "SS" and Action Space "AS" are mapped that comprises of the wind power evaluation network and a wind power action selection strategy utilizing an Epsilon Greedy policy to select an action based on the Q value. This is formulated as given below.

$$(A, S) = \{1 - \varepsilon, A = \operatorname{argmax} Q(S, A)\varepsilon, A \neq \operatorname{argmax} Q(S, A)\}. \tag{7}$$

From the above equation (7), the value of "ε" is selected between "0" and "0.5" so that a proper balance between exploitation and exploration is obtained during wind power evaluation and wind power action selection. Followed this the loss function "L" and reward "R" are measured as given below.

$$L = \frac{1}{n} \sum_{i=1}^{n} [A(i) - A'(i)]^2. \tag{8}$$

From the above equation (8), the loss function "L" is measured according to the measured wind speed "$A(i)$" and the predicted wind speed "$A'(i)$" respectively. Finally, the reward "R" is measured according to the resultant loss function as given below.

$$R = \begin{cases} +1 + \alpha_{33}(L_i) - \alpha_{22}(L_{i+1}), \text{when}[L_{i+1} < L_i] \\ -1 + \alpha_{33}(L_i) - \alpha_{22}(L_{i+1}), \text{when}[L_{i+1} > L_i]. \end{cases} \tag{9}$$

From the above equation (9) the reward "R" is estimated based on the loss function derived from the previous state "L_i" and current state "L_{i+1}" respectively, "$\alpha_{33}(L_i)$" denotes the wind direction state-space of loss function derived from the previous state "L_i," "$\alpha_{22}(L_{i+1})$" theoretical power curve state space of loss function derived from the current state "L_{i+1}." Finally, the wind power prediction evaluation function is estimated as given below.

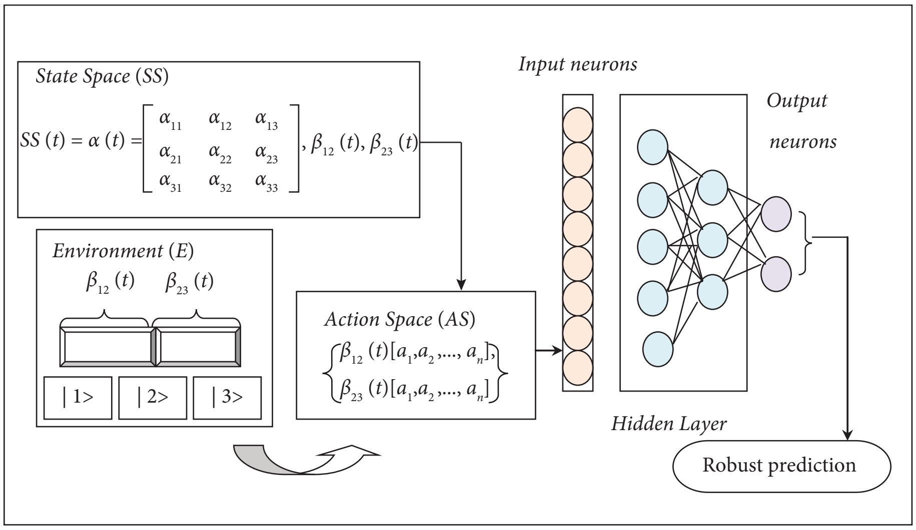

Figure 3: Block diagram of deep quantum reinforced wind power prediction model.

$$Q_{i+1}\left(SS_i, AS_i\right) = Q_i\left(SS_i, AS_i\right) + LR_i\left[R\left(SS_i, AS_i\right)\right] + DP\ Q_i\left(SS_{i+1}, AS_{i+1}\right) - Q_i\left(SS_i, AS_i\right). \tag{10}$$

According to the resultant evaluation function as in the above equation (10) with the aid of learning rate "LR" and discount parameter, "DP" for each wind power values "i," State Space derived from the previous state and current state "SS_i" and "SS_{i+1}," and Active space derived from the previous state and current state "AS_i," and "AS_{i+1}," robust and accurate wind power prediction with minimum error is said to be ensured. The pseudo-code representation of Deep Quantum Reinforced Wind Power Prediction is given below.

