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An Efficient Scheme for Determining the Power Loss in Wind-PV Based on Deep Learning

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ABSTRACT Power loss is a bottleneck in every power system and it has been in focus of majority of the researchers and industry. This paper proposes a new method for determining the power loss in wind-solar power system based on deep learning. The main idea of the proposed scheme is to freeze the feature extraction layer of the deep Boltzmann network and deploy deep learning training model as the source model. The sample data with closer distribution with the data under consideration is selected by defining the maximum mean discrepancy contribution coefficient. The power loss calculation model is developed by configuring the deep neural network through the sample data. The deep learning model is deployed to simulate the non-linear mapping relationship between the load data, power supply data, bus voltage data and the grid loss rate during power grid operation. The proposed algorithm is applied to an actual power grid to evaluate its effectiveness. Simulation results show that the proposed algorithm effectively improved the system performance in terms of accuracy, fault tolerance, nonlinear fitting and timeliness as compared with existing schemes.

INDEX TERMS Renewable energy, PV, optimization, deep learning, power loss.

I. INTRODUCTION

In recent years, the distributed power generation-based PV systems have achieved rapid development. The large number of distributed photovoltaic access has brought a certain impact on the reactive power of the distribution network, which is likely to cause problems such as the voltage limit of the grid connection point and the user power factor exceeding the standard. One of the main factors restricting the development of photovoltaics in highlighted in these references [1]–[5]. With the continuous innovation and breakthrough of renewable energy power generation technology worldwide, like in the countries like Pakistan, India etc. policy support for the development of renewable energy has increased, therefore, the renewable energy has shown an accelerated development trend [6]. With the implementation of new energy development strategy, the photovoltaic power generation industry has developed tremendously, and photovoltaic grid-connected systems are gradually becoming large-scale development [7], [8]. At present, several megawatt-level grid-connected photovoltaic power stations have been installed in different places [9].

The network loss rate is an important research topic for the economic operation of the power system. As an important economic indicator for measuring and evaluating the production and operation of the power supply unit, the calculation of the network loss rate can help the power supply unit to conduct a more targeted network loss analysis and loss reduction jobs [10]. With the rapid development of modern power systems, the power grid has basically formed a

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large grid interconnection. The characteristics of distance transmission and heavier load, and the introduction of power system competition mechanism, make the equipment running in the grid often reach its rated value. For this kind of high-strength power system, the power flow calculation often fails to converge or has no solution [11]. Solving the power flow problem is a complex nonlinear programming problem, which usually needs to be solved by an iterative method. The iterative calculation process is slow, resulting in poor timeliness. Therefore, it is generally only used for offline calculations. In addition, the data required for calculation will be missing, incomplete collection or collection errors [12]. Therefore, finding a fast, accurate, and highly error-tolerant theoretical online calculation method for the loss of data, so as to formulate practical loss reduction measures to reduce the loss of the network, is an urgent problem for power companies to solve [13], [14].

At present, the network loss rate calculation methods mainly include traditional power flow calculation methods, intelligent algorithms, and big data processing technologies based on cloud computing platforms. The calculation methods of network loss rate for processing high-dimensional data electrical networks are mostly based on data mining methods, including neural networks, support vector machines, cluster analysis, cloud computing and a combination of multiple methods. Reference [15] puts forward a calculation method of network loss rate based on the statistical data of network loss rate and its influencing factors, which is a combination of analytic hierarchy process and multiple gray correlation techniques, which solves the problem of complex calculations, but handles high-dimensional data There are shortcomings in calculation speed and accuracy. The authors in [16] proposes a joint network loss rate calculation method for vertical-lateral error matching, which improves the calculation accuracy, but there are insufficient calculation speeds when processing high-dimensional data. The authors in [17], [18] proposes a calculation method based on neural network, which solves the problem of calculation speed in high-dimensional data, but it has a strong dependence on initial parameters, and improper selection of initial data will produce larger errors. Therefore, genetic algorithms are often used. The initial parameters are optimized to reduce errors.

Wind power and photovoltaic power generation are intermittent and uncertain. The power transmission caused by wind power and photovoltaic grid connection and the impact on the power system flow make the change trend of the grid loss rate and the output of wind power photovoltaic. It is closely related, and the data collection system of the new energy power generation system is imperfect, making the data missing situation more serious. The current shallow learning methods have limited processing capabilities for high-dimensional data input features, and cannot well achieve the problem of calculating the network loss rate when the power system is high-dimensional.

Deep learning theory [19], as the latest research result in the field of machine learning, has achieved fruitful research results in image and speech processing [20], [21] with its powerful modeling and representation capabilities. However, the application research of combining it with the related problems of power system is very limited. The authors in [22] introduced deep learning technology to the calculation of wind power and photovoltaic power, and achieved good calculation results. The authors in [23] combined variational modal decomposition and particle swarm optimization with deep confidence networks to calculate short-term electricity consumption. In [24], the authors proposed a method based on deep belief network to improve power system transient stability evaluation (TSA) The method of accuracy. Reference [25] proposed a joint calculation method of short-term electrical, thermal, and gas load based on deep structure multi-task learning. So far, there is no relevant research on the application of deep learning in the calculation of network loss rate.

The combination of migration and deep learning improves the learning ability and generalization ability of deep learning. The authors in [26] proposed a sentiment analysis method based on deep representation learning and Gaussian process knowledge transfer learning, which effectively improves the performance of text sentiment classification. In [27], the authors aimed at the practical application of deep face learning models in big data, and proposed a solution to this problem by migrating a pre-trained deep face model to a specific task.

This paper proposes a new method for determining the power loss in wind-solar power system based on deep learning. The main contributions of the paper are as follows:

- The power loss calculation model is developed by configuring the deep neural network through the sample data.
- The deep learning model is deployed to simulate the non-linear mapping relationship between the load data, power supply data, bus voltage data and the grid loss rate during power grid operation.
- The proposed algorithm is applied to an actual power grid to evaluate its effectiveness.
- The DBN-DNN deep learning calculation method has higher calculation accuracy than the traditional shallow structure back propagation (BP) neural network calculation method. In this paper, the calculation accuracy of the DBN-DNN model is 4.95% higher than that of the BP neural network, which shows that the DBN-DNN model has more advantages in processing high-dimensional input data of the power system.
- The deep learning, migration learning and the calculation of the grid loss rate of the actual regional power grid containing wind power and photovoltaic power in the power system are combined to verify the practicability and feasibility of the model.

The remaining of the paper is organized as follows. In Section II, the deep transfer learning method is discussed. In Section III, the theoretical power loss calculation method is described. In Section IV, the case analysis is

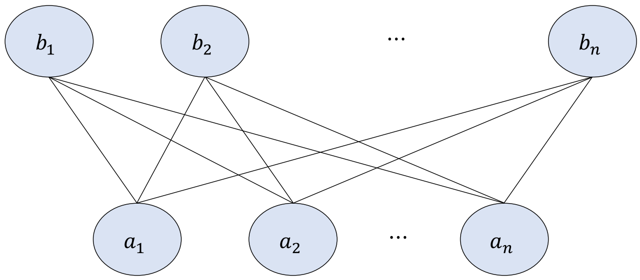

FIGURE 1. Structure of restricted Boltzmann machine.

performed with numerical results while Section V concludes the paper.

