Deep Learning in Power Systems Research: A Review

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***Abstract*—With the rapid growth of power systems measurements in terms of size and complexity, discovering statistical patterns for a large variety of real-world applications such as renewable energy prediction, demand response, energy disaggregation, and state estimation is considered a crucial challenge. In recent years, deep learning has emerged as a novel class of machine learning algorithms that represents power systems data via a large hypothesis space that leads to the state-of-the-art performance compared to most recent data-driven algorithms. This study explores the theoretical advantages of deep representation learning in power systems research. We review deep learning methodologies presented and applied in a wide range of supervised, unsupervised, and semi-supervised applications as well as reinforcement learning tasks. We discuss various settings of problems solved by discriminative deep models including stacked autoencoders and convolutional neural networks as well as generative deep architectures such as deep belief networks and variational autoencoders. The theoretical and experimental analysis of deep neural networks in this study motivates long-term research on optimizing this cutting-edge class of models to achieve significant improvements in the future power systems research.**

***Index Terms*—Autoencoder, convolution neural network, deep learning, discriminative model, deep belief network, generative architecture, variational inference.**

I. Introduction

THE reliability and accuracy of data-driven models in power systems operation and analysis closely rely on the selection of data representation (i.e., features extracted from the underlying data) [1]. As a result, most of the concerns regarding the application of classic data-driven models in power systems is focused on the design of preprocessing techniques using unsupervised dimensionality reduction algorithms including the principal component analysis (PCA) [2], linear discriminant analysis (LDA) [3], and t-distributed stochastic neighbor embedding (t-SNE) [4]. Such feature extraction techniques dramatically increase the time and memory complexity of data-driven algorithms and lead to insufficient accuracy as they mainly cannot capture highly nonlinear and highly varying patterns inside the ambient space of the data [1].

Recent machine learning studies on wind forecasting [5]–[8], photovoltaic (PV) power prediction [9]–[12], state estimation [13], [14], power grid synthesis [15], and energy disaggregation [16]–[18] show that developing data-driven models with less dependencies on explicit preprocessing methods (e.g., PCA) leads to dramatically better performance in terms of classification and regression accuracy. Instead of having an explicit preprocessing approach, the deep learning studies form a composition of multiple nonlinear latent layers in a multi-layer artificial neural network (ANN). The ANN parameters (i.e., weights and biases) are generally trained in a greedy unsupervised layer-by-layer fashion [19], where each layer performs a nonlinear feature extraction on the features computed by its previous layer.

Based on the theoretical aspects, deep learning algorithms proposed in power engineering applications are generally categorized into three major classes:

1) Discriminative deep ANNs aim to directly learn a highly nonlinear decision boundary between different classes and regression regions of the power system data [20]–[22]. In this category, the rectified linear unit (ReLU) ANN is presented for real-time reliability management response [23], online small signal stability assessment [24], and faulted line localization [25]. Moreover, the stacked autoencoder (SAE) is developed as a highly nonlinear version of the PCA for unsupervised pattern recognition for wind energy prediction [7], [26], PV power forecasting [27], and fault diagnosis [28]. In addition, the long short-term memory (LSTM) ANN is presented as a supervised temporal feature extractor with a deep recurrent formulation to model the sequential behavior of the time-dependent power systems measurements [17], [29]. Convolutional neural network (CNN) is another major class of discriminative models that captures coherent structures in power system measurements using convolutional and pooling operations [30]. The mixture of these operations incorporates the spatial charactristics of measurements into their temporal features to solve spatiotemporal tasks in the area of renewable energy forecasting [9], transient stability analysis [31], and fault detection [32].

2) Probabilistic deep ANNs consider feature learning as a procedure to find a parsimonious set of hidden variables that

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best describe the probability density function (PDF) of the data. The PDF is further mapped to the target class/value of the problem. Deep belief network (DBN) is a well-known probabilistic graphical model that learns the PDF of the data given its conditionally independent latent features. The features are learned by Gibbs sampling in order to provide an accurate estimation of the probabilistic behavior of the input data for probabilistic applications that need to address large uncertainty factors in the data. DBN is mainly applied to wind and solar power prediction [33], [34], transient stability assessment [35], day-ahead and week-ahead load prediction [36], as well as probabilistic state estimation [37]. Moreover, the Generative Adversarial Network (GAN) is presented that compares its generated data samples with the actual dataset to increase the accuracy of its learned PDF. As this model efficiently learns the major characteristics of the PDF, it is recently introduced to important outlier and fault detection problems for small-sample wind turbines [38] and smart grid cyber attack detection [39]. Furthermore, GANs are recently employed for model-free renewable scenario generation [40]. The variational autoencoders (VAEs) are presented as a novel version of deep generative ANNs that learn the PDF of the data by learning a high dimensional latent variable which is mapped to the original data samples. VAE is shown to create accurate data samples used for power grid synthesis [15], unsupervised anomaly detection in energy time series [41], [42], and electric vehicle load generation [43].

3) Deep Reinforcement Learning (DRL) algorithms are a major class of machine learning approaches that seek to learn an optimal policy based on the feedback from the environment computed by a reward function. This function reflects how much the problem's objective is satisfied based on the current state of the system. In contrast to the conventional deep learning that merely estimates a discrete target function for classification and continuous target function for regression, DRL aims to decline a general error function defined by the experience in a fully observable or partially observable environment. Hence, this method solves more general classes of problems compared to the classic deep learning. Due to its feedback-based nature, DRL is widely employed for control problems including voltage control [44], adaptive emergency control [45], as well as self-learning control for energy efficient transportation [46]. Also, DRL is applied to optimization problems for learning the optimal bidding strategies in electricity markets [47], [48], demand response strategies for energy management [49]–[51], as well as finding the optimal wind and storage cooperative schedule to decrease the effect of the uncertainty in renewable generation in smart grids [52]. Moreover, this class of methodologies are recently introduced to cyber attack detection and recovery [53], dynamic power allocation [54], and power system data integrity defense [55].

