Data-driven management mechanism of demand response resources in active distribution networks

Jianbing Yin¹, Zeyu Xu², Lin Chen¹ and Dairui Li³,*

¹ Hangzhou Power Supply Company, State Grid Zhejiang Electric Power Co., Ltd, Hangzhou, Zhejiang, 310016, China
² East China Grid Company Limited, Pudong, Shanghai, 200120, China
³ Polytechnic Institute, Zhejiang University, Hangzhou, Zhejiang, 310015, China
* Corresponding author’s e-mail: lidr@zju.edu.cn

Abstract. As power distribution networks have been transferring from passive to active, conventional physical-driven models are incompetent to deal with the challenges of flexible and fast-changing operating conditions. Alternatively, data-driven methods, especially deep learning methods, have unique advantages in tackling those challenges. To this end, the paper first introduces the opportunities brought by the massive amount of data in active distribution networks (ADNs). Then the paper employs neural networks to identify load categories and their potential capacity of demand response to interact with ADNs. Furthermore, a generalized dispatch framework is presented to coordinate flexible loads for peak-valley electricity alleviation, with long-short-term-memory networks as an example. Last, the paper sheds light on the limitations of deep learning applications such as data cleaning and cybersecurity attacks.

1. Introduction

An increasing number of distributed energy resources (DERs) are connected to the demand side, bringing severe challenges to the planning, design and operation of traditional distribution networks. To address a host of issues caused by DERs, the concept of the active distribution network (ADN) was proposed. Traditional distribution networks supply electricity to customers in one direction, while the incorporation of DERs transforms distribution networks from passive to active, with bidirectional power flows [1]. ADNs accommodate power electronic devices, advanced metering infrastructure (AMI), modern communication technologies, making it possible for the distribution system operator (DSO) to interact with customers and DERs in real-time [2]. In such interaction, loads with transferable and adjustable characteristics are defined as flexible loads. This interaction can benefit DSO from time and spatial adjustment of electricity consumption according to stable power supply requirements, which is known as demand response (DR).

Through precise DR management and DR resources dispatch, the pressure of peak-valley loads can be alleviated. On the condition that numbers of different kinds of equipment and appliances are obtained, it will be clear for the load dispatching system to instruct the adjustment of flexible loads. However, ADN incorporates a large number of end-users and DERs, with extensive and complex load structure. On the user side, due to the various household appliances and their flexible working modes, the electricity consumption of users changes from time to time. It is impractical to record and trace the power supply of each customer. Furthermore, there is a large individual difference in electricity consumption habits, making it more complicated to coordinate the basic power supply of customers with...
less peak-valley burden. In ADNs, smart meters deployed at the user-end can collect high-frequency electricity data, with which electricity consumption habits of users can be exploited. Adopting appropriate big data mining techniques, such as clustering, fitting, prediction, correlation grouping or association rules, to analyse these massive data can obtain hidden information for ADNs planning, power grid safety assessment, and system operation optimization [3]. Traditional methods to identify loads categories mainly include random forests, support vector machines, hidden Markov models and other physical-based models. However, because of massive customer quantities and explosively growing data, traditional data processing methods find it hard to meet fast and accurate calculation requirements. Besides, in regards to complex structures and numerous data sources of ADNs, the traditional physical-based model takes considerable time on modelling construction and numerical solution.

To cope with a series of issues in DR and improve the revenue of DSO, highly efficient methods deserve further research. Machine learning, especially deep learning, outperforms other methods in dealing with nonlinear problems because of highly interconnected and parallel nonlinear processing elements. Deep learning can construct a particular form of network structure, directly exploring the mapping relationship between input and output loads categories. The intricate connection between neurons shelters the inner physical mechanism, so the network can be treated as a black box to avoid the complicated restriction of uncertainties.

Early artificial neural networks, also known as a multi-layer perceptron, usually contain one hidden layer. Nevertheless, their ability to depict complex functions with limited samples and computing units are subject to certain restrictions. Meanwhile, their model generalization ability is also restrained [4]. As an extension of artificial neural networks, deep learning has multiple hidden layers to extract data features, which can investigate the essential characteristics of the data [5].

A deep learning structure comprises an input layer, multiple hidden layers, and an output layer. Every time the input passes through a neuron, it will be given weight and bias, and then a nonlinear activation function is applied. After layer-by-layer transmission, the output in a specific dimension is obtained. However, this output is only the initial result, which will be compared with the corresponding label through loss function. By calculating the gradient of the loss function with respect to each weight, the error can be backpropagated [6], and the weights of the network are updated for the next set of samples. The above process is repeated until the output result meets the desired accuracy. The well-trained network can be applied to a new data set with the same distribution pattern [7], with which regression and classification tasks can be accomplished. By changing the connections of neurons, neural networks fitting for different types of tasks can be designed. Neural networks that are receiving popularity now include convolutional neural networks (CNN) and recurrent neural networks (RNN). CNN is more suitable for processing data structures in the form of images, while RNN is more skilled in analysing data with sequential structures [8].