II. DEEP TRANSFER LEARNING

In this section, the analysis and illustrations of deep belief network, deep belief network based deep neural network (DBN-DNN), maximum mean difference (MMD) and MMD contribution coefficient is presented underlying concepts are explained.

A. DEEP BELIEF NETWORK

The deep belief network (DBN) is a generative structure model with multiple hidden layers. This machine is stacked with restricted Boltzmann machine (RBM), which has powerful feature extraction capabilities. The restricted Boltzmann machine [28], [29] is a Markov random field model, which has a 2-layer structure, as shown in Figure 1. The lower layer is the input layer, containing m input units v_i, used to represent input data, and each input unit contains a real-valued offset a_i; the upper layer is the hidden layer, containing m hidden units h_i, which represent the input extracted by RBM abstract feature of data, each hidden unit contains a real-valued bias b_j. The RBM has the characteristics of no connection within the layer and full connection between the layers, that is, there is no connection between nodes in the same layer, and each node is connected to the adjacent layer. All nodes in are fully connected, and there are real-valued weights w_{ij} on the connections, which ensures the independence of conditions between layers.

The RBM model is an energy model. For a set of state quantities (v, h), its energy function can be defined as $E_\theta(v, h)$, where θ is the network parameter, $\theta = \{a_i, h_i, w_{ij}\}$. The hidden layer and the visible layer total probability distribution can be defined as $P(v, h)$, namely

$$\begin{cases} E_\theta(v,h) = -\sum_{i=1}^{n}\sum_{j=1}^{m} w_{ij}v_i h_j - \sum_{i=1}^{m} a_i v_i - \sum_{j=1}^{n} b_j h_j \\ P(v,h) = \frac{1}{z_\theta} e^{-E(v,h)} \end{cases} \tag{1}$$

where z_θ is the partition function, $z_\theta = \sum_{v,h} e^{-E(v,h)}$. According to the conditional independence between RBM layers, if the input data is given, the node value of the output layer satisfies the following conditional probability:

$$P(v_i = 1|v, \theta) = \varphi\left(b_j + \sum_{i=1}^{n} w_{ij} v_i\right) \tag{2}$$

where $\varphi(x) = 1//1 + e^{(-x)}$ is the sigmoid activation function. Correspondingly, when the data of the output layer is determined, the conditional probability of the value of the input node is:

$$P(v_i = 1|v, \theta) = \varphi\left(a_i + \sum_{i=1}^{n} w_{ij} h_j\right) \tag{3}$$

Given a set of training samples $S = \{v^1, v^2, \ldots, v^n\}$, training RBM is to adjust the parameter θ, to fit the given training learning sample so that the probability distribution represented by the corresponding RBM under this parameter is as close as possible to the training distribution of learning data is consistent. Usually the network parameters are adjusted by the method of maximum likelihood estimation. Therefore, the goal of training RBM is to maximize the likelihood function $L(\theta)$ of the network to obtain the parameter θ, namely $L(\theta, v) = \prod_{i=1}^{n} p(v^i)$. To simplify the calculation, write it as Logarithmic form:

$$\ln L(\theta, v) = \sum_{i=1}^{n} \ln p\left(v^i\right) \tag{4}$$

$$\theta = \arg\max L(\theta) = \arg\max \sum_{i=1}^{n} p\left(v^i\right) \tag{5}$$

Here, contrast divergence algorithm [16] is used to train RBM.

B. DEEP LEARNING MODEL BASED ON DBN-DNN

The deep learning model in this paper is the deep learning theoretical network loss rate calculation model DBN-DNN, which is a combination of deep neural network (DNN) and DBN. The deep learning network based on the DBN-DNN combination is a complex nonlinear mapping from input to output. It does not require precise expressions of the relationship between input and output, and can obtain complex nonlinear mapping between input and output through a large amount of learning, so that the deep learning network has the ability to express the characteristics of data layer by layer and deeply mine the value of data. First, use the greedy unsupervised learning algorithm to initialize the entire DBN deep belief network model. After layer-by-layer training, the abstract feature vector learned by DBN is used as the input of the deep neural network, so that the deep neural network can perform quickly, effectively, stably and reliably. training. Finally, the BP algorithm is used to supervise the training of DNN to fit the label data, as shown in Figure 2.

C. MAXIMUM MEAN DIFFERENCE

Transfer learning can help the target task to learn with the help of related fields (source fields) or task knowledge. Knowledge can be borrowed or transferred between the source domain, task and target domain, and tasks, which indicates that the source must be some correlation or similarity between domain data and target domain data. Therefore, it is important to measure the similarity or difference of data distribution between two fields or tasks in transfer learning. Based on our knowledge, there is still no unified method for measuring the similarity or difference of data distribution between domains or tasks. At present, the common methods

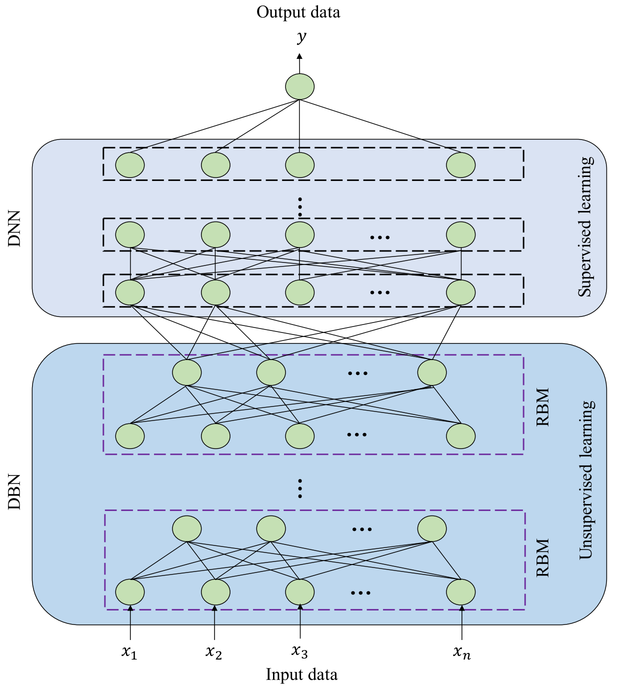

FIGURE 2. Deep learning model based on DBN-DNN.