This paper reviews the three major categories of deep neural networks in the domain of power systems research. First, the deep discriminative approach is introduced in Section II. Various variations of this class of models are explained, and compared both mathematically and experimentally using several real-world power system datasets. Section III introduces probabilistic deep learning methods such as DBN and its Gaussian variation as well as the recently proposed GANs and VAEs. The applications and theoretical advantages of these techniques are discussed in this section. Then, in Section IV, the paper reviews DRL algorithms and their vast area of applications in power systems optimization and control. Finally, the conclusions are provided in Section V.

II. Discriminative Deep Learning

Discriminative modeling is one of the major areas in machine learning that tends to estimate a function f_θ parameterized by $\theta \in \mathbb{R}^p$ that directly maps an input to the true output of the problem. Let us consider a training dataset $D_{\text{tr}} = \{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$ that contains n training samples (x_i, y_i) with input x_i corresponding to the true output/label y_i, and a test dataset $D_{\text{ts}} = \{(x_{n+1}, y_{n+1}), (x_{n+2}, y_{n+2}), \ldots, (x_{n+m}, y_{n+m})\}$ with m unobserved test samples. The goal is to learn the optimal parameter θ^* where the average distance between $f_{\theta^*}(x)$ and y is the lowest for all samples $(x, y) \in D_{\text{tr}}$. The test error is the average error between the trained $f_{\theta^*}(x)$ and y for all $(x, y) \in D_{\text{ts}}$.

To obtain a nonlinear mapping between the inputs and outputs, the classic multilayer perceptron (MLP) defines an input layer $h^0 \in \mathbb{R}^{d_0}$ and L computational layers $\{h^1, h^2, \ldots, h^L\}$ where each layer $h^i \in \mathbb{R}^{d_i}$ $(i \in [1, L])$ is a nonlinear function of previous layer defined by $h^i = g^i(\boldsymbol{W}^i h^{i-1} + b^i)$ where g^i is a nonlinear transformation function usually computed by a sigmoid or hyperbolic tangent function, $\boldsymbol{W}^i \in \mathbb{R}^{d_i} \times \mathbb{R}^{d_{i-1}}$ is the weight matrix and $b^i \in \mathbb{R}^{d_i}$ is the bias of the activation function in layer h^i. Using the hidden layers, the MLP provides a nonlinear transformation between the input $h^0 = x$ and output $h^L = y$ in the dataset.

To train each layer h^i, the gradient descent (GD) method moves parameters $\boldsymbol{W}^i$ and b^i in the opposite direction of the gradient of the training error with respect to $\boldsymbol{W}^i$ and b^i, respectively. As the gradients dramatically decline with the increase in L, there is a trade-off between the number of computational layers L and the strength of GD to update the model. As L becomes larger to address more complex problems, GD becomes ineffective due to the vanishing gradients. Hence, the classic MLP does not provide sufficient generalization capability to accurately solve complex real-world problems. As a result, discriminative deep learning is proposed to efficiently train deep ANNs with $L > 1$ in order to have a high capacity mapping f_θ while providing an effective training procedure to update the parameters.

A. Rectified Linear Unit ANN

ReLU ANN defines a rectified linear unit activation function $ReLU(x) = \max(0, x)$ at the computational layers of MLP rather than using the classic nonlinear activation functions. Since the gradient of $ReLU(x)$ with respect to a positive input x is always 1 regardless of x, this function solves the vanishing gradient problem of the MLP. Hence, this model is applied to power systems applications that require highly nonlinear feature extraction.

Table I summarizes the applications of discriminative modeling in the power systems area. As shown in this table, a

TABLE I
DISCRIMINATIVE DEEP LEARNING IN POWER SYSTEMS APPLICATIONS

Applications	Dataset	Model	Performance Metric	Result
Reliability Management Response [23]	IEEE-RTS96	ReLU	Coefficient of determination (R^2 Score)	0.964
		SAE		0.951
Stability Assessment [24], [56], [30], [31], [57]	IEEE 39-bus	ReLU	Classification Accuracy	94.1%
		SAE		92.6%
		CNN		97.8%
Fault Detection [24], [28], [58], [32]	IEEE 39-bus	ReLU	Detection Accuracy, Location Accuracy Rate	93.20%, 91.12%
		SAE		94.18%, 91.71%
		CNN		96.09%, 94.31%
PMU Event Classification [59]	16-machine 68-bus Test System	ReLU	Classification Accuracy	94.11%
		SAE		95.07%
		LSTM		96.34%
		CNN		98.17%
Hourly Wind Power Prediction [7], [26], [29], [60]	Western Wind Dataset	ReLU	RMSE, MAPE	1,38%, 1.74%
		SAE		1.24%, 1.68%
		LSTM		1.13%, 1.53%
		CNN		1.07%, 1.26%
Hourly PV Power Prediction [9], [27], [29]	National Solar Radiation Database	ReLU	RMSE, MAPE	1.29%, 1.54%
		SAE		1.09%, 1.37%
		LSTM		0.97%, 1.10%
		CNN		0.85%, 0.92%
Load Modeling [61]	16-machine 68-bus Test System	ReLU	RMSE, MAPE	0.0435, 0.0120
		LSTM		0.008, 0.0071
Hourly Load Forecasting [62]	Industrial Power Demand Dataset	ReLU	Normalized RMSE	0.069
		SAE		0.051
		LSTM		0.032
Power Fluctuation Identification [63]	Market Trading Reports	ReLU	MAE, MAPE	0.042, 107.91%
		LSTM		0.038, 105.72%
Energy Disaggregation [16], [17]	Reference Energy Disaggregation Dataset	SAE	Precision, Recall, F-score	84.63%, 61.04%, 70.62%
		LSTM		89.83%, 65.72%, 75.93%

ReLU ANN is implemented in [23] to estimate the cost of real-time resource allocations decisions in operation planning of the modified IEEE-RTS96 single area network [64]. Also, in [24], various ReLU ANN architectures are trained to learn the small signal stability assessment of the classic 16-machine 68-bus test system [65]. As shown in [24], when the number of layers increases from 2 to 6, the assessment accuracy is significantly increased since the ReLU ANN's hypothesis space becomes larger. In addition, the ReLU ANN is applied to real-time faulted line localization in IEEE 39-bus and 68-bus power systems which resulted in 98% and 93% location accuracy rate for line-to-ground and double line-to-ground faults, respectively. Furthermore, in [59], ReLU ANNs are shown to yield 98.17% accuracy for the classification of 6 events including generation loss, load loss, as well as line-to-ground faults in the IEEE 68-bus system.