As given in the above Deep Quantum Reinforced Learning Wind Power Prediction Algorithm 2, the objective remains in minimizing the wind power prediction error. To achieve this objective a reward function based on quantum modifies the wind power state that in turn reduces the transfer time involved in predicting wind power for various LV Active Power to reduce the effect of losses and contribute to the minimization of wind power prediction error.

3. Experimental Setup

In this section, the simulation of the proposed Homogenized Point Mutual Information and Deep Quantum Reinforced (HPMI-DQR) wind power prediction method and the three existing methods namely EEMD-CSO-LSTMEFG [1], VMD-K means-LSTM [2], EALSTM-QR [22], LCWGAN-GP [28] has implemented in Java programming language using 2018 SCADA data of a wind turbine in Turkey taken from the https://www.kaggle.com/berkerisen/wind-turbine-scada-dataset [35]. Wind energy is considered to be technically feasible when its power density is greater than or equal to 500 W/m^2, for a height equal to or exceeding 50 m above the ground, which requires a minimum wind speed between 7-8 m/s. Wind energy is measured in kilowatt-hours (kWh) or megawatt-hours (MWh), plus the period (e.g. per year and hour). In Wind Turbines, SCADA Systems measure and save data like wind speed, wind direction, generated power, etc. for 10-minute intervals. This file was obtained and acquired from a wind turbine SCADA system that is working and generating power in Turkey. Google is the quantum computing hardware used in the proposed HPMI-DQR method. The implementation is performed with the hardware and software specification of the Windows 10 Operating system, core i3-4130 3.40 GHZ Processor, 4 GB RAM, 1 TB (1000 GB) Hard disk, ASUSTek P5G41C-M Motherboard, and Internet Protocol. To conduct the simulation, the HPMI-DQR method considers several wind data in the range of 500–5000 from the wind turbine SCADA dataset. The data's in the file are listed in Table 1.

The validation is calculated in terms of experimental evaluation with the wind turbine SCADA dataset. The proposed technique applies the holdout method for cross-validation. In machine learning, cross-validation is an estimated model employed for discovering the result of invisible data. It is separated into two sets such as the training set and the validation set. Most data (70%) was used for training, and the test (20%) was taken for validation. Then, the 10-fold cross-validation is utilized for measuring the results. Also, this validation is to provide better accuracy performance. With the aid of the data provided above, performance analysis is made with three different parameters involving, wind power prediction time, wind power prediction accuracy, and true positive rate and wind energy generation with different numbers of data.

4. Result and Discussion

In this paper, the performance evaluation of proposed HPMI-DQR, and existing various algorithms such as EEMD-CSO-LSTMEFG [1], VMD-K means-LSTM [2],

Input: dataset "DS," sample data "$D = D_1, D_2, \ldots, D_n$," feature set "$FS(t) = FS_1, FS_2, \ldots, FS_n$"
Output: computationally efficient informative and relevant feature selection "RF"
(1) Initialize "$n = 4$"
(2) Initialize "$n[0] = DT, n[1] = LVAP, n[2] = WS, n[3] = TPC, n[4] = WD$"
(3) Begin
(4) For each dataset "DS" and sample data "D"
(5) Formulate the feature set for wind power prediction as in equation (1)
(6) Measure individual distribution association between the probability of co-occurrence as in equation (2)
(7) Measure joint distribution association between the probability of co-occurrence as in equation (2)
(8) Measure homogenized PMI as in equation (3)
(9) If "$HPMI(FS_i, FS_j) = 1$" then relevant features "RF"
(10) If "$HPMI(FS_i, FS_j) = 0$" then features are not relevant "NR"
(11) If "$HPMI(FS_i, FS_j) = -1$" then features are less relevant "LR"
(12) Return (relevant features "RF")
(13) End for
(14) End

ALGORITHM 1: Homogenized point mutual (HPM) feature selection.