The remainder of the paper is organized as follows: Section 2 presents a methodology of deep-learning-assisted demand response; Section 3 introduces some limitations on deep learning in ADNs; Section 4 concludes the paper.

2. Deep-learning-assisted DR management methodology

This section presents a two-stage deep learning application framework in ADNs. Firstly, the necessity of DR resources identification and its method are explained. Secondly, a framework of DR resources dispatch with neural networks is presented.

2.1. Identification of DR resources

In ADNs, due to fluctuation and randomness of DERs, flexible power exchange of electric vehicles, various combinations of household appliances and the intermittent operation of energy storage equipment, the loads change frequently. It is vital to recognize the major DR resources categories and their working time of each feeder, because precise DR resources dispatch and demand response management are based on timely-updated power flow and flexible loads. However, it is time-consuming
and impractical to construct real-time physical models and solve the numerical solution. But by adopting a deep learning method, certain features can be extracted from a wide range of data while load information can be exploited [1].

![Figure 1. The identification process of DR resources](image1)

The data used in DR resources identification mainly includes electrical operation data. Specifically, phasor measurement units (PMUs) located at a subset of the buses provide access to line phase angles, and active/reactive power injections, as well as voltage magnitudes, can be collected from AMIs and smart meters. The procedure of DR resources identification is shown in figure 1. The input includes active and reactive power injections, voltage amplitudes and phase angles. In the first layer of the neural network, the power flow equations are regressed for loads connection estimation. Then the rest layers disaggregate the total loads into rigid loads and various flexible loads. Last, the accurate flexible loads structure of the ADN is exported. Benefited from powerful non-linear processing ability, the deep learning method can update flexible loads on a practical time scale. Identification results are useful for the subsequent load dispatch.

2.2. Dispatch of DR resources

Influenced by high temperatures in summer and cold weather in winter, the electricity consumption of these two seasons is higher than spring and autumn. Besides, due to people’s similar working routine, the peak of electricity consumption usually appears around noon and night on weekdays. When it comes to midnight, the majorities of residents are in bed, leaving almost no large appliances working. To ensure a safe and reliable power supply, large investment in expanding line capacity are paid every year to satisfy the peak electricity demand. The unstable electricity consumption exerts a heavy financial burden on the grid constructor. However, it is economically beneficial to schedule flexible DR resources appropriately according to the real-time need of power balance.

![Figure 2. A LSTM neural network structure](image2)

In view of various DERs output fluctuating without regular mathematical patterns, and increasing bidirectional interaction on the demand side, it is difficult to solve enormous unknown variables with
limited time. However, deep learning provides an alternative approach to well coordinate computation speed with data volume. This advantage makes it possible for deep learning to support online decision-making, such as the demand side dispatch. Take minimum equipment investment as the objective function to calculate the possible DR resources dispatch results, with power balance between DERs and loads being boundary condition. Compared with the ordinary machine learning methods such as decision trees and support vector machines, deep learning methods always get a better score as long as enormous data is involved. Although the power flow is always changing, renewable power generation and customer power consumption operate in a periodic pattern. Hence, there usually exists a certain time correlation in historical data, which makes it easier to implement deep learning methods. One competitive structure is LSTM neural network. It is designed for processing sequential data. In the meantime, it can avoid the problems of gradient disappearance and gradient explosion [3].

A typical LSTM neural network structure is shown in figure 2. It has an input gate, an output gate and a forget gate. This sort of structure can memorize and forget the input data to varying degrees according to different data features. Multiple memory units will form a common network. The input of LSTM usually selects three-phase active power, reactive power, voltage amplitude, phase angle and meteorological data as characteristic variables. The selection and combination of different features will have an impact on the output accuracy of the network. Generally, picking input features that are more relevant to the output result can achieve better results [5]. Moreover, the real-time DR resources dispatch schemes can achieve more efficient and accurate results based on DR resources identification. In other words, DR resources categories identification gives a rough estimation of ADNs first, then more precise and personalized demand response management can be realized. A DR resources dispatch framework is shown in figure 3. The DR resources identification results, together with meteorological data, are input into the LSTM neural network where the hidden characteristics of ADN can be extracted to support DR resources dispatch decision. The network output can show how many flexible loads are needed to achieve relatively stable electricity consumption and the exact adjustment instruction.

3. Challenges of deep learning

In this section, some challenges of deep learning methods are introduced. First, we focus on bad data issues, and provide a novel data cleaning method based on generative adversarial networks. Then the cybersecurity of deep learning is discussed.

3.1. Data cleaning

There is a mass of dirty data obtained in ADNs because of the occasional electrical device failure and manual recording errors. However, the data-driven approaches rely on these data heavily. If the data is not cleaned, deep learning performance can be affected, which results in a large deviation between deep learning analysis and actual results [10]. Accordingly, it is essential to clean data and improve data quality for a well-behaved data-driven model. In recent years, a deep generation model called generative adversarial networks (GAN) [11] has been widely used to fill incomplete images, which has made advanced progress. Inspired by the method, this paper proposes a novel method of data cleaning and repairing for distribution network data, which is based on GAN.