B. Stacked Autoencoder

To train a deep ANN with input h^0 and L computational layers h^i $(i = 1, 2, \ldots, L)$, the SAE trains L AEs $\{AE^i\}_{i=1}^{L}$. Each AE^i is a MLP ANN with one hidden layer with an encoding activation function f_{enc} where a high-dimensional input $h^{i-1} \in R^{d_{i-1}}$ is encoded into a lower dimensional latent feature vector $h^i = f_{\text{enc}}(h^{i-1}) \in R^{d_i}$ which is further mapped back (decoded) to the original input h^{i-1} in the output layer $o^i = f_{\text{dec}}(h^i)$ using the decoding function f_{dec}. Hence, the GD error of AE^i is computed by $\|o^i - h^{i-1}\|_2^2$ to train the weight W_{enc}^i and bias b_{enc}^i of its encoding layer as well as the weight W_{dec}^i and bias b_{dec}^i of its decoder. To update the parameters of the SAE, starting from $i = 1$, each AE^i is trained and the trained encoder parameters W_{enc}^i and b_{enc}^i are used to initialize W^i and b^i of the layer i, respectively. Finally, the whole SAE ANN is trained using GD on the training data D_{tr}.

Due to the unsupervised feature learning at each AE, the SAE model is suitable for situations where the training data is limited or contains remarkable uncertainty and noise factors. Hence, this method respectively outperforms the MLP, nonlinear autoregressive exogenous (NARX) ANN, and time delay ANN (TDANN) by 23.66%, 21.54%, and 14.81% in terms of the mean absolute percentage error (MAPE) for short-term wind speed prediction [7], [26]. Moreover, as shown in Table I, the SAE outperforms ReLU in both classification tasks (e.g., stability assessment [24] and PMU event classification [59]) as well as regression tasks with large data variations (e.g., wind and PV power prediction [26], [27] and load forecasting [62]). Furthermore, due to its powerful greedy layer-wise training process, the SAE yields an average transformer fault diagnosis accuracy of 95.4% in the IEC 60599 and IEC TC 10 databases [66]. In addition, SAE improves the transient stability analysis accuracy of extreme learning machines (ELMs) by 6.59% in the IEEE 39-bus system [56].

C. Long Short-term Memory Network

LSTM is a widely used deep recurrent ANN that extracts powerful temporal features from a time series $x_1, x_2, \ldots, x_T$. At each time step, $0 \leqslant t \leqslant T$, LSTM observes a sample x_t and updates its temporal memory C^t that describes the state of the time series at t, and produces a temporal feature vector h^t that summarizes LSTM's temporal information after the observation x_t. The recursive structure of LSTM features is defined by:

$$\begin{cases} i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \\ f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f) \\ o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o) \\ \tilde{C}_t = tanh(W_C.[h_{t-1}, x_t] + b_C) \\ C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \\ h_t = o_t * tanh(C_t) \end{cases} \tag{1}$$

where i_t is the input gate that decides the magnitude of information flow into the time-dependent memory C_t using the sigmoid activation σ with weight W_i and bias b_i. f_t is the forget gate that determines how much information needs to be removed from C_t using weight W_f and bias b_f. o_t is the LSTM's output at time t using weight W_o and bias b_o while h_t is the extracted tempoal feature at time t. At each time step t, the memory is updated by $\tilde{C}_t$ as a nonlinear function parameterized by W_C and b_C.

In contrast to the classic recurrent MLPs, the LSTM does not encounter the vanishing gradient problem; hence, can be efficiently trained using GD. As a result, as shown in Table I, this method is applied to a large variety of time-dependent applications such as wind, PV, and load prediction [26], [27], [36] as well as load modeling [61] and power fluctuation identification [63]. As Table I shows, the LSTM generally outperforms both ReLU and SAE in the domain of time-dependent applications due to its recurrent structure and powerful temporal memory. In [29], a novel attention mechanism-based LSTM is developed to improve the hourly solar energy prediction of MLP by 6.17% and 0.27 in terms of MAPE and root mean squared error (RMSE), respectively. Also, the LSTMs in [67] and [60] have shown the state-of-the-art performance in wind prediction tasks. Moreover, in [61], a LSTM is defined in a multimodal neural architecture to simultaneously capture the temporal characteristics of dynamic load parameters as well as the voltage and power changes in the IEEE 68-bus test system [65]. It is shown that the LSTM captures real-time dynamic behaviors of load parameters with 38.42% and 25.64% better RMSE and MAPE, respectively, compared to the TDNN method due to its larger hypothesis space and overcoming the overfitting problem. Similar accuracy improvements are recently reported in other time-dependent applications including power fluctuation identification [63], data-based line trip fault prediction [58], and industrial load forecasting [62].

D. Convolutional Neural Network

CNNs contain a two dimensional input layer I, a set of hidden convolution and pooling layers, and a fully connected output layer. Each neuron in the convolution layer is a nonlinear kernel that divides the input into small slices called receptive fields. The output of convolution operation at the k-th kernel in the l-th convolution layer is computed by:

$$f_l^k(p, q) = \sum_c \sum_{x,y} i_c(x, y).e_l^k(u, v) \tag{2}$$

where $i_c(x, y)$ is the (x, y) element of the c-th channel of input I, and $e_l^k(u, v)$ is the (u, v) element of the k-th kernel of layer l. The pooling layer sweeps an average or maximum function over small patches of the convolution output in (2) to further reduce the dimension of the extracted features which enhances the sparsity of the kernel parameters and avoids overfitting on the training set. Finally, the fully connected layer maps the extracted features to the target label of the underlying classification or regression task.