to measure the distribution difference between domains are: KL divergence, Bregman divergence, maximum mean difference (MMD) measurement [30], [31], etc. Among the above-mentioned three kinds of measurement methods for the distribution difference between the domains or tasks, MMD is the most widely used. Suppose there is a source data $\boldsymbol{x}^{(s)} = \left[x_1^{(s)}, x_2^{(s)}, \ldots, x_n^{(s)}\right]$ satisfying the distribution and a target data satisfying the q distribution $\boldsymbol{x}^{(t)} = \left[x_1^{(t)}, x_2^{(t)}, \ldots, x_n^{(t)}\right]$. Let H denote the regenerated kernel Hilbert space (RKHS) [32], $\phi(\cdot) : X \rightarrow H$ denote the non-linear feature mapping function from the original feature space to RKHS. Since RKHS is usually a high-dimensional or even infinite space, the corresponding kernel generally chooses to represent an infinite-dimensional Gaussian kernel [33], [34]:

$$k\left(x, x'\right) = e^{-\left(\frac{\|x-x'\|}{2\sigma^2}\right)e^{j\theta}} \tag{6}$$

The MMD of $\boldsymbol{X}^{(s)}, \boldsymbol{X}^{(t)}$ in RKHS can be expressed as

$$\varepsilon_{\mathrm{MMD}} = \left\| \frac{1}{n_s} \sum_{i=1}^{n_s} \varphi\left(x_i^{(s)}\right) - \frac{1}{n_t} \sum_{j=1}^{n_t} \varphi\left(x_j^{(t)}\right) \right\|_H \tag{7}$$

For the convenience of calculation, we usually use the square form of $\varepsilon_{\mathrm{MMD}}$, namely $\varepsilon_{\mathrm{MMD}}^2$. Expand it to

$$\begin{aligned} &= \frac{1}{N_T^2} \sum_{i=1}^{N_T} \sum_{j=1}^{N_T} < \varphi(\boldsymbol{x}_i), \varphi(\boldsymbol{y}_j) >_H \\ &+ \frac{1}{N_S^2} \sum_{i=1}^{N_S} \sum_{j=1}^{N_S} < \varphi(\boldsymbol{x}_i), \varphi(\boldsymbol{y}_j) >_H \\ &- \frac{2}{N_S N_T} \sum_{i=1}^{N_T} \sum_{j=1}^{N_S} < \varphi(\boldsymbol{x}_i), \varphi(\boldsymbol{y}_j) >_H \end{aligned} \tag{8}$$

Introduce the kernel trick here:

$$< \varphi(\boldsymbol{x}), \varphi(\boldsymbol{y}) >_H < k(\boldsymbol{x}, .), k(\boldsymbol{y}, .) >_H = k(\boldsymbol{x}, \boldsymbol{y}) \tag{9}$$

D. MAXIMUM MEAN DIFFERENCE CONTRIBUTION COEFFICIENT

In order to find out the irrelevant or not relevant data of the source data and the target data, this paper defines the maximum mean difference contribution coefficient (CCMMD) of each source data. Let ρ_i denote the maximum mean difference contribution coefficient of the i-th sample. Suppose $\varepsilon_{\mathrm{MMD}k\neq i}$ lacking the i-th source data sample is

$$\begin{aligned} \varepsilon_{\mathrm{MMD}}^2 &= \frac{1}{N_T^2} \sum_{i=1}^{N_T} \sum_{j=1}^{N_T} \varphi(\boldsymbol{x}_i)^T \varphi(\boldsymbol{y}_j) \\ &+ \frac{1}{N_S^2} \sum_{i=1}^{N_S} \sum_{j=1}^{N_S} \varphi(\boldsymbol{x}_i)^T \varphi(\boldsymbol{y}_j) \\ &- \frac{2}{N_S N_T} \sum_{i=1}^{N_T} \sum_{j=1}^{N_S} \varphi(\boldsymbol{x}_i)^T \varphi(\boldsymbol{y}_j) \end{aligned}$$

Equation (8) is simplified to

$$\begin{aligned} \varepsilon_{\mathrm{MMD}}^2 &= \frac{1}{N_T^2} \sum_{i=1}^{N_T} \sum_{j=1}^{N_T} k(\boldsymbol{x}_i, \boldsymbol{y}_j) \\ &+ \frac{1}{N_S^2} \sum_{i=1}^{N_S} \sum_{j=1}^{N_S} k(\boldsymbol{x}_i, \boldsymbol{y}_j) \\ &- \frac{2}{N_S N_T} \sum_{i=1}^{N_T} \sum_{j=1}^{N_S} k(\boldsymbol{x}_i, \boldsymbol{y}_j) \end{aligned} \tag{10}$$

MMD measures the overall mean difference between source data and target data. It can be used to represent the distribution difference between two data sets and is widely used in transfer learning. It can be seen from equation (7) that when MMD measures the distribution difference between source data and target data, all source data is used. If there is irrelevant data, it will affect the result. Therefore, we must consider each importance of the source data.

$$\varepsilon_{\mathrm{MMD}k\neq i} \left\| \frac{1}{n_s} \sum_{i=1, i\neq k}^{n_s} \varphi\left(x_i^{(s)}\right) - \frac{1}{n_t} \sum_{j=1}^{n_t} \varphi\left(x_j^{(t)}\right) \right\|_H \tag{11}$$

where $k = 1, 2, \ldots, n$, then ρ_i is

$$\rho_i = \frac{\left(\varepsilon_{MMDk\neq i} - \varepsilon_{MMD}\right)}{\varepsilon_{MMD}} \tag{12}$$

If $\rho_i > 0$, it means that the i-th sample has contributed to MMD. On the contrary, if $\rho_i \leq 0$, it means that the i-th sample has "negative" contribution to MMD. By calculating the ρ_i of each source data, the sample data with $\rho_i > 0$ is filtered out, and the source data that is closer to the target data distribution is obtained, which is used to fine-tune the high-level DNN neural network.

III. THEORETICAL POWER LOSS RATE CALCULATION

A. POWER LOSS CALCULATION

This paper uses the deep learning model to simulate the non-linear mapping relationship between the load data, power supply data, bus voltage data and the grid loss rate during power grid operation. Considering the strong feature extraction ability and strong fitting performance ability of the deep learning model, the active power data, reactive power data and bus voltage data of each node in the electrical network equivalent model are used as the input matrix $\boldsymbol{X}$ of the depth model, and the corresponding network theory, the network loss rate is used as the output matrix $\boldsymbol{T}$. Assuming that the power grid has n nodes, including m PQ nodes, $n-m-1$ PU node, and 1 balance node, the input and output matrices of the deep learning model are shown in equations (13) and (14):