Input: dataset "DS," sample data "$D = D_1, D_2, \ldots, D_n$," feature set "$FS(t) = FS_1, FS_2, \ldots, FS_n$"
Output: Robust wind power prediction with minimum prediction error
Initialize relevant features "RF," time "t"
(2) Initialize environment variables using the logical function "$\beta_{12}(t)$" and "$\beta_{23}(t)$"
(3) Begin
(4) For each dataset "DS" with feature set "$FS(t)$" and sample data "D"
(5) Establish state space as in equations (4) and (5)
(6) Establish action space and action space selection as in equations (6) and (7)
(7) Estimate loss function as in equation (8)
(8) Estimate reward as in equation (9)
(9) Estimate wind power prediction evaluation function as in equation (10)
(10) End for
(11) End

ALGORITHM 2: Deep quantum reinforced learning wind power prediction.

TABLE 1: Dataset description.

S. No.	Feature	Description
1	Date/time	(For 10 minutes intervals)
2	LV active power (kW)	The power generated by the turbine for that moment
3	Wind speed (m/s)	The wind speed at the hub height of the turbine (the wind speed that the turbine use for electricity generation)
4	Theoretical power curve (KWh)	The theoretical power values that the turbine generates with that wind speed which is given by the turbine manufacturer)
5	Wind direction (∘)	The wind direction at the hub height of the turbine (wind turbines turn in this direction automatically)

EALSTM-QR [22], and LCWGAN-GP [28] are compared. These algorithms in aspects of wind power prediction time, accuracy, true positive rate, and wind energy generation. The tested algorithms were applied to a wind turbine dataset consisting of numerous wind data. The performance of the wind power prediction is tested based on the deep learning method, HMPI, and Deep Quantum Reinforced model. In our integration, we eliminated the irrelevant features, improving accuracy and reducing the prediction error. Then, the actual wind power prediction is performed with lesser prediction error. The results of four different techniques are discussed with the aid of tables and graphical representation.

4.1. Performance Analysis of Wind Power Prediction Time. A small portion of time is said to be consumed during the prediction of wind power. In other words, wind power prediction time refers to the time consumed in predicting the wind power by the turbine. This is mathematically formulated as given below.

$$WPP_{\text{time}} = \sum_{i=1}^{n} D_i * \text{Time}[Q_{i+1}(SS_i, AS_i)]. \quad (11)$$

From the above equation (11), wind power prediction time "WPP_{time}" is measured, the number of sample data denoted as "D_i" and time consumed in wind power prediction based on the evaluation function represented as "$\text{Time}[Q_{i+1}(SS_i, AS_i)]$." It is measured in terms of milliseconds (ms). Table 2 shows the wind power prediction time results for the proposed HPMI-DQR and four state-of-the-art methods, EEMD-CSO-LSTMEFG [1], VMD-K means-LSTM [2], EALSTM-QR [22], and LCWGAN-GP [28] on the test dataset.