As the convolution and pooling layers process their local input patches simultaneously, the CNN yields the state-of-the-art performance in tasks where the local spatial and temporal correlations of the data play a crucial role. Therefore, this model outperforms ReLU ANNs as well as SAE and LSTM in applications where the data has a strong spatiotemporal structure such as the wind and PV power prediction [26], [27] as well as PMU event classification [59]. In [9], this model is applied to 6-hr ahead spatiotemporal solar irradiance prediction which obtains 21.62% and 16.78% better RMSE and MAPE, respectively, compared to the LSTM due to modeling the correlation between the radiation at neighboring solar sites by the convolution operation in (2). In addition, in [31], CNN is applied to the transient stability assessment of the IEEE 39-bus system. In a short period of time after a disturbance, the bus voltage phasors sampled from PMUs from various points of the system are given to the CNN to judge if the system is stable, aperiodic unstable or oscillatory unstable. CNN's classification accuracy is 98.7% while recent variations of support vector machines and decision trees lead to 95.2% and 92.1% accuracies. Furthermore, CNN is shown to yield promising results in fault diagnosis [32], harmonic power grid analysis [30], and voltage stability assessment [57].

Besides the kernel-based CNN in (2), recent studies proposed spectral graph convolutions to capture spatial patterns of the graph-structured power system datasets [15]. Given an N-node graph with D-dimensional features $X \in \mathbb{R}^{N \times D}$, adjacency matrix $\boldsymbol{A}$, and degree matrix $\boldsymbol{D}$, the convolution operation of the graph CNN is computed by:

$$f(X, \boldsymbol{A}) = \sigma(\boldsymbol{D}^{-1/2} A D^{-1/2} X \boldsymbol{W}) \tag{3}$$

where $\boldsymbol{W}$ is the trainable convolution weight matrix. The graph CNN is recently employed for short-term wind speed prediction [68] in Northern US. Due to capturing spatial characteristics of the wind data, this model provides 11.61% and 17.98% better RMSE and MAPE compared to the DBN, respectively. Moreover, this model yields 20.04% better reliability for probabilistic solar energy prediction compared to the LSTM [9].

E. Advantages and Restrictions of Deep Discriminative Modeling

Table II summarizes the advantages and restrictions of various deep discriminative models in power engineering research. As shown in this table, the ReLU ANN has a simple implementation with low training time complexity and fast feed-forward approach. However, this supervised model does not explicitly model the time-dependent or spatial features in the datasets. Similar to the ReLU ANN, the SAE cannot directly capture the spatial and temporal patterns. However, SAE is an unsupervised feature learner which is more suitable

TABLE II
ADVANTAGES AND RESTRICTIONS OF DEEP DISCRIMINATIVE MODELS

Models	Advantages	Restrictions
ReLU	1- Simple implementation 2- Fast feed-forward process 3- Low training time complexity	1- Lack of temporal and spatial feature extraction 2- Lack of the feature coherence 3- Limited to supervised applications
SAE	1- Simple Implementation 2- Fast feed-forward process 3- Unsupervised feature extraction	1- Large estimation bias 2- Lack of temporal and spatial feature extraction 3- Lack of feature coherence 4- High chance of overfitting
LSTM	1- Extracting accurate temporal features 2- Flexible input dimensions	1- High chance of overfitting 2- Lack of spatial data modeling 3- High sensitivity to the initial state 4- Limited to supervised applications
CNN	1- Accurate spatial feature extraction 2- Sparse data representation 3- Simple training process using gradient descent 4- Distributed implementation	1- Lack of temporal data modeling 2- High training time complexity 3- High training memory complexity 4- Limited to supervised applications

for applications with limited number of training samples such as cyber attack detection. In addition, SAE is suitable for problems with large amounts of uncertain data points including wind speed prediction, solar energy forecasting, and dynamic load modeling.

Due to its recurrent structure, the LSTM can model temporal dependencies between time-dependent observations and work with variable input lengths. However, since the number of LSTM parameters is generally larger than classic recurrent ANNs, this supervised model has a higher chance of overfitting and high sensitivity to the observation noise.

Using filtering and pooling layers, the CNN is able to provide powerful sparse representations from spatial datasets using simple gradient-based techniques. As the filters can be trained in a distributed manner, the CNN is a very efficient method for pattern recognition in large-scale systems. However, since this supervised model does not contain a recursive structure, it cannot accurately capture time-dependent structures of the data.

III. PROBABILISTIC DEEP LEARNING

In contrast to discriminative deep learning where an explicit function maps x to y where $(x, y) \in D_{\text{tr}}$, the objective of probabilistic deep neural architectures [69] is to capture the PDF $P(x)$ for all samples in the dataset D_{tr}. Then, an explicit function is learned to map $P(x)$ to $P(y|x)$, hence learning the true output y for all samples $(x, y) \in D_{\text{tr}}$.

A. Deep Belief Network

The DBN is a deep MLP with input h^0 and L computational layers h^i $(i = 1, 2, \ldots, L)$. Each layer h^i is a Restricted Boltzmann Machine (RBM) RBM^i, a generative graphical model that encodes the PDF of its input layer h^{i-1} into its latent feature vector h^i. At each RBM^i $i = 1, 2, \ldots, L$, the conditional PDF of the j-th neurons in the visible layer h^{i-1} and hidden layer h^i is computed by:

$$\begin{cases} P(h_j^i = 1|h^{i-1}) = \sigma\left(\sum_k W_{kj}^i . h_k^{i-1} + b_j^i\right) \\ P(h_j^{i-1} = 1|h^i) = \sigma\left(\sum_k W_{jk}^i . h_k^i + b_j^{i-1}\right) \end{cases} \tag{4}$$

To train W^i, the Contrastive Divergence method [8] is employed that adds the gradient of $P(h^{i-1})$ with respect to W^i to increase the likelihood of observing the visible vector h^{i-1} given the latent vector h^i. Similar approach is used to train b^i and b^{i-1} in an unsupervised fashion. When the unsupervised training is done for all layers, a dense layer $o = h^{L+1}$ is added on top of the last layer h^L and the whole neural network is trained by the supervised GD similar to the SAE.