$$\boldsymbol{X} = \begin{bmatrix} P_{1,1} & P_{1,2} & \cdots & P_{1,M} \\ Q_{1,1} & Q_{1,2} & \cdots & Q_{1,M} \\ \vdots & \vdots & \vdots & \vdots \\ P_{m,1} & P_{m,2} & \cdots & P_{m,M} \\ Q_{m,1} & Q_{m,2} & \cdots & Q_{m,M} \\ P_{m+1,1} & P_{m+1,2} & \cdots & P_{m+1,M} \\ U_{m+1,1} & U_{m+1,2} & \cdots & U_{m+1,M} \\ \vdots & \vdots & \vdots & \vdots \\ P_{n-1,1} & P_{n-1,2} & \cdots & P_{n-1,M} \\ U_{n-1,1} & U_{n-1,2} & \cdots & U_{n-1,M} \\ \theta_{n,1} & \theta_{n,2} & \cdots & \theta_{n,M} \\ U_{n,1} & U_{n,2} & \cdots & U_{n,M} \end{bmatrix} \tag{13}$$

$$\boldsymbol{T} = [\boldsymbol{\Delta} P_1 \quad \boldsymbol{\Delta} P_2 \quad \ldots \quad \boldsymbol{\Delta} P_M] \tag{14}$$

where M is the number of sections

B. MODEL BUILDING AND SOLVING

The theoretical network loss rate calculation model based on deep migration learning is shown in Figure 3. First of all, it uses the grid load, wind power, photovoltaic, bus voltage and other operating data as the input data of the DBN-DNN deep learning model, and the network loss rate as the output data, train the deep learning model, and freeze the DBN layer. Then, since the real-time running data such as wind power, photovoltaics, and load of the grid to be calculated will have a distribution difference with the training data over time, the maximum mean difference distance MMD in migration learning is introduced to measure the difference between the task data to be calculated and the training data. Distribution difference, and defines the maximum mean difference contribution of the training data. Sample data that is closer to the distribution of the data to be calculated is migrated from the training data to fine-tune the DNN to obtain the TDBN-DNN deep migration learning model, and use TDBN-DNN to treat the calculation task data loss rate is calculated.

The specific steps of the model solving are described below.

1) *Data processing*. Due to the different value ranges and units of load data, power output data, and bus voltage data, in order not to be affected by the dimension, to prevent the absolute value of the characteristics from being different and the data "to eat the small" situation, the input data is standardized:

$$\alpha'_{i,j} = \frac{\alpha_{i,j} - \alpha_{\min,j}}{\alpha_{\max,j} - \alpha_{\min,j}} \tag{15}$$

where $\alpha_{i,j}$ is the i-th sample data of the j-th data feature, $i = 1, 2, \ldots M$, $j = 1, 2, \ldots, 2n$; $\alpha'_{i,j}$ is the j-th normalized data of the i-th sample data of the feature; $\alpha_{\min,j}$ is the minimum value of the j-th data feature in the sample data; $\alpha_{\max,j}$ is the maximum value of the j-th data feature in the sample data.

2) *Pre-trained deep learning model*. First, according to the sample size and real-time requirements, it determines the number of hidden layers of the deep learning network and the number of nodes, and initialize the network parameters. Then it uses standardized grid power, load, voltage and other sample data as the input data, and the corresponding section loss rate is the label data. The greedy unsupervised learning algorithm is used to train the entire DBN deep confidence network model layer by layer. Finally, the feature vector of the output of DBN is given to DNN a better initial value, and the BP algorithm is used to supervisory train the DNN with the corresponding section loss rate such that to fit the label data.

3) *Transfer deep learning models*. First, it freezes the underlying general-purpose network that is generally considered a deep learning model. Then, the MMD is used to measure the distribution difference between the source training data and the target data, and the CCMMD of each sample in the source data is calculated, and the sample data with $\rho_i > 0$ is selected. Finally, it uses the selected source sample data to fine-tune the pre-trained DNN to obtain the deep transfer learning model TDBN-DNN.

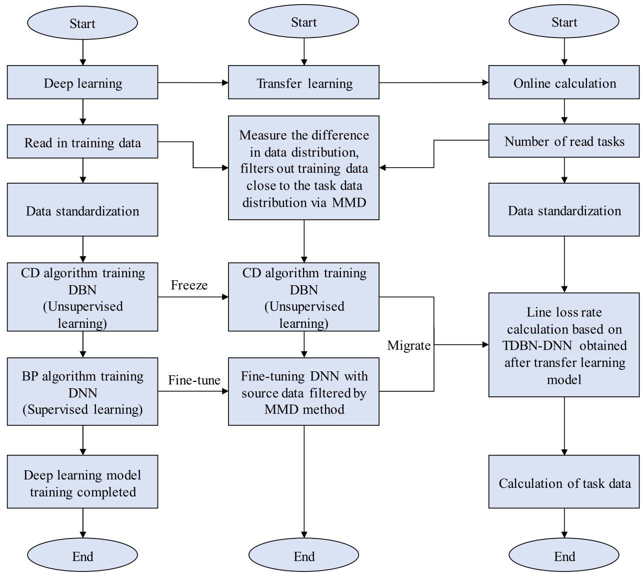

FIGURE 3. Proposed algorithm flowchart.

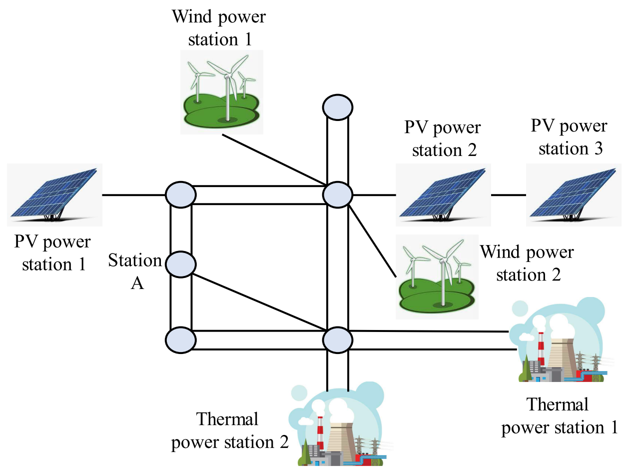

FIGURE 4. Structure of the 220kV power station based on RES.

4) *Network loss rate calculation*. After the task target input data is standardized, it inputs this data into the TDBN-DNN network loss rate calculation model to obtain the calculated network loss rate value.

IV. CASE STUDY ANALYSIS

The calculation example system is derived from the actual power grid into a certain area in northern Pakistan, and the calculation example data and the power grid operating structure are obtained from a scientific research project. Various types of wind power and photovoltaic power sources connected to the grid in this region, such as wind power stations, photovoltaic power stations, wind and solar storage power stations, etc., due to the large access capacity, the uncertainty and volatility of the wind power and photovoltaic power output have a significant impact on the grid loss rate. The simulation analysis software program used for evaluating and experimentation of the proposed study is MATLAB. The training and learning data are from August 1, 2019 to August 20, 2020, and the task data to be calculated is August 21, 2020, with the sample time of 15 minutes.