The deterministic results of 10 minutes interval wind power prediction in each wind farm concerning different numbers of data in the range of 500 to 5000 are shown in Figure 4. At the prediction interval of 10 minutes ranging from 500 to 1500, all the four methods have a good performance. Let us consider the 500 wind data collected from the dataset for conducting the experiments. The HPMI-DQR consumes 985.25ms time for predicting wind power. Whereas, the prediction time of EEMD-CSO-LSTMEFG [1], VMD-K means-LSTM [2], and EALSTM-QR [22], LCWGAN-GP [28] are 1085.05ms, 1215.45ms, 1285.85ms, 1355.45ms respectively. The remaining nine runs are calculated for each method. The obtained overall results indicate that the overall wind power prediction time of the HPMI-DQR method is reduced by 12% compared to [1], 23% compared to [2], 29% compared to [22], and 34% compared to [28]. It shows that the additional inputs of historical data for each method successfully maintained the wind power prediction time. With the increase of the forecast horizon or the number of data, the wind power prediction time also reduces. The predictive wind power curve of the proposed HPMI-DQR method acquires the actual wind power curve in wind turbines' SCADA systems. In some moments, with the data ranging between 500 and 5000, the wind power prediction time changes dramatically, therefore affecting the prediction rate of all four methods. But on the whole, the HPMI-DQR has better performance compared with the existing three state-of-the-art methods [1, 2, 22, 28]. The reason behind the improvement was due to the application of the Homogenized Point Mutual Information model. By applying this model, homogenized informative and relevant features were selected with the Point Mutual function. Based on these features, the prediction was made. The homogenization function was employed for achieving computational efficiency. By using this function, assured low-frequency bias features are eliminated for reducing the wind power prediction time.

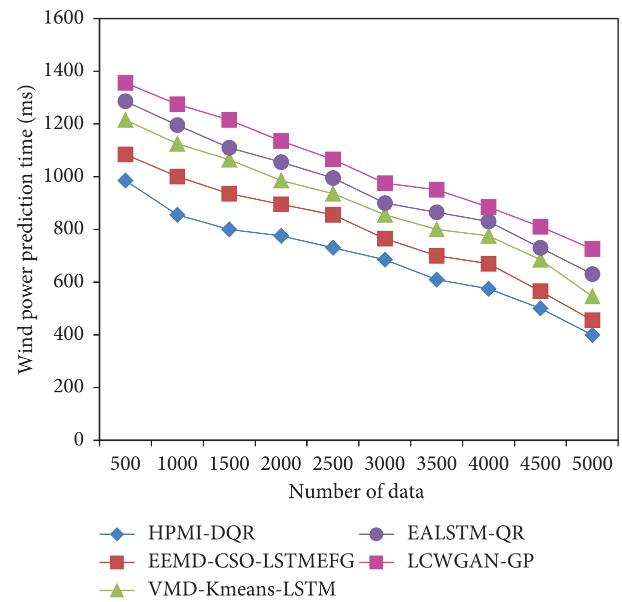

FIGURE 4: Graphical representation of wind power prediction time.

4.2. Performance Analysis of Wind Power Prediction Accuracy.

The second paramount metric of consideration for wind power prediction is the accuracy acquired during the process. In other words, a transparent method to estimate the quality of the learned method is to see how the predictions given by the model are accurate. This is mathematically given as below.

$$WPP_{acc} = \sum_{i=1}^{n} \frac{D_{AP}}{D_i} * 100. \quad (12)$$

From the above equation (12), "WPP_{acc}" denotes the wind power prediction accuracy, "D_i" indicates the sample data involved in simulation and "D_{AP}" represents the number of wind data accurately predicted. It is measured in terms of percentage (%). Table 3 shows the calculation results of wind power prediction accuracy on the whole test set using five methods.

The wind power prediction accuracy values in Table 3 embody the overall wind power prediction performance. As the specified requirement of wind turbines' SCADA system that is working and generating power in Turkey for 10-minute time intervals, the detailed results of wind power prediction accuracy for four different methods are calculated, as shown in Figure 5. The number of data is taken in the horizontal direction and the wind power prediction accuracy is observed at the vertical axis. As shown in the graphical chart, there are four various colors of lines such as blue, brown, green, and violet that denotes the prediction accuracy of four techniques namely HPMI-DQR, EEMD-CSO-LSTMEFG [1], VMD-K means-LSTM [2], EALSTM-QR [22], and LCWGAN-GP [28] respectively. It can be seen from this figure that wind power prediction accuracy according to the HPMI-DQR method is higher than the others and can satisfy the prediction requirement successfully. We should note that the wind power prediction accuracy of [1, 2, 22, 28] is not so competitive for 10-minute time intervals as the wind power prediction accuracy values of [1, 2, 22, 28] are a bit smaller. Let us consider 500 wind

