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Internet of Things Based Smart Grids Supported by Intelligent Edge Computing

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ABSTRACT In this paper, an edge computing system for IoT-based (Internet of Things) smart grids is proposed to overcome the drawbacks in the current cloud computing paradigm in power systems, where many problems have yet to be addressed such as fully realizing the requirements of high bandwidth with low latency. The new system mainly introduces edge computing in the traditional cloud-based power system and establishes a new hardware and software architecture. Therefore, a considerable amount of