Deep Learning-based Distributed Optimal Control for Wide Area Energy Internet

Gang Yang, Junwei Cao and Haochen Hua
Research Institute of Information Technology
Tsinghua University
Beijing, P. R. China
e-mail: jcao@tsinghua.edu.cn

Ziqiang Zhou
Research Institute of Electric Power
State Grid Zhejiang Electric Power Company
Hangzhou, P. R. China

***Abstract*—The concept of energy Internet (EI) emphasizes comprehensive utilization of the whole energy system and has been considered as a new development stage of the smart grid. As the core device of an EI, the energy router (ER) is used to connect various electrical equipment. The access of ERs brings new challenges for the energy management issues in EI. In this paper, an improved ER's structure is investigated, and the network structure of the wide area EI in an off-grid mode is introduced. In addition, in order to maximize the utilization of renewable energy sources (RESs) and to reduce power transmission loss, we propose a novel distributed energy management approach based on deep learning algorithm. Only the local information exchange among the neighboring ERs is required and the global optimization effect is achieved. Finally, simulation results within a 100-routers test system are provided to illustrate the effectiveness of the proposed approach.**

Keywords*—deep learning;energy Internet;energy management;energy routers

I. Introduction

In recent years, global energy shortage and environmental issues have drawn increasing attention, urging countries all over the world to focus on the development of renewable energy, such as solar energy, wind energy and tidal energy[1]-[3]. In order to make full use of renewable energy sources(RESs), the concept of energy Internet (EI) is proposed[4]-[6].In the EI scenario, power flows from suppliers to customers in an open and peer-to-peer Internet style. The core of implementing such energy routing mechanism is the energy exchange device called energy router (ER)[7].For areas where RESs are widely utilized, the construction of wide area EI is especially valuable for the following three reasons [6], [8]. First, the excessive energy generated by RESs can be stored for future use, such that the utilization of fossil fuelsis reduced and the ecological environment is improved. Second, through the rational design of energy routing schemes, optimized power transmission and power scheduling can be realized to reduce energy loss. Third, the dependence on the main grid can be reduced. Within an EI scenario, thedesign ofER and its routing algorithms are two key factors which affect the operating performances of the EI.

Conventional powergridscannot effectively support the access of large-scale RESs,due to their distribution, intermittency and volatility [9], [10]. Moreover, the centralized control and management of thegrid is difficult to meet the requirements of large-scale utilization of RESs [11].Thus, the introduction of intelligent distributed energy management technology becomes an important part of building the future EI.

There exista number of energy management algorithms developed for traditional power systems, including analytical methods such as graph theory approach [12], Newton's approach [13] and H_∞ control approach [14], and heuristic methods such as genetic algorithms [15] and particle swarm optimization [16]. Note that most of the above methods are performed in a centralized manner and take effect slowly. However, with the transformation from traditional power systems to EI, the traditional centralized and distributed power supply approach may encounter the following problems.

The centralized control methods, such as the graph theory approaches, require highbandwidth communication infrastructures to ensure that information of all operating equipment can be gathered in time. Besides, a central controller with high computational ability is required to ensure massive data operations. Moreover, such methods lead to not only great implementation cost, but also a high sensitivity to communication lines. Therefore, the centralized control methods can only solve the energy management problems in local area EI, rather than the wide area EI.

The distributed control algorithms based on genetic algorithms only require the information of the neighboringnodes[15]. Therefore, the communication traffic volume is very low and the distributed control algorithm is more robust than the centralized method. However, the optimization iteration is limited between two nodes, and the information utilization of the surrounding nodes is limited. Meanwhile, the convergence rate of the algorithm is slow, and the single iteration can only achieve about 15% effect of the global optimal result[15]. Because each iteration takes time to communicate between nodes, the power supply-demand balance is changed during the time foriterations, and the global optimal effect achieved by iterations is of little practical significance.