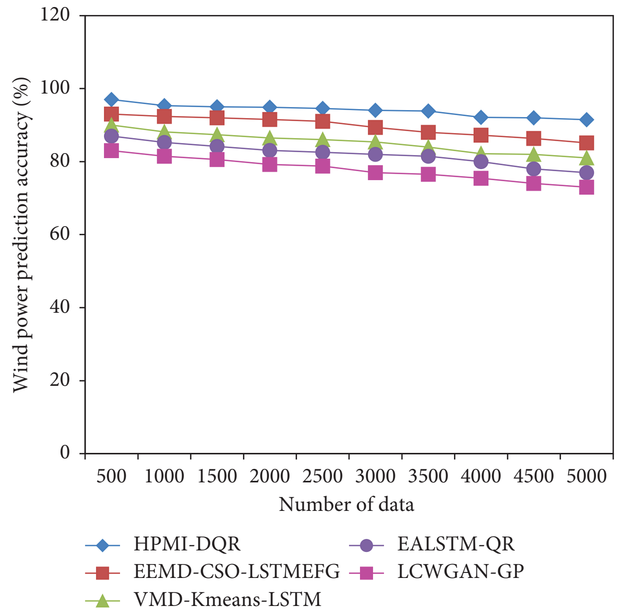

FIGURE 5: Graphical representation of wind power prediction accuracy.

data for conducting the experiments in the first iteration. By applying the HPMI-DQR, 485 wind data are correctly predicted and the prediction accuracy is 97% whereas the prediction accuracy percentage of the existing [1, 2, 22, 28] are 93%, 90%, 87% and 83% respectively. Followed by, different performance outcomes are observed for all methods. For every method, ten dissimilar results are observed. The performance of the proposed HPMI-DQR is compared to other existing methods. From the above, we can conclude that the HPMI-DQR is a better method for deterministic wind power prediction compared with the other two methods in this paper. The reason behind the improvement was due to the identification of the relationship between State Space and Action Space via mapping that includes both the wind power evaluation network and wind power action selection strategy utilizing an Epsilon Greedy policy. With this the accuracy rate using HPMI-DQR is said to be improved by 5% compared to [1], 10% compared to [2], 15% compared to [22], and 20% compared to [28].

4.3. Performance Analysis of the True Positive Rate. The true positive rate is measured in this work. This is mathematically formulated as given below.

$$TPR = \sum_{i}^{n} \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}. \tag{13}$$

From the above equation (13), the true positive rate TPR' is estimated based on the true positive rate (i.e., wind power data accurately predicted) TP' and the false-negative rate (i.e., wind power data is incorrectly predicted) FN' respectively. Table 4 shows the tabulation results of the true positive rate on the whole test set using five methods.

Finally, Figure 6 given above shows the true positive rate for 5000 different data acquired at different timestamps for 10 minutes time intervals. The different number of wind sample data is considered in the range from 500 to 5000 to conduct the simulation purpose. From the figure, it is clear that the true positive rate is decreased for each method, therefore, increasing the number of wind sample data also. From these results, the proposed HPMI-DQR method achieves better performance at a true positive rate when compared to existing methods. From Figure 6 it is clear that the true positive rate is improved gradually for the proposed HPMI-DQR when compared to other existing methods. This efficient improvement of the true positive rate achieved using HPMI-DQR was due to the application of the Deep Quantum Reinforced Wind Power Prediction algorithm. By applying this algorithm, the reward function was measured based on the quantum values, therefore, modifying the wind power state and hence minimizing the transfer time involved in predicting wind power and influences of losses. As a result, the true positive rate is improved in the proposed HPMI-DQR by 12% when compared to existing [1], 21% when compared to [2], 30% when compared to [22], and 37% when compared to [28] respectively.