A. CALCULATION EXAMPLE

The calculation examples used in this paper include regional 110kV and 220kV power grids. The power supply is all distributed on the 220kV side, as shown in Figure 4, including 1 wind power station, 1 wind and solar storage power station, 3 photovoltaic power stations, 2 thermal power stations, thermal power plant 1 contains a single 330MW unit, thermal power plant 2 contains 2 units 300MW unit. Part of the wind power and photovoltaic power plants generation is connected to the 110kV busbar. Because the remaining new energy power of the regional power grid is sent from station A, and when the power supply of the regional power grid is insufficient, it may also be powered by the high-voltage side of station A, which is responsible for the power balance of the regional power grid. Therefore, station A is selected as the balanced node in the calculation.

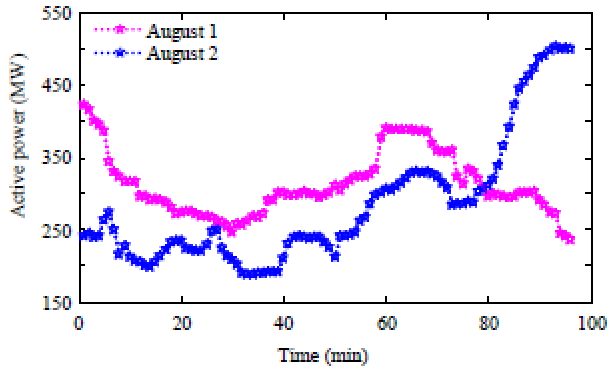

FIGURE 5. Comparison of the active output power versus time.

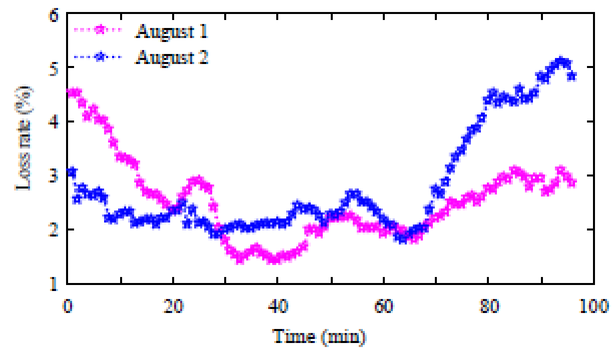

FIGURE 6. Comparison of the power loss rate with time.

B. SAMPLE DATA

In this paper, the DBN-DNN model source training data adopts the data of August 2019 (1-20), and the data of the task to be calculated adopts the data of August 21, 2020. Due to the randomness of the output of wind power and photovoltaic power, the model training and calculation are difficult. The input data produces data distribution differences, and at the same time, it will also have a greater impact on the fluctuation of the network loss rate, as shown in Figures 5 and 6.

Figures 5 and 6 respectively show the variation curves of the total active power output and grid loss rate of the regional power grid based wind power and photovoltaic power supply on August (1-2). For the local power grid, the active power output of the wind power and photovoltaic power supply has great randomness and volatility. In addition, a small part of the wind power and photovoltaic power is consumed locally, and the remaining power is sent out on a large scale, which brings great grid loss to the regional grid, and to a certain extent affects the trend of the grid loss rate, resulting in daily grid loss rate is quite different.

C. COMPARISON OF DBN-DNN AND BP ALGORITHMS

In order to highlight the powerful non-linear fitting ability of high-dimensional input data of the deep training model than the shallow network, the calculation effect of the deep learning model DBN-DNN and the single hidden layer BP neural network model is compared. The deep learning model DBN-DNN consists of 2 RBMs and 5 layers of ordinary

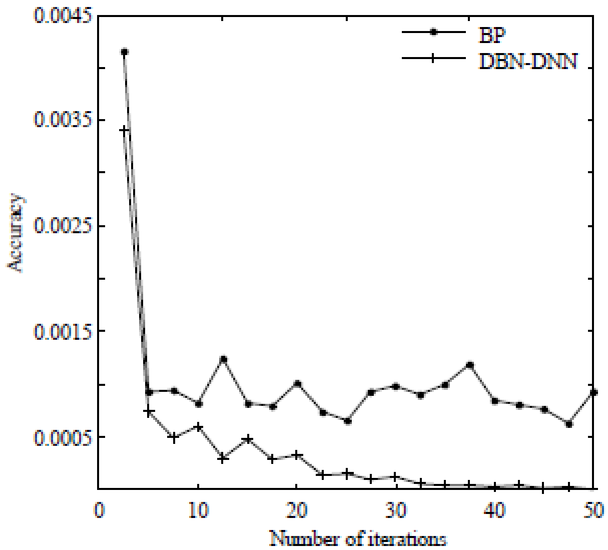

FIGURE 7. Accuracy comparison of the algorithms versus number of iterations.

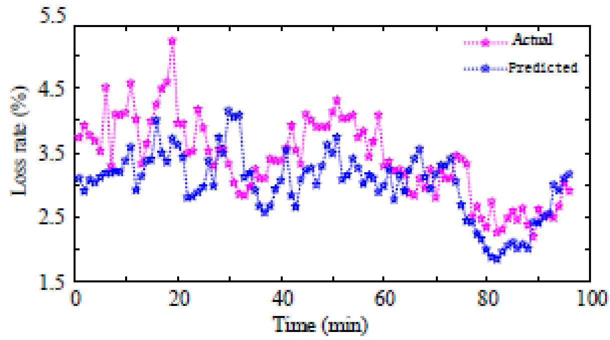

FIGURE 8. Comparison of the power loss rate versus time for BP neural network.

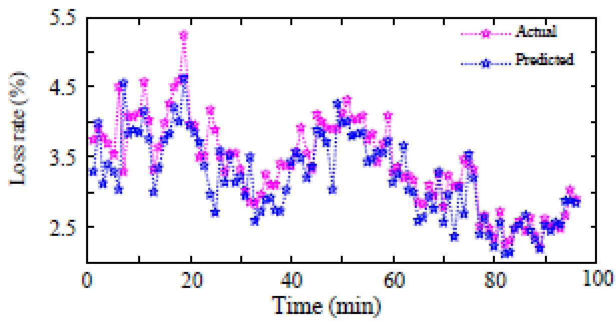

FIGURE 9. Comparison of the power loss rate versus time for DBN-DNN algorithm.

neural networks. The number of neurons in each layer is 146, 40, 25, 10, 1, respectively. The learning rate is $\eta = 0.01$, and the number of learning rounds is $e_{\text{poch}} = 50$. The performance goal is $g_{\text{oal}} = 0.001$. The number of hidden layer neurons in normal BP is 104. The average accuracy obtained from the average absolute percentage error is used as the evaluation index of the calculation effect. The representations are based on:

$$M_{\text{APE}} = \frac{1}{n}\sum\nolimits_{i=1}^{n}\left|\frac{x\,(i) - y\,(i)}{x\,(i)}\right| \times 100\% \tag{16}$$

$$M_{\text{A}} = 1 - M_{\text{APE}} \tag{17}$$

where $x\,(i)$ and $y\,(i)$ are the actual value and calculated value at time i respectively; n is the amount of calculated sample data.