Table III shows the large variety of DBN's applications in power systems area. As shown in this table, the DBN leads to accurate wind and PV power prediction results due to capturing uncertainties in the energy time series [8]. Moreover, DBN shows a promising performance in transient stability classification with 94.69% accuracy in the Central China Regional Power Grid [35]. Furthermore, in [37], this method is recently applied to the state estimation of the US PG&E69 distribution network that led to a remarkably small MAPE of 0.091% which shows the large hypothesis space and low bias of this probabilistic model.

B. Generative Adverserial Network

Assuming a training set D_{tr}, GAN is an unsupervised deep ANN that learns $P(x)$ s.t. $x \in D_{\text{tr}}$ using a generator ANN $G(z)$ that observes some input noise $z \sim P(z)$ and outputs a sample x' drawn from the generators PDF P_g. The produced sample x' as well as the training samples $x \in D_{\text{tr}}$ are given to a discriminator ANN D, a binary classifier which decides if the generated sample x' comes from the true PDF $P(x)$ or the PDF of generated samples P_g. Training the generator and discriminator simultaneously, we improve the generator to create realistic samples by decreasing the distance between the real PDF $P(x)$ and the generated PDF P_g. To train the discriminator D, the following unsupervised objective is applied:

$$\max_D \ \mathbb{E}_{x \sim P(x)}[\log \ D(x)] + \mathbb{E}_{x' \sim P_g}[\log(1 - D(x'))] \tag{5}$$

Here, $D(x)$ is trained to differentiate between the samples generated from $G(z)$ and the true samples $x \sim P(x)$. Using (5), to simultaneously optimize ANNs $G(z)$ and D, the following min-max objective is optimized using the GD method:

TABLE III
PROBABILISTIC DEEP LEARNING IN POWER SYSTEMS APPLICATIONS

Applications	Dataset	Model	Performance Metric	Result
Wind Speed Prediction [33]	Shangchuan Island Wind Farm	DBN VAE	RMSE, MAPE	0.5494, 6.39% 0.4832, 4.81%
PV Power Prediction [9], [34]	North China Baoding Dataset	DBN VAE	RMSE, MAPE	17.55 kW, 3.76% 15.48 kW, 3.63%
Transient Stability Assessment [35]	Central China Regional Power Grid	DBN VAE	Classification Accuracy	94.69% 98.14%
Hourly Load Forecasting [41], [42]	Texas Urbanized Area Dataset	DBN VAE	RMSE, MAPE	0.4851, 5.81% 0.4032, 5.02%
State Estimation [37]	US PG&E69 Distribution Network	DBN VAE	MAPE, Maximum Absolute Error	0.091, 0.073 0.084, 0.069
Fault Detection [38], [41], [42]	Northern China Wind Farm (SCADA)	DBN VAE GAN	Classification Accuracy	79.11% 84.85% 87.32%
Cyber Attack Detection [39]	5-bus Smart Grid	GAN VAE	Classification Accuracy	95.34% 92.18%
Renewable Scenario Generation [40]	Wind & Solar Integration Dataset	GAN VAE	Kullback–Leibler Divergence	0.61 0.52
Power Grid Synthesis [15]	Columbia University Synthetic Power Grid (CUSPG)	GAN VAE	Topological Distance, Power Flow Distance	0.678, 3.41 MW 0.0512, 3.06 MW

$$\min_{G}\max_{D} J_{D,G} = \mathbb{E}_{x\sim P(x)}[\log\ D(x)]+ \mathbb{E}_{z\sim P(z)}[\log(1-D(G(z)))] \tag{6}$$

To test the model on a testing set D_{ts}, the Kullback-Leibler (KL) divergence is used as a distance metric between the estimate PDF and the true PDF of samples $x \in D_{\text{ts}}$.

As shown in Table III, GAN leads to a promising performance in a diverse set of complex classification problems including fault detection [41] and cyber attack classification [39], as well as regression problems such as scenario generation for the wind and solar power [40]. Compared to the classic DBN, GAN has a larger hypothesis space which leads to higher generalization capacity. Hence, as Table III shows, GAN outperforms DBN in both fault detection and cyber attack classification. Moreover, since GAN explicitly models the joint PDF of the data, it can be directly applied to realistic data synthesis problems such as power grid synthesis [15], [38] while DBN does not have such a capability.

C. Variational Autoencoder

Similar to GANs, the objective of VAE is to learn the PDF $P(x)\ s.t.\ x \in D_{\text{tr}}$ in an unsupervised fashion. The VAE consists of an encoder ANN $q_\theta(z|x)$ parametrized by θ and a decoder ANN $p_\phi(x|z)$ with parameters (weights and biases) ϕ. The encoder maps x into the latent representation z which has a Gaussian distribution estimated by $q_\theta(z|x)$. Then, to find the optimal z that is powerful enough to best reconstruct x, the decoder maps z into the actual input x. Hence, training the VAE consists of maximizing the likelihood of x as well as minimizing the KL divergence KL of the distribution of z (i.e. $q_\theta(z|x)$) and its actual distribution $N(0,\boldsymbol{I})$ where $\boldsymbol{I}$ is the identity matrix. Therefore, the loss function of the VAE is computed by:

$$J_{\text{VAE}} = \sum_{x\in D_{\text{tr}}}\left[KL[q_\theta(z|x)\|N(0,\boldsymbol{I})]-\mathbb{E}_{q_\theta(z|x)}[\log\ p_\phi(x|z)]\right] \tag{7}$$

Training the VAE using GD, the decoder $p_\phi(x|z)$ provides an accurate estimation of the data PDF $P(x)$ when marginalized over all valid z.