4.4. Performance Analysis of the Wind Energy Generation. Finally, wind energy generation refers to the amount of wind energy generated at the wind speed (meters/second). Wind energy generation is mathematically formulated as,

$$WEG = \frac{\mathrm{amountofwindenergygenerated}}{\mathrm{windspeed\,(meters/second)}}. \tag{14}$$

From the above equation (14), the wind energy generation "WEG" is estimated based on the wind energy and wind speed is meters/second respectively. Table 5 shows the tabulation results of wind energy generation on the whole test set using five methods.

Table 2: Wind power prediction time analysis using HPMI-DQR, EEMD-CSO-LSTMEFG [1], VMD-K means-LSTM [2], EALSTM-QR [22], and LCWGAN-GP [28].

Number of data	Wind power prediction time (ms)				
	HPMI-DQR	EEMD-CSO-LSTMEFG	VMD-K means-LSTM	EALSTM-QR	LCWGAN-GP
500	985.25	1085.05	1215.45	1285.85	1355.45
1000	855.25	1000.35	1125.25	1195.55	1275.25
1500	800.05	935.55	1065.05	1110.05	1215.55
2000	775.45	895.45	985.35	1055.25	1135.85
2500	730.55	855.45	935.55	995.45	1065.35
3000	685.15	765.05	855.25	900.05	975.45
3500	610.05	700.55	800.15	865.55	950.75
4000	575.25	670.35	775.25	830.45	885.25
4500	500.45	565.55	685.45	730.45	810.15
5000	400.15	455.25	545.35	630.25	725.35

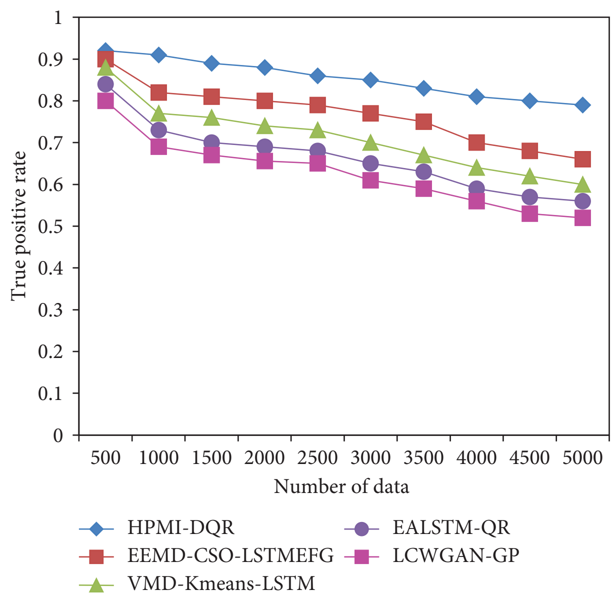

Figure 6: Graphical representation of the true positive rate.

Table 3: Wind power prediction accuracy analysis using HPMI-DQR, EEMD-CSO-LSTMEFG [1] and VMD-K means-LSTM [2], EALSTM-QR [22], and LCWGAN-GP [28].

Number of data	Wind power prediction accuracy (%)				
	HPMI-DQR	EEMD-CSO-LSTMEFG	VMD-K means-LSTM	EALSTM-QR	LCWGAN-GP
500	97	93	90	87	83
1000	95.35	92.35	88.15	85.25	81.45
1500	95	92	87.35	84.15	80.55
2000	94.85	91.55	86.45	83.05	79.25
2500	94.55	91	86	82.55	78.75
3000	94.05	89.35	85.35	82	77
3500	93.85	88	84	81.45	76.55
4000	92.15	87.25	82.15	80	75.45
4500	92	86.33	82	78	74
5000	91.5	85.15	81	77	73

Finally, Figure 7 given above shows the wind energy generation of five methods on the different number of wind speeds. The wind energy generation is considered in the range from 50 to 500 and wind speed 100 to 1000 to conduct the simulation purpose. From the figure, it is clear that the wind energy generation is decreased for each method, therefore, increasing the wind speed also. From these results, the proposed HPMI-DQR method achieves better performance on wind energy generation when compared to existing methods. From Figure 7 it is clear that the wind

Table 4: True positive rate analysis using HPMI-DQR, EEMD-CSO-LSTMEFG [1], VMD-K means-LSTM [2], EALSTM-QR [22], and LCWGAN-GP [28].