Figure 7 shows a comparison of the training effect of the deep learning model DBN-DNN and the single hidden layer BP neural network model. It can be seen from Figure 7 that the training effect based on the DBN-DNN combined calculation model is significantly better than the shallow BP neural network, which makes the DBN-DNN calculation model better fit.

Figures 8 and 9 are the calculation results of the shallow BP neural network and DBN-DNN model respectively. It can be seen intuitively from Figures 8 and 9, that the DBN-DNN deep learning model for high-dimensional input data has better nonlinear fitting capabilities than shallow BP neural networks, and the calculation accuracy is higher. The $M_{\text{A}} = 84.41\%$ for BP neural network and the $M_{\text{A}} = 89.36\%$ for the DBN-DNN deep learning model. Therefore, the accuracy increased by 4.95%.

D. COMPARISON OF DBN-DNN AND TDBN-DNN ALGORITHMS

In order to highlight the powerful non-linear fitting ability, Since the amount of source training data is relatively large relative to the amount of task data, and the amount of data to be calculated is small, in order to test whether the amount of task data affects the migration result when the source training data is migrated based on the maximum mean difference contribution coefficient method, auxiliary sample data is introduced and set are 10 auxiliary sample batches, and the data of August 22, August (22-23), August (22-24),…, August (22-31) are taken as 10 sample data, the number of samples is 96,192,…, 960 in sequence. Then take the data under different auxiliary samples as the target data, migrate data close to the target data distribution from the source data, calculate the MMD value of each auxiliary sample, the source data, and the migrated data respectively, and use the migration data of each auxiliary sample The TDBN-DNN model obtained after fine-tuning the network calculates the target task data, and the Gaussian kernel width control parameter $\sigma = 2$.

Figure 10 shows the samples migrated from the source training data under different auxiliary samples. The result is that the number of migrated data for each auxiliary sample differs very little, all around 1023 samples.

Figure 11 shows the MMD value of each auxiliary sample and the data before and after the migration. When the number of auxiliary samples is small, the MMD value of the source data is relatively large. When the number of the first auxiliary sample is 96, the maximum mean difference MMD is 0.0912, because the smaller the number of auxiliary samples, the more local the information represented, and the greater the difference with the source data. When the number

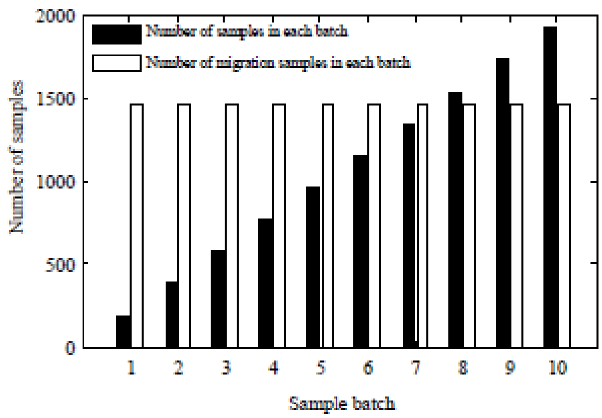

FIGURE 10. Comparison of the number of samples versus sample batch.

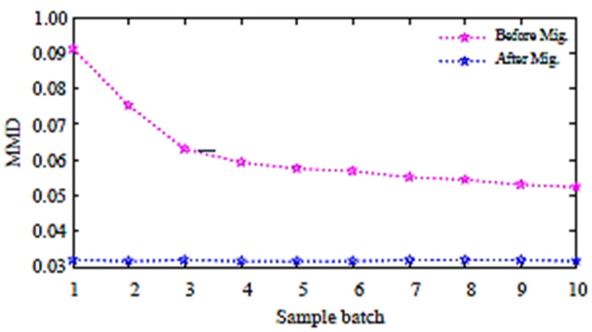

FIGURE 11. Comparison of the MMD versus sample batch.

of auxiliary samples is 384, the MMD value is 0.0592. When the number of auxiliary samples increases, the MMD value decreases slowly. When the number of auxiliary samples is 960, the MMD value is 0.0523. The MMD value of each auxiliary sample data and the migrated data is basically reduced, which is 0.03 lower than before the migration on average. After fine-tuning the DBN-DNN network for the migration data of each auxiliary sample, the average accuracy of TDBN-DNN's calculation of the target task data is shown in Table 1.

The average calculation accuracy of the migrated TDBN-DNN model of the 10 auxiliary samples in Table 1 is about 95%, and the average value is 95.48%, which is 6.12% higher than the DBN-DNN network calculation result on average. This shows that the number of auxiliary samples basically does not affect the migration results. The number of auxiliary samples is different, but the number of samples migrated is basically the same, and the calculation accuracy after each batch of fine-tuning networks is basically the same. In addition, although the auxiliary data MMD value of TDBN is only 0.03 lower than that before the migration, but the calculation accuracy of TDBN-DNN is significantly improved compared with DBN-DNN.

In this example, the calculation result of TDBN-DNN obtained by fine-tuning the DBN-DNN network is shown in Figure 12 after the data migration of the task to be calculated for migration learning.

TABLE 1. Comparison of the calculation accuracy of tdbn-dnn versus sample batch.

Auxiliary sample batch	M_A(%)	M_{APE}(%)
1	95.29	4.71
2	96.17	3.83
3	94.85	5.15
4	95.64	4.36
5	96.10	3.90
6	95.77	4.23
7	94.81	5.19
8	95.55	4.45
9	94.63	5.37
10	95.56	4.44

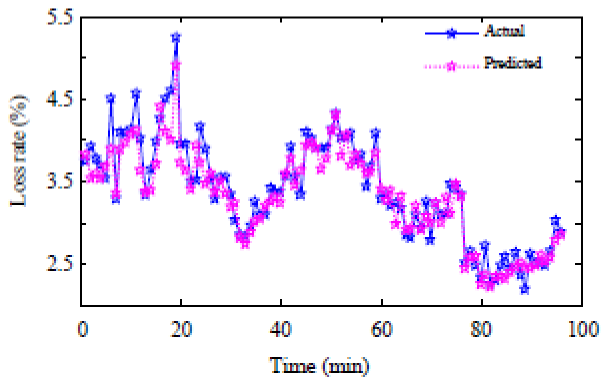

FIGURE 12. Comparison of the power loss rate of the deep migration learning.

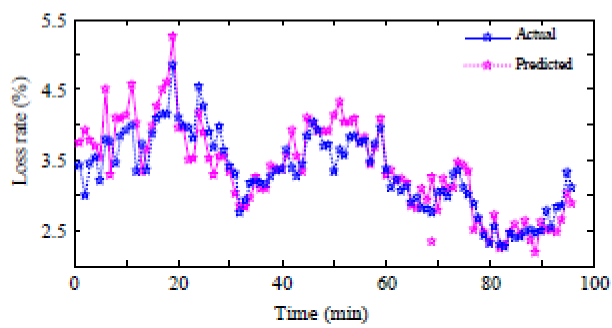

FIGURE 13. Comparison of the power loss rate of the T-BP.