As shown in Table III, the VAE is applied to learn the conditional PDF of future wind speed/power given its previous measurements for short-term wind prediction [33]. Moreover, similar technique is applied in [15] and [34] to hourly and 6-hour ahead prediction of PV power with $2.07kW$ and $6.53kW$ better RMSE compared to the DBN, respectively. In addition to regression, VAE outperforms DBN in complex classification tasks with 3.45% accuracy improvement in transient stability assessment [35] and 5.74% better fault detection accuracy [38]. Moreover, VAE is utilized to learn the PDF of the physical and topological characteristics of power networks for power network synthesis. As shown in Table III, VAE generates realistic power networks that accurately imitate not only the topological properties (e.g., diameter and density) but also the power flow statistics (maximum, minimum, and median flow) of the large-scale transmission network in CUSPG dataset [70].

D. Advantages and Restrictions of Deep Generative Modeling

Table IV presents the advantages and restrictions of deep generative modeling in power system research. As shown in this table, DBN, GAN, and VAE can handle measurement uncertainties while providing a powerful unsupervised data representation. Compared to GAN and VAE, the DBN has smaller sample complexity which leads to less number of training examples required for feature extraction. However, since this model employs Gibbs sampling in its training process, it has a large training time complexity. Also, DBN has a strong independence assumption on its latent variables which makes it less suitable for pattern recognition in highly nonlinear datasets.

In contrast to DBN, the GAN and VAE directly learn the data distributions with no prior assumptions. Thus, these models can be effectively applied to power system data synthesis. Due to its larger architecture, GAN requires more number of training examples compared to the DBN. Also, GAN has limited feature diversity and lacks parameter convergence

TABLE IV
ADVANTAGES AND RESTRICTIONS OF DEEP GENERATIVE MODELS

Models	Advantages	Restrictions
DBN	1- Modeling uncertainties 2- Unsupervised feature extraction 3- Small sample complexity	1- Large training time complexity 2- Strong prior knowledge (conditional independence) 3- Lack of parameter convergence guarantee
GAN	1- Modeling uncertainties 2- Unsupervised feature extraction 3- Data Synthesis	1- Large sample complexity 2- Lack of parameter convergence guarantee 3- Limited diversity 4- Diminished gradient 5- Sharp but unreliable estimations
VAE	1- Modeling uncertainties 2- Unsupervised feature extraction 3- Data Synthesis 4- Providing probabilistic classification and regression 5- Reliable estimation of the actual probability distribution	1- Large sample complexity 2- Low sharpness of estimated distribution 3- Large testing time complexity

guarantees. While VAE has similar sample complexity compared to GAN, it provides a more reliable distribution estimation. However, the smaller sharpness of VAE compared to GAN makes GAN a better choice for probabilistic applications.

IV. DEEP REINFORCEMENT LEARNING

Besides classification and regression, deep ANNs are employed in reinforcement learning settings where the problem is modeled as a Markov decision process (MDP) (S, A, P_a, R_a) with the state set S, action domain A, and state transition probability $P_a(s, s') = P(s_{t+1} = s'|s_t = s, a_t = a)$ to model the likelihood of going from state s_t at time t to state s_{t+1} at time $t + 1$. This transition leads to observing the immediate reward $R_a(s_t = s, s_{t+1} = s')$ from the problem's environment. The goal is find the optimal policy $\pi^*(s_t)$ that determines action a_t to maximize the expected discounted reward sum $R_{\text{avg}} = \mathbb{E}\big[\sum_{t=o}^{\infty} \gamma^t R_a(s_t, s_{t+1})\big]$. The discounting factor $0 \leqslant \gamma \leqslant 1$ decides the contribution of the historical rewards to R_{avg}. The optimal policy $\pi^*(s)$ for a state $s \in S$ is computed by:

$$\pi^*(s) = \arg\max_a Q(s, a) \tag{8}$$

where $Q(s, a)$ is the optimal state-action value function that estimates the reward of taking action a in state s.

A. Deep Q-network (DQN)

DQN [44] directly learns $Q(s, a)$ and employs (8) to find the optimal policy. To provide high generalization power and low estimation bias, the DQN implements $Q(s, a)$ by a deep neural network Q_{ANN} that observes an input $\langle s, a\rangle$ and outputs $Q(s, a)$. To train Q_{ANN}, the Temporal Difference (TD) error δ is defined as the difference between the current $Q(s, a)$ and the value function after the transition to s' computed by:

$$\delta = Q(s, a) - (R_a(s_t = s, s_{t+1} = s') + \gamma \max_a Q(s', a)) \tag{9}$$

To train the DQN (i.e., minimize δ), the Huber loss is computed by $J(\delta) = \frac{1}{2}\delta^2$ if $|\delta| \leqslant 1$ and $J(\delta) = |\delta| - \frac{1}{2}$ otherwise. Applying GD, one can minimize $J(\delta)$ with respect to the weights and biases of Q_{ANN}.

Table V shows the applications of DLR in the power engineering domain. As shown in this table, DQN is recently applied for optimal voltage control of a 200-bus system [44]. Moreover, this model shows a promising load shedding result of 26 MW for optimal emergency control of the IEEE 39-bus system [45]. Furthermore, DQN is employed for power grid cost efficiency with transportation energy optimization, and showed 14.1% improvement compared to the classic binary control method [46]. The high generalization power of this method has encouraged the researcher to apply DQN for various real-world applications ranging from electricity marketing [47] and demand-response learning [49] to smart grid scheduling [52] and cyber attck detection [53].