Number of data	True positive rate				
	HPMI-DQR	EEMD-CSO-LSTMEFG	VMD-K means-LSTM	EALSTM-QR	LCWGAN-GP
500	0.92	0.9	0.88	0.84	0.8
1000	0.91	0.82	0.77	0.73	0.69
1500	0.89	0.81	0.76	0.7	0.67
2000	0.88	0.8	0.74	0.69	0.656
2500	0.86	0.79	0.73	0.68	0.65
3000	0.85	0.77	0.7	0.65	0.61
3500	0.83	0.75	0.67	0.63	0.59
4000	0.81	0.7	0.64	0.59	0.56
4500	0.8	0.68	0.62	0.57	0.53
5000	0.79	0.66	0.6	0.56	0.52

Table 5: Wind energy generation using HPMI-DQR, EEMD-CSO-LSTMEFG [1], VMD-K means-LSTM [2], EALSTM-QR [22], and LCWGAN-GP [28].

Wind speed (meters/seconds)	Wind energy generation				
	HPMI-DQR	EEMD-CSO-LSTMEFG	VMD-K means-LSTM	EALSTM-QR	LCWGAN-GP
100	220	170	190	210	160
200	320	240	260	300	230
300	360	290	310	330	280
400	400	360	370	390	350
500	460	400	420	440	390
600	420	360	380	400	340
700	330	270	290	310	260
800	290	220	240	260	210
900	270	200	230	250	190
1000	200	140	170	190	130

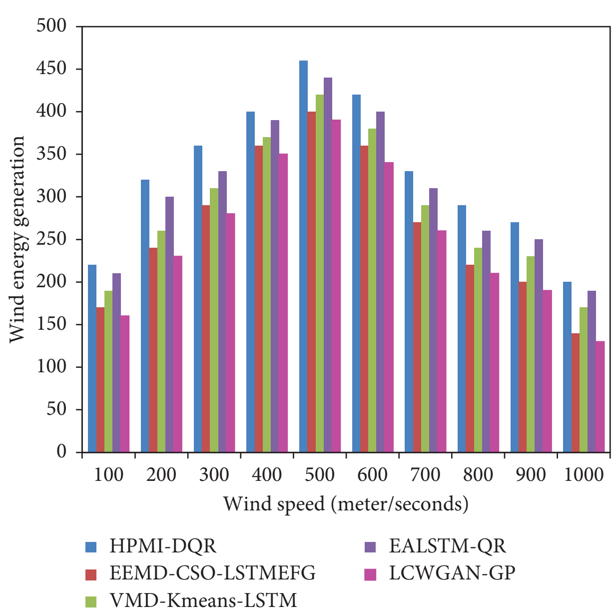

Figure 7: Graphical representation of the wind energy generation.

energy generation is improved gradually for the proposed HPMI-DQR when compared to other existing methods. This efficient improvement of wind energy generation achieved using HPMI-DQR was due to the application of the Deep Quantum Reinforced Wind Power Prediction algorithm. By applying this algorithm, the reward function was measured based on the quantum values, therefore, modifying the wind energy and hence minimizing the transfer time involved in generating wind energy and influences of losses. As a result, the wind energy generation is improved in the proposed HPMI-DQR by 26% when compared to existing [1], 15% when compared to [2], 6% when compared to [22], and 32% when compared to [28] respectively.

5. Conclusion

A novel deep-learning model has been proposed for predicting wind power and wind energy in real-life applications such as wind turbines. The HPM Feature Selection model has been employed for selecting pertinent features. Further, Quantum Deep Reinforcement Learning is used to perform wind power prediction. Experiments have been executed to validate the proposed method.