Figure 4 shows the data cleaning results based on GAN, which presents the process of filling missing data, repairing abnormal data, and data enhancement in detail. For the first two cases, data in a generated sample at the corresponding location of missing data or abnormal data will be extracted separately to replace dirty data. But before that, the sample closest to the real situation is supposed to be selected from countless generated samples. Thus, the noise vector is trained using a gradient descent algorithm, which can ensure that the generated data resembles the actual value as far as possible. Besides, the trained GAN can be used to produce data of the smaller class to solve the problem of class imbalance. Given the above, the proposed method takes the data correlation and fluctuation pattern into account, which makes the repaired data conform to a real situation with higher accuracy.
3.2. Cybersecurity of deep learning models

A large amount of user load data is required in power system load forecasting and power market pricing. However, as the optical fibre is widely used in electric power communication, the communication channel is faced with cybersecurity threats such as data theft, tampering, and loss. Therefore, the cybersecurity of deep learning models is a critical issue to be concerned about. An ideal deep learning security solution should meet three requirements, as shown in figure 5. Firstly, the training and testing process should be non-polluted. Secondly, for the output, the deep learning model should be robust enough to deal with noisy input. Last, users cannot view any parameter or model structural information.

Figure 4. Data cleaning results based on GAN

Figure 5. The deep learning process and safety requirements

The current attack methods mainly include poisoning attacks, adversarial attacks, and reverse engineering attacks. For different attack algorithms, different modules can be designed to improve the security of deep learning algorithms. To defend against poisoning attacks, anomaly detection methods can be used to disinfect the training set, and the objective function can be modified to analyse the accuracy of the model. Furthermore, the defence methods of adversarial attacks include confrontation training, gradient masking, denoising, defence distillation, etc. Among them, confrontation training
improves the robustness of the model by introducing confrontation samples in the training data. It is one of the most effective defence methods for confrontation attacks. As for reverse engineering attacks prevention, reducing or modifying the output information can increase the difficulty of the attacks. What is more, methods to protect user privacy can be exploited to resist data inverse attack, including homomorphic encryption technology, secure multi-party computing technology, and differential privacy technology.

4. Conclusions
As traditional distribution networks transform from passive to active, massive amounts of data are accumulated. The advent of deep learning provides an efficient approach to deal with a series of fast-changing issues due to flexible DR resources structure. A two-stage deep-learning-assisted method is proposed in this paper to improve the revenue and stability of the power grid by using electrical measurement data and meteorological data. Compared with conventional physics-driven model, deep learning method owns the advantage of non-linear modelling, fast computation, powerful feature extraction and online decision-making ability. The complicated neuron connection can be regarded as a black box, so only the input and output features need to be focused. Through the proposed method, flexible loads can be identified and optimal DR resources dispatch schemes can be designed to better support decision of online DR. However, there exist some challenges of deep learning utilization as well. The data cleaning and potential cyberattack on deep learning models are worth further researching.

References
[1] Series I. (2009) Microgrids and active distribution networks. The institution of Engineering and Technology, London.
[2] Martins V F, Borges C L. (2011) Active distribution network integrated planning incorporating distributed generation and load response uncertainties. IEEE Transactions on power systems, 26(4): 2164-2172.
[3] Akhavan-Rezai E, Haghifam M, Fereidunian A. (2009) Data-driven reliability modeling, based on data mining in distribution network fault statistics. In: IEEE Bucharest PowerTech. Bucharest. pp. 1-6.
[4] Mayer H A, Schweiger R. (1999) Evolutionary and coevolutionary approaches to time series prediction using generalized multi-layer perceptrons. In: Proceedings of the 1999 Congress on Evolutionary Computation-CEC99 (Cat. No. 99TH8406). Washington, DC. pp. 275-280.
[5] Lecun Y, Bengio Y, Hinton G. (2015) Deep learning. Nature, 521(7553): 436-444.
[6] Goh A T. (1995) Back-propagation neural networks for modeling complex systems. Artificial intelligence in engineering. Artificial intelligence in engineering, 9(3): 143-151.
[7] Li, Y., Zhang, X., Chen, D. (2018) Csrnet: Dilated convolutional neural networks for understanding the highly congested scenes. In: Proceedings of the IEEE conference on computer vision and pattern recognition. Salt Lake City. pp. 1091-1100.
[8] Mikolov, T., Kombrink, S., Burget, L., Černocký, J., Khudanpur, S. (2011) Extensions of recurrent neural network language model. In: 2011 IEEE international conference on acoustics, speech and signal processing (ICASSP). Prague. pp. 5528-5531.
[9] A Deka, D., Backhaus, S., Chertkov, M. (2017) Structure learning in power distribution networks. IEEE Transactions on Control of Network Systems, 5(3): 1061-1074.
[10] Ge, C., Gao, Y., Miao, X., Yao, B., Wang, H. (2020) A Hybrid Data Cleaning Framework Using Markov Logic Networks. IEEE Transactions on Knowledge and Data Engineering.
[11] Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Bengio, Y. (2014) Generative adversarial nets. In: Advances in neural information processing systems. Montreal. pp. 2672-2680.