B. Double DQN (DDQN)

To reduce the overestimation effect of the state-action value $Q(s, a)$ in (9), the DDQN uses a target deep ANN parameterized by θ' to compute the update value $\max_a Q(s', a)$ while the state-action $Q(s, a)$ is computed by a deep ANN with the original DQN parameters θ. As shown in Table V, this method improves the classic DQN with 2.2% improvement in cost efficiency for transportation energy optimization [46] and $£43 * 10^3$ improvement in electricity market bidding profit [47].

C. Deep Deterministic Policy Gradient (DDPG)

DDPG is an actor-critic DRL algorithm. The actor $\mu(s)$ models the policy as a deep ANN that observes a states s and generates the corresponding continuous action a. The critic Q is a deep ANN that estimates $Q(s, a)$ for the state-action input $< s, a >$. To compute the state's value, the actor's output is given to the critic to calculate $Q(s, a)$. Similar to DQN, The critic's TD-error function J_Q is computed using the Bellman equation:

$$J_Q = \big(Q(s, \mu(s)) - (R_a(s, s') + \gamma Q'(s', \mu'(s')))\big)^2 \tag{10}$$

where Q' and μ' are the target critic and actor deep ANNs, respectively. The target ANNs Q' and μ' are time delayed copies of Q and μ that slowly track the learned state-action values. The actor's loss function J_μ is computed by $Q(s, \mu(s))$ which is maximized to increase the DDPG's return while J_Q is minimized. To learn Q and μ using GD, the gradients of J_Q and J_μ with respect to their weights and biases are computed, respectively. Moreover, the target networks Q' and μ' are updated by respectively adding a small fraction of their corresponding parameters in the original networks Q and μ at each DRL episode. Table V shows the significant

TABLE V
DEEP REINFORCEMENT LEARNING APPLICATIONS IN POWER SYSTEMS

Applications	Dataset	Model	Performance Metric	Result
Voltage Control [44]	Realistic 200-bus System (SCADA)	DQN DDPG	Average Control Reward	161.54 124.83
Emergency Control [46]	IEEE 39-bus	DQN DDPG	Load Shedding	26 MW 23 MW
Transportation Energy Optimization [46]	California Freeway Performance Measurement System (PeMS)	DQN DDQN	Cost Efficiency (compared to binary control)	14.1% 16.3%
Electricity Market [47], [48]	Synthetic Market Dataset	DQN DDQN DDPG	Profit(£)	5.2 * 10ˆ5 5.63 * 10ˆ5 5.86 * 10ˆ5
Demand-Response Strategy Learning [49]–[51]	Steel Powder Manufacturing Dataset	DQN TD-based Actor-Critic DRL	Operation Cost($)	161.93 134.85
Power Scheduling [52]	Shaanix Wind Farm Dataset	DQN Improved DQN	Average Income($)	$ 4268.17 $ 4730.21
Cyber Attack Detection [53], [55]	IEEE 9-bus System	DQN DDPG	Transient Energy	0.120 p.u. 0.056 p.u.

experimental advantage of DDPG compared to DQN-based methods. While DQN cannot handle high-dimensional action spaces, the DDPG learns policies in these conditions. Thus, DDPG is shown to generally provide better accuracy in both regression problems such as autonomous voltage control [44], emergency control [45], strategic bidding [47] as well as classification tasks including cyber attack detection [53] and data integrity protection [55].

D. Advantages and Restrictions of Deep Reinforcement Learning

Table VI provides a summary of DRL advantages and restrictions in power system applications. As shown in this table, both DQN and DDQN have stable and robust training procedures. Therefore, they are very suitable for datasets with high uncertainty factors. However, these methods cannot guarantee their parameter convergence. Also, DQN and DDQN mainly optimize deterministic policies in discrete action spaces. Thus, compared to the DDPG, they are less suitable for real-world applications with continuous actions. Although DDPG may suffer from parameter instability during training, it provides a fast and guaranteed convergence to a promising stochastic local policy.

V. FUTURE RESEARCH DIRECTIONS

The future research on deep learning algorithms in the area of power engineering is summarized in Fig. 1. As shown in this diagram, the combination of sparse coding and dictionary learning methods with discriminative models is one of the significant future domains that require further study. The sparse models can decrease the sample complexity of deep learning algorithms and help deep neural networks to better decompose, compress, and reconstruct the input data. Hence, this approach would lead to a remarkable accuracy improvement in Behind-The-Meter net load disaggregation, deep nonintrusive load monitoring, PMU data compression and noise reduction, customer behavior estimation, and the Internet of Things data analytic. The graph knowledge representation in discriminative learning is another major area of future research. In this class of approaches, the deep neural network captures highly nonlinear and highly varying characteristics of graph-structured datasets. This category of models is very effective to improve the accuracy of spatiotemporal renewable energy and load forecasting techniques. Also, it can be effectively employed for real-time state estimation, load and system parameter identification, as well as topology detection. The last class of future works in the domain of discriminative models is the deep Bayesian learner. This model incorporates the Bayes rule into ReLU ANNs to create robust probabilistic deep learning solutions that can effectively handle the uncertainties in the datasets. The future applications of this method include probabilistic dynamic load modeling, probabilistic pattern recognition of Behind-The-Meter sensor data, as well as power quality disturbance detection and

TABLE VI
ADVANTAGES AND RESTRICTIONS OF DEEP REINFORCEMENT LEARNING MODELS

Models	Advantages	Restrictions
DQN	1- Stability of the learning algorithm 2- Robustness to measurement uncertainties	1- Lack of policy convergence guarantee 2- Slow policy convergence 3- Assuming deterministic policies 4- Lack of compatibility with continuous action spaces 5- Overestimating the state-action values
DDQN	1- Stability of learning algorithm 2- Robustness to measurement uncertainties 3- Realistic estimation of state-action values	1- Lack of policy convergence guarantee 2- Slow policy convergence 3- Assuming deterministic policies 4- Lack of compatibility with continuous action spaces
DDPG	1- Fast convergence to the optimal policy 2- Guaranteed convergence in complicated state-action spaces 3- Learning stochastic policies 4- Compatibility with continuous action spaces	1- Instability of the learning algorithm 2- High sensitivity of parameters to noise