It can be seen from Figure 13 that the calculation accuracy of the BP neural network obtained by training the BP neural network after the migration is 90.15%, which is significantly higher than the calculation accuracy of the BP neural network before the migration is 84.41%, which verifies the role of the migration calculation this time. The accuracy and time of the four calculation models involved in the calculation example are depicted in Table 2.

TABLE 2. Comparison of the calculation accuracy of the proposed and existing algorithms.

Parameter	T-BP	BP	DBN-DNN	TDBN-DNN
$M_{APE}(\%)$	14.85	15.59	10.64	4.70
$M_A(\%)$	90.15	84.41	89.36	95.30
Time (s)	3.42	3.12	5.88	6.09

The calculation effect of TDBN-DNN is better than that of DBN-DNN network, and the calculation accuracy is increased by 5.49%. The calculation effect of T-BP is better than BP neural network, and the calculation accuracy is increased by 5.74%, which shows that in the case of wind power photovoltaic power supply, Migration learning improves the calculation performance of BP neural network and deep learning model by migrating data from the source data that is closer to the distribution of the data to be calculated. In addition, the calculation time of the four models is counted. The structure of the deep model is better than that of the shallow layer. The structure is more complex, and the calculation time is about 2s longer. However, because the model eliminates the complicated power flow iteration process, it has a great time advantage compared with the original power flow calculation time of 91s, which verifies the validity of the model. Under the construction of modern smart grids, with the rapid development of the Internet of Things in the power system, the use of artificial intelligence platforms can meet real-time requirements while meeting a certain accuracy, and quickly complete the calculation of the network loss rate, which has important exploratory research significance.

E. TOLERANCE ANALYSIS OF TDBN-DNN

In view of the lack of data in traditional power flow calculations, the incomplete collection or the inability to calculate when the data is collected incorrectly, the simulation verifies the calculation performance of the deep transfer learning TDBN-DNN model when the data is missing, and tests its fault tolerance effect.

The TDBN-DNN deep transfer learning model is a complex non-linear fitting model that simulates input data and output data. For data that meets the input dimension, fitting calculations can be performed, and the results are output. In order to verify the deep transfer TDBN-DNN learning model calculation effect of missing data. According to the above research example, samples with different missing numbers are designed. The input data of the above-mentioned simulated area power grid is 146 dimensions, 96 section data points a day, and the set of missing data sample input is missing 1, 2, …, 7 dimensions, the amount of missing data corresponding to one day is 96, 192, …, 672, and the percentage of missing data is 0.07%, 0.14%, …, 4.79%. The calculation results of each missing sample are shown in Table 3.

TABLE 3. Comparison of the calculation with missing data.

Parameter	DBN-DNN	TDBN-DNN		
Missing dimension	$M_{APE}(\%)$	$M_A(\%)$	Missing percentage	Missing amount
1	4.56	95.44	0.68	961
2	4.98	95.02	1.37	192
3	5.13	94.87	2.01	288
4	6.25	93.75	2.74	384
5	6.89	93.11	3.42	480
6	928	90.72	4.10	576
7	13.33	86.67	4.79	672

It can be seen from Table 3 that in the case of missing data, the deep migration TDBN-DNN learning model can still be calculated, which has certain data fault tolerance, and the percentage of data missing is within 3.42%. In this example, the section data is missing 5 when 480 data are missing throughout the day, the calculation results still have high accuracy. When the percentage of missing data reaches 4.1%, the accuracy of the calculation begins to decrease significantly. When the percentage of missing data reaches 4.79%, the accuracy is 86.67% which is far from the computing performance of TDBN-DNN.

V. CONCLUSION

This paper proposes a calculation model based on TDBN-DNN to determine the grid loss rate of the wind-PV power system. The simulation experiment is carried out with a power grid in northern Pakistan as an example. The results show that:

1) The DBN-DNN deep learning calculation method has higher calculation accuracy than the traditional shallow structure BP neural network calculation method. In this paper, the calculation accuracy of the DBN-DNN model is 4.95% higher than that of the BP neural network, which shows that the DBN-DNN model has more advantages in processing high-dimensional input data of the power system.

2) After transfer learning, the TDBN-DNN deep transfer learning model has improved calculation accuracy and speed. The MMD value of the data migrated from the source data and the data to be calculated is lower than before the migration. The calculation accuracy of the TDBN-DNN model is 5.49% higher than that of the DBN-DNN model, and the calculation speed is greatly improved, which verifies the model's performance Effectiveness.

3) The deep transfer learning TDBN-DNN calculation model has certain data fault tolerance under the premise of meeting high accuracy. When data is missing, the model can still perform calculations.

In this paper, deep learning, migration learning and the calculation of the grid loss rate of the actual regional power grid containing wind power and photovoltaic power in the power system are combined to verify the practicability and feasibility of the proposed model. The simulation results show the effectiveness of our proposed model which provides an effective solution to overcome the power rate loss issue in the hybrid wind-PV power generation system.

As a future work, we are going to implement and test the proposed model in a distributed power generation system and to perform the analysis and evaluation of the results.

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REFERENCES

[1] S. Shamshirband, T. Rabczuk, and K.-W. Chau, "A survey of deep learning techniques: Application in wind and solar energy resources," *IEEE Access*, vol. 7, pp. 164650–164666, 2019.
[2] K. Y. Yap, C. R. Sarimuthu, and J. M.-Y. Lim, "Grid integration of solar photovoltaic system using machine learning-based virtual inertia synthetization in synchronverter," *IEEE Access*, vol. 8, pp. 49961–49976, 2020.
[3] M. H. Mostafa, S. H. E. A. Aleem, S. G. Ali, A. Y. Abdelaziz, P. F. Ribeiro, and Z. M. Ali, "Robust energy management and economic analysis of microgrids considering different battery characteristics," *IEEE Access*, vol. 8, pp. 54751–54775, 2020.
[4] A. I. Omar, S. H. E. A. Aleem, E. E. A. El-Zahab, M. Algablawy, and Z. M. Ali, "An improved approach for robust control of dynamic voltage restorer and power quality enhancement using grasshopper optimization algorithm," *ISA Trans.*, vol. 95, pp. 110–129, Dec. 2019.
[5] H. M. Sultan, A. A. Z. Diab, O. N. Kuznetsov, Z. M. Ali, and O. Abdalla, "Evaluation of the impact of high penetration levels of PV power plants on the capacity, frequency and voltage stability of Egypt's unified grid," *Energies*, vol. 12, no. 3, pp. 1–22, 2019.
[6] S. Al-Dahidi, M. Louzazni, and N. Omran, "A local training strategy-based artificial neural network for predicting the power production of solar photovoltaic systems," *IEEE Access*, vol. 8, pp. 150262–150281, 2020.
[7] C.-J. Huang and P.-H. Kuo, "Multiple-input deep convolutional neural network model for short-term photovoltaic power forecasting," *IEEE Access*, vol. 7, pp. 74822–74834, 2019.
[8] M. N. Akhter, S. Mekhilef, H. Mokhlis, and N. M. Shah, "Review on forecasting of photovoltaic power generation based on machine learning and Metaheuristic techniques," *IET Renew. Power Gener.*, vol. 13, no. 7, pp. 1009–1023, May 2019.
[9] Y. Yan, Y. Qian, H. Sharif, and D. Tipper, "A survey on smart grid communication infrastructures: Motivations, requirements and challenges," *IEEE Commun. Surveys Tuts.*, vol. 15, no. 1, pp. 5–20, 1st Quart., 2013.
[10] F. R. Badal, P. Das, S. K. Sarker, and S. K. Das, "A survey on control issues in renewable energy integration and microgrid," *Protection Control Modern Power Syst.*, vol. 4, no. 1, pp. 1–47, Dec. 2019.
[11] S. Impram, S. V. Nese, and B. Oral, "Challenges of renewable energy penetration on power system flexibility," *Energy Strategy Rev.*, vol. 31, pp. 1–12, Sep. 2020.
[12] Q. Alsafasfeh, O. A. Saraereh, I. Khan, and B. J. Choi, "A robust decentralized power flow optimization for dynamic PV system," *IEEE Access*, vol. 7, pp. 63789–63800, 2019.
[13] Q. Alsafasfeh, O. A. Saraereh, I. Khan, and S. Kim, "Solar PV grid power flow analysis," *Sustainability*, vol. 11, no. 6, pp. 1–25, 2019.
[14] Q. Alsafasfeh, O. Saraereh, I. Khan, and S. Kim, "LS-solar-PV system impact on line protection," *Electronics*, vol. 8, no. 2, p. 226, Feb. 2019.
[15] S. Wang, H. Chen, B. Pu, H. Zhang, S. Jin, and X. Liu, "Analysis of network loss energy measurement based on machine learning," in *Proc. IEEE Int. Conf. Inf. Autom. (ICIA)*, Wuyishan, China, Aug. 2018, pp. 1113–1117.
[16] R. Sharifi, S. H. Fathi, and V. Vahidinasab, "Customer baseline load models for residential sector in a smart-grid environment," *Energy Rep.*, vol. 2, pp. 74–81, Nov. 2016.
[17] V. L. Brano, G. Ciulla, and M. Di Falco, "Artificial neural networks to predict the power output of a PV panel," *Int. J. Photoenergy*, vol. 193083, pp. 1–12, Jan. 2014.
[18] M. Yao, Y. Zhu, J. Li, H. Wei, and P. He, "Research on predicting line loss rate in low voltage distribution network based on gradient boosting decision tree," *Energies*, vol. 12, no. 13, p. 2522, Jun. 2019.
[19] J. Schmidhuber, "Deep learning in neural networks: An overview," *Neural Netw.*, vol. 61, pp. 85–117, Jan. 2015.
[20] T. Hori, C. Hori, Y. Minami, and A. Nakamura, "Efficient WFST-based one-pass decoding with on-the-fly hypothesis rescoring in extremely large vocabulary continuous speech recognition," *IEEE Trans. Audio, Speech Lang. Process.*, vol. 15, no. 4, pp. 1352–1365, May 2007.
[21] T. Li, V. K. Narayana, and T. E. Ghazawi, "Exploring graphics processing unit (GPU) resource sharing efficiency for high performance computing," *Comput.*, vol. 2, no. 4, pp. 1–39, 2013.
[22] B. Chen, P. Lin, Y. Lai, S. Cheng, Z. Chen, and L. Wu, "Very-short-term power prediction for PV power plants using a simple and effective RCC-LSTM model based on short term multivariate historical datasets," *Electronics*, vol. 9, no. 2, pp. 1–19 2020.
[23] Y. Jin, H. Guo, J. Wang, and A. Song, "A hybrid system based on LSTM for short-term power load forecasting," *Energies*, vol. 13, no. 23, pp. 1–32, 2020.
[24] R. Zhang, J. Wu, M. Shao, B. Li, and Y. Lu, "Transient stability prediction of power systems based on deep belief networks," in *Proc. 2nd IEEE Conf. Energy Internet Energy Syst. Integr. (EI)*, Beijing, China, Oct. 2018, pp. 1–6.
[25] M. Sajjad, Z. A. Khan, A. Ullah, T. Hussain, W. Ullah, M. Y. Lee, and S. W. Baik, "A novel CNN-GRU-based hybrid approach for short-term residential load forecasting," *IEEE Access*, vol. 8, pp. 143759–143768, 2020.
[26] R. Wadawadagi and V. Pagi, "Sentiment analysis with deep neural networks: Comparative study and performance assessment," *Artif. Intell. Rev.*, vol. 53, no. 8, pp. 6155–6195, Dec. 2020.
[27] M. Z. Khan, S. Harous, S. U. Hassan, M. U. G. Khan, R. Iqbal, and S. Mumtaz, "Deep unified model for face recognition based on convolution neural network and edge computing," *IEEE Access*, vol. 7, pp. 72622–72633, 2019.
[28] H.-B. Wang, Y. Xue, X. Zhen, and X. Tu, "Domain specific learning for sentiment classification and activity recognition," *IEEE Access*, vol. 6, pp. 53611–53619, 2018.
[29] G. Wang, J. Qiao, J. Bi, Q.-S. Jia, and M. Zhou, "An adaptive deep belief network with sparse restricted Boltzmann machines," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 31, no. 10, pp. 4217–4228, Oct. 2020.
[30] G. E. Hinton, "Training products of experts by minimizing contrastive divergence," *Neural Comput.*, vol. 14, no. 8, pp. 1771–1800, Aug. 2002.
[31] L. Li and M. Cai, "Cross-species data classification by domain adaptation via discriminative heterogeneous maximum mean discrepancy," *IEEE/ACM Trans. Comput. Biol. Bioinf.*, early access, Apr. 30, 2019, doi: 10.1109/TCBB.2019.2914103.
[32] S. Mehrkanoon and J. A. K. Suykens, "Regularized semipaired kernel CCA for domain adaptation," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 29, no. 7, pp. 3199–3213, Jul. 2018.
[33] Y. Liu, Y. Xu, J. Yang, and S. Jiang, "A polarized random Fourier feature kernel least-mean-square algorithm," *IEEE Access*, vol. 7, pp. 50833–50838, 2019.
[34] Y. Lu, L. Wang, J. Lu, J. Yang, and C. Shen, "Multiple kernel clustering based on centered kernel alignment," *Pattern Recognit.*, vol. 47, no. 11, pp. 3656–3664, Nov. 2014.

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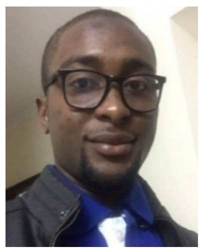

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