The mathematical performance of the aforementioned methods is directly related to the accuracy of the model[17]. Model-free energy management solutions are considered as independent valuable solutions[18]. Nowadays, most model-free algorithms are based on the deep learning approaches. The application of deep learning in the field of energymanagement has been popular. In[19], deep learning algorithm isadopted as a function approximator to estimate the state-action value function and is applied for residential load control. A multi-level deep learning model that provides big data analysis and emergency management of power system is developed in [20].In [21],the authorsproposed a reinforcement learningbased algorithm to optimize the coordination of different energy storage systemsin a microgrid(MG). However, since the structure of the EI is more complicated than that of the MG, the existing algorithms cannot be simply applied in theEI.

In this paper, different approachesaredemonstrated to solve the energy management problem for wide area EI. We introduce an improvedER structure.Multiple ERs andother electrical equipmentareadopted to constitute the consideredEI scenario. To obtain energy management results, we useconvolutional neural network (CNN)[22] to extract features automatically.

The contribution of this paper can be outlined as follows:

1) An improved ER structure and the topology for a generalized EI scenarioareintroduced.
2) This is the very first time that deep learning algorithm is adopted to solve the energy management issues in the wide area EI.
3) The experimental results show that the deep learning based distributed approach is better than other distributed approaches.

The rest of the paper is organized as follows: Section II introduces the system modeling of the wide area EI. In Section III, the details ofdistributedenergy managementapproach based on deep learning are introduced.In Section IV,threesimulation cases are given to verify the effectiveness of the proposed method. Finally, we conclude our paper in Section V.

II. SYSTEM MODELINGOF WIDE AREA EI

A. The Structure of Energy Router

According to the topological requirements of wide area EI[23],the basic structure of an ER connecting various electrical equipmentwithin a wide area EI is shown in Fig.1.The ER is composed of three information and power exchange structures, several input/output ports and a controller, and it is based on low voltage DC bus.All the local power equipmentisconnected to the DC bus by standard input/output ports for power exchange.

The exchange structure is designed to implement equal connections between two ERs. The exchange structure consists of two parts, the power exchange structure and the information exchange structure. The power exchange structureconsists of a DC/DC converter which directly connects to the DC bus and is the energy conversion unit.Since all theexchange power is controllable, energy management algorithms can be adopted to control the power flowaccurately.The information exchange structureconsists of a net wire which canbe used to exchange information with the otherERs and is connected to the controller.

As is shown in Fig.1, the ports are divided into two categories: AC electrical equipmentconnected ports (shown on the left side)and DC electrical equipment connected ports(shown on the right side).On the left side, the two upper ports aredesigned for micro-turbines (MTs)and wind turbinegenerators (WTGs), respectively. In case thatpower provided by RESs and ES devices is insufficient for power consumption, MTs can be controlled to generate electrical energy. Otherports on the left side aredesigned for normal loads, e.g., AC 220V household electric appliances.

On the right side,the two upper ports are designed for RESs, such as photovoltaic panels (PVs) and fuel cells (FCs);the middle port is designed for energy storage (ES) devices;and other ports are used for normal DC loads, such as DC 48V for LED lightings.ES devices can be used for balancing power in ER. Due to the small power capacity of ES devices, a faster power regulation frequency is required. This is one of the reasons for the introduction of distributed control in wide area EI energy management.