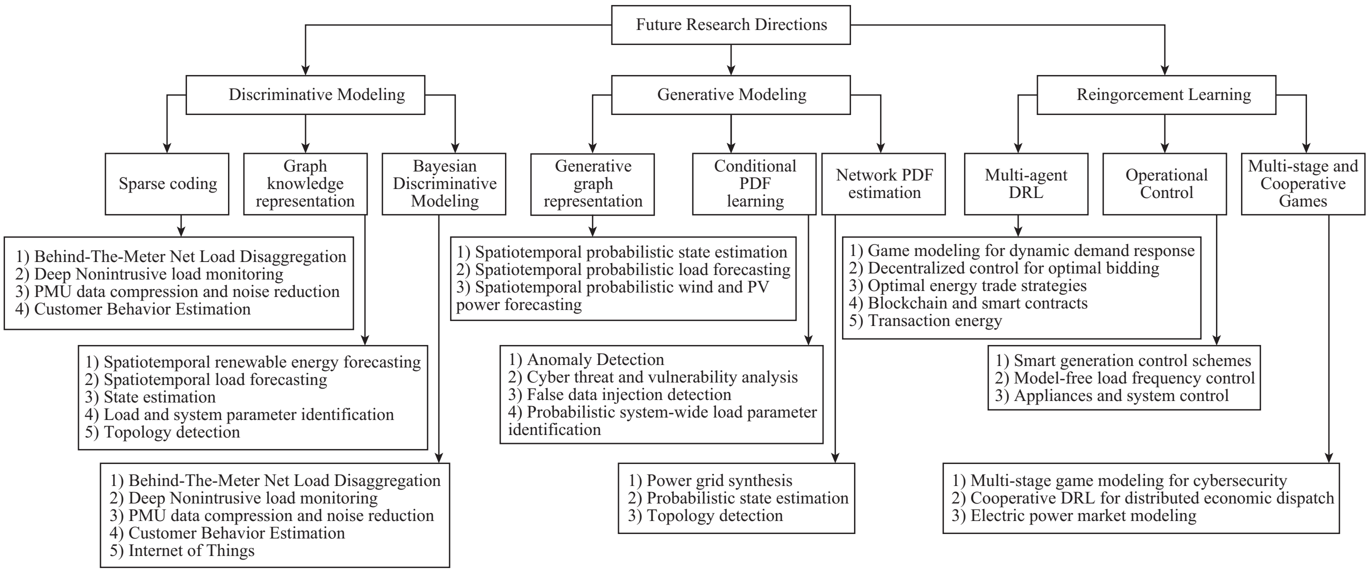

Fig. 1. Future research directions in the area of deep representation learning.

classification.

One of the major future works in the area of generative modeling is the generative graph representation model. This approach combines graph CNNs with GANs and VAEs to provide accurate probabilistic representations of graph-structured energy datasets and power grids. The future applications of this approach include spatiotemporal probabilistic state estimation, spatiotemporal probabilistic load forecasting, as well as the spatiotemporal probabilistic wind and solar energy forecasting. Another major class of future generative models is the conditional PDF learners. In contrast to the classic GAN and VAE, this category of models can learn the conditional PDF of an observation given another observation. Thus, it is able to remarkably improve the accuracy of machine learning algorithms in various power system applications such as anomaly detection, cyber threat detection and classification, false data injection detection, and probabilistic load parameter identification. In addition to this class of models, the network PDF estimation models are another category of future works that compute the joint PDF of node and edge features of large-scale power networks. This class of algorithms improves future generative solutions for power network synthesis, probabilistic state estimation, and power grid topology detection.

In the area of DRL, the multi-agent DRL can significantly improve the game modeling solutions between power companies and customers for dynamic demand response. Also, this technique can provide decentralized control strategies for optimal bidding between the companies and customers. Moreover, the multi-agent DRL can improve energy market strategies and establish smart contracts in peer-to-peer electricity trades with Blockchain. Future DRL works can also advance operational control strategies. These models can be applied to smart generation control in multi-area interconnected grids, model-free load frequency control, as well as the appliances and system control (e.g., smart grid emergency control and autonomous grid operational control). Moreover, future DRL techniques can be combined with multi-stage games to provide reliable solutions for modeling the interactions between cyber attackers and cyber defenders. Also, cooperative DRL can be utilized for distributed economic dispatch while satisfying the power balance and other operational constraints.

VI. Conclusion

With the growing time and memory complexity of power system applications, the need for advanced statistical pattern recognition tools has lead to the use of deep learning methodologies. This novel class of methods can be mainly categorized into discriminative, generative, and reinforcement learning approaches. This review studies the deep discriminative models that provide an explicit method to map their complex input directly to the problem's solution. Due to their high generalization capacity, these models are widely applied to stability assessment, fault detection, as well as renewable generation prediction. Then, deep generative approaches are reviewed that provide a probabilistic approximation of data PDFs; hence, learning complex probabilistic structures for a wide range of power engineering applications including state estimation, renewable scenario generation, and power grid synthesis. Finally, deep reinforcement learning algorithms are discussed that seek to optimize an objective using the observed rewards captured from the problem's environment. The theoretical and experimental analysis of the employed method motivates future research in the area of deep learning to further extend the applications of this powerful class of models in new perspectives of power engineering.

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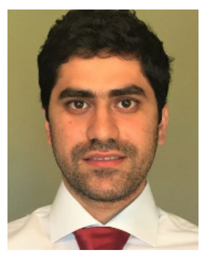

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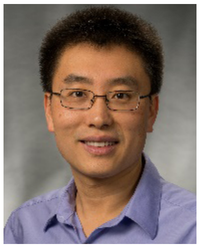

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