The major conclusions are summarized as follows:

(i) The important and informative features are chosen with aid of the Point Mutual function. Also, the homogenization function is employed to achieve computational efficiency. By using this function, certain minimal frequency bias features are eradicated and wind power prediction time is minimized by 25% compared to state-of-the-art methods.

(ii) The relationship between state space and action space for the corresponding environment value is provided as input by using Quantum Deep Reinforcement Learning. Next, the Epsilon Greedy policy is applied to predict an action or predict wind power by Q value. With this, the wind power prediction accuracy, true positive rate, and wind energy generation are improved by 13%, 25%, and 20% than the existing methods.

(iii) With the HPMI-DQR method, the wind power prediction, true positive rate, as well as wind energy generation are estimated precisely. The proposed method validates to outperform the commonly-used conventional wind power prediction techniques. From the analysis, it is evident that the proposed HPMI-DQR method provides better results compared to state-of-the-art methods.

(iv) Only the means of accurate wind power prediction are considered in this work. But, the proposed method of accuracy was not sufficient for the proper planning and operation of power systems with complicated patterns. Wind power plants have a comparatively smaller impact on the environment than conventional power plants concern. In our future work, a novel deep learning method will be introduced to accurate and timely relevant feature selection and prediction of wind power.

Nomenclature

$FS(t) = (DT, LVAP, WS, TPC, WD)$:	Feature set matrix
DT:	Prediction of date/time
LVAP:	LV active power
WS:	Wind speed
WD:	Wind direction
TPC:	Theoretical power curve
FS_i and FS_j:	Discrete random variables
HPMI:	Homogenized PMI
DS:	Dataset
$D = D_1, D_2, \ldots, D_n$:	Sample data
$FS(t) = FS_1, FS_2, \ldots, FS_n$:	Feature set
RF:	Relevant feature
NR:	Not relevant
LR:	Less relevant
E:	Rectilinear order of quantum
$\beta_{12}(t)$ and $\beta_{23}(t)$:	Two logical gates
t:	Time
SS:	State-space
$(\alpha_{11}, \alpha_{12}, \alpha_{13})$:	Wind speed state space
$(\alpha_{21}, \alpha_{22}, \alpha_{23})$:	Theoretical power curve state space
$(\alpha_{31}, \alpha_{32}, \alpha_{33})$:	Wind direction state space
AS:	Action space
n:	Discrete quantities of the TVAP
L:	Loss function
R:	Reward
$A(i)$:	Wind speed
$A'(s)$:	Predicted wind speed
L_i:	Loss function derived from the previous state
L_{i+1}:	Current state
LR:	Learning rate
DP:	Discount parameter
WPP_{time}:	Wind power prediction time
D_i:	Sample data
$\text{Time}[Q_{i+1}(SS_i, AS_i)]$:	Time consumed in wind power prediction based on the evaluation function
WPP_{acc}:	Wind power prediction accuracy
D_{AP}:	Number of wind data accurately predicted
WPP_{err}:	Wind power prediction error
MV:	Measured value
PV:	Predicted value

Abbreviation

HPMI-DQR:	Homogenized point mutual information and deep quantum reinforced
HPMI:	Homogenized point mutual information
LSTMEFG:	Long short-term memory network-enhanced forget-gate network
CSO:	Cuckoo search optimization algorithm
EEMD:	Ensemble empirical mode decomposition
VMD:	Variational mode decomposition
LSTM:	Long short term memory
SDAE:	Stacked denoising auto encoder
ATL-DNN:	Adaptive transfer learning in deep neural networks
DBN-MRT:	Deep belief network based meta-regression technique
ANNs:	Artificial neural networks
DRL:	Deep reinforcement learning

QDRL: Quantum deep reinforcement learning.

Data Availability

https://www.kaggle.com/berkerisen/wind-turbine-scada-dataset.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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