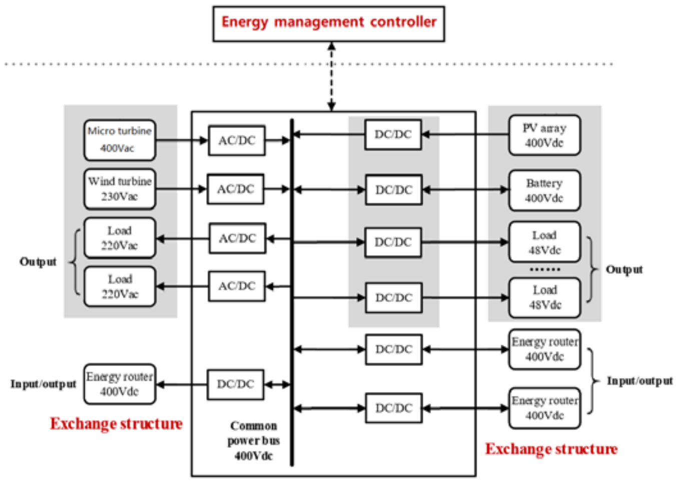

Fig. 1. Basic structure of an ER.

B. System Modeling

In this paper, graph theory is implemented to describe the energy management problem in wide area EI.An illustration of wide areaEI is shown in Fig.2 which is identicalwiththe digraph in Fig.3. Consider the scenario of EI consisting of n ERs.Let us denote all the ERs as $R=\{R_1,R_2,K ,R_n\}$ and notation P stands for power transmission between ERs.The direction of power flows is expressed by the sequence of the routers' numbered corner marks. For example, P_{12}implies that power is assumed to be transmitted from R_1 toR_2.

In practical applications, the lossofpower transmission is unavoidable, which is proportional to the power transmitting distance. Therefore, different power transmission lines correspond to different powerloss. Define W_{ij} as the loss rate of the link from R_i to R_j . The power losses of all transmission lines in the EI is defined as:

$$T = \sum P_{ij} W_{ij} \quad (1)$$

Since the energy stored in ES devices is originally provided by RESs, we claim that all the energy consumed by loads is essentially generated by RESs. We define P_{Mi} as the output power of MTs in R_i. In order to achieve the power balance in the considered EI, to maximize the usage of RESs, and to minimize powertransmission loss, we express the optimization goal as follows:

$$\min(\sum P_{ij} W_{ij} + \sum P_{Mi}) \quad (2)$$

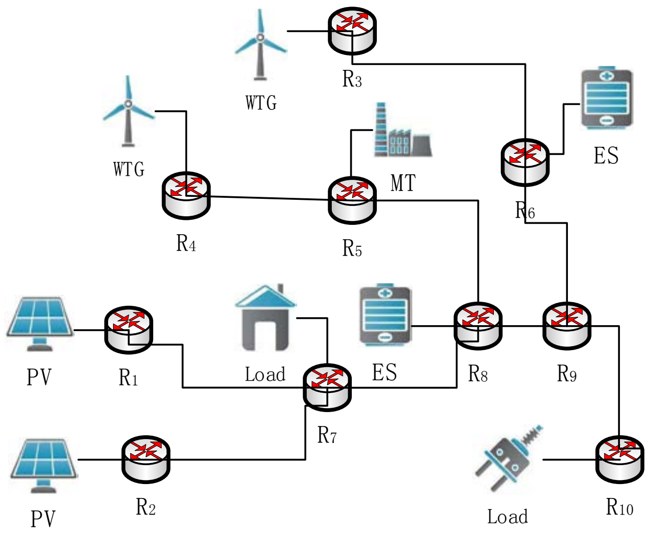

Fig. 2. An illustration of wide areaEI.

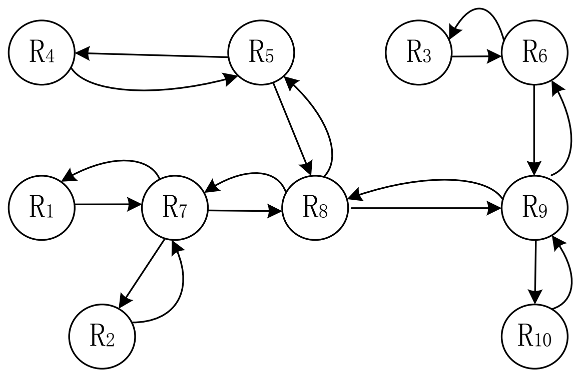

Fig. 3. Digraph of EI.

III. Proposed DistributedEnergy Management ApproachBased on Deep Learning

In this section, we describe the distributed energy management approachbased on deep learning. The framework consists of three modules: data processing module, CNN training module and CNN forecasting module.

A. Data Processing

Since there is no standard datasetfor the problem of energy management in wide area EI, and deep learning algorithmrequires massive data for training, the data generating method is described first.

In order to simulate the operation state of wide area EI, first, a wide area EI model with 100 ERs is built.Each ER is connected withRESs (e.g., PVs, WTGs), loads and ES devices.Then, we obtain the real-time running information of each ER and power equipment connected to the ER.The real-time running information about one ER includeseight categories:loadpower,PV power, WTG power, ES device power, state of charge (SOC) ofES devices,total capacity of ES devices,MT power and MT's maximum output power. The information is stored as $X = \{x_1, x_2, \ldots, x_{100}\}$.

Moreover,the algorithm based on graph theory[12] is used to calculate the power that should be transmitted between ERs.The results can be used as control commands to the simulation system and it is stored as $Y = \{y_1, y_2, \ldots, y_n\}$. We continue the simulation until thetime scalelasts up to one month.Then we get 60*24*30=43200pairs of X and Y.

Next, we preprocess the time series X and Y.Data preprocessing contains normalization and structure changing. First, all data are normalized with their maximum values.The power values(such as load power) are relative large in the data, while the SOCofES devicesis small. The denormalized data may lead to system error.

Thenext part of preprocessing is restructuring the normalized X and Y into training and test data.Both data contains Y as labels (desired output) and X as input variables. In order to make full use of the information of multiple ERs, each ERobtains the power equipment's information and sends information to other ERs.Different from previous works, this information can be transmitted by other ERs for h times($h > 0$). Taking Fig. 3 as an example, ER_7 is able to access ER_1, ER_2, ER_8, ER_9 and ER_5 within 2-hop.Therefore, if each ERis connected to threeotherERswithout repetition, the number of ERs that one ER can get information from (including itself) is determined by the following formula:

$$N_{router} = 3 \times (2^h - 1) + 1 \quad (3)$$

In this paper, we assume $h = 3$, and with a time window index $m = N_{router}$, the input variable structure for every ER is 22times 22times 8, wherethe first 22 means the time windows, the second 22 is the number of ERs involvedand 8 means each ER has 8 categories of real-time parameters. Therefore, for simulation systemwith100 ERs, the total number of data after restructuring is (43200-22)*100≈4.32million.

Test data are used for evaluating accuracy of the proposed energy management model and they are not used for training. In the experiment, we choose data in thelast 10% of time periodas test data, and the rest data is used to train deep learning model.

B. Deep Learning Model for Training &Forecasting

In this section,we present our deep learning method for power transmissionforecasts. For each time, we employ theCNNto make forecasting of each exchange structure in one ER.

The model is composed of a main network and three sub-networks. The main network is designed to extract features of the input information, and the sub-network is designed to forecast the power transmission values for each exchange structure.The full architectureis shown in Fig. 4.

With more layers, the learning abilityof neural network is increasing, but the risk of overfittingwill be increasing [24]. To achieve better results, we apply 9 layers in the main network and 6 layers in each sub-network. The details are shown in Table I and II.

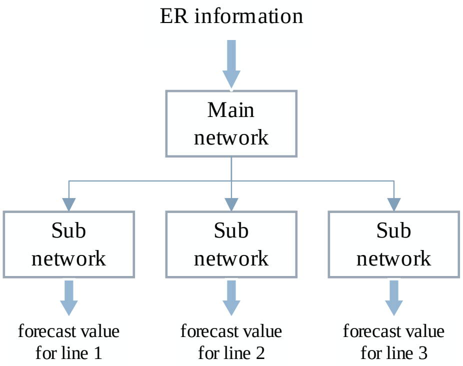

Fig. 4. Full architecture of CNN network.

TABLE I

THE LAYOUT OF THE MAIN NETWORK

type	Patch size/stride	Input size
Conv padded	3X3/1	22X22X8
Conv padded	3X3/1	22X22X128
Conv padded	3X3/2	22X22X128
Batch_normalization		11X11X256
Conv padded	3X3/1	11X11X256
Conv padded	3X3/2	6X6X512
Batch_normalization		3X3X1024
Conv padded	3X3/1	3X3X1024
Conv padded	3X3/2	3X3X1024

TABLE II

THE LAYOUT OF THE SUB-NETWORK

type	Patch size/stride	Input size
Conv padded	3X3/1	3X3X1024
Batch_normalization		3X3X1024
AveragePool	3X3/1	3X3X1024
linear	logits	1X1X1024
linear	logits	1X1X32
linear	logits	1X1X1

Once CNN is created, it is trained with training data, and CNN learns nonlinear relations between ER's information and the transmission power in each line.

By using the trained CNN, we obtain forecasts of transmission power values. Then model accuracy is evaluated by test data. The mean absolute percentage error (MAPE) is used for error measurement.

IV. SIMULATION RESULTS

In this section, in order to evaluate the functionality of the proposed controller, a series of experiments were performed on a qualitative scenario, and results are presented.Our goal with the following experiments is to determine 1) whether or not the proposed distributedmodelhas the ability to learn, 2)how the number of ERs' information transmissions affect the control results,3)whether or not the model is more effective than the other distributed ones.

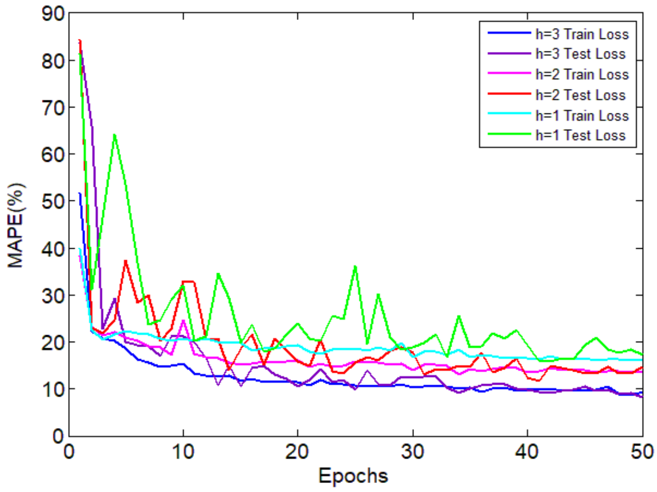

Fig. 5. Training result.

First, we present the training results of our method in Fig. 5. The hop number is set as 1,2 and 3, respectively. The results showthat the proposed distributedmodelcan learnthe nonlinear relationship between ERs' information and power transmission values, and with more informationacquired, the obtained results are more accurate.Therefore, in the followingexperiments, we set $h=3$.

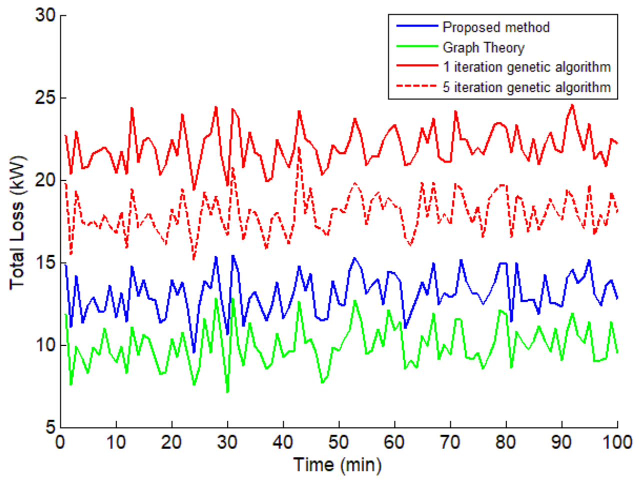

Fig. 6. Experiment results under 4 controllers.

Then, we compare the total cost of wide area EI which is expressed as (2) under 4 controllers in simulation, including power transmission values forecasted by our method, graph theory based centralized control method, and distributed control algorithm based on genetic algorithm within 1 iteration and 5 iterations. The resultsare shown in Fig. 6.Although the centralized control method achieves the best results, in the field of EI, we should focus on developing the decentralized control method. It is notable that our proposed method has better performance than the genetic algorithms under 1 and 5 iterations.

Finally, in order to verify the similarity between the forecastvalues and the true values, we choose ten ERs randomly and obtain theirforecastvaluesrespectively. Then, statistical analysis is made for the forecast values and the true values. The result is shown in Fig. 7. It can be seen that the distribution of forecast value and true value is basically the same.

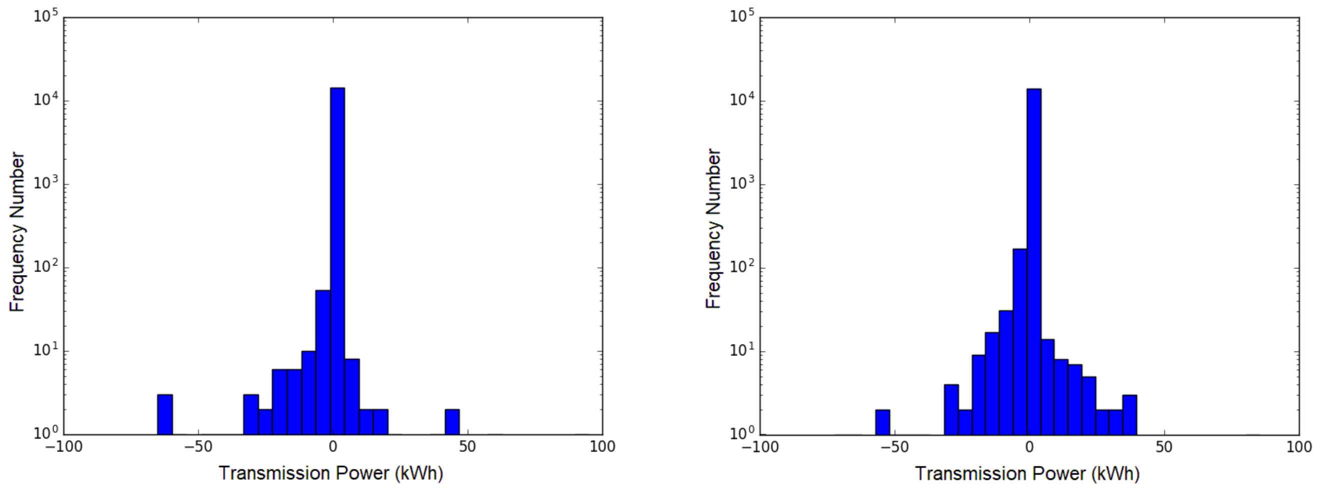

Fig. 7. **Left:**the distribution of forecast value. **Right:**the distribution of true value.

V. Conclusion

This paper introducesan improved design forER, which has three exchange structures and is responsible for energytransmission and conversion.Then a novel deep learning based distributed approach is proposed to solve the energy management problem for wide area EI which is composed ofERs, RESs, loads, MTsand ES devices.Such EIis assumed to function normally in an off-grid mode.Finally, simulationresults show theeffectiveness of the proposed approach.The future work will include:1)An advanced deep learning algorithmshall be designed to improve the predict accuracy; 2)Considering other requirements in the EI, a multi-objective optimization algorithm will beinvestigatedin order toget robust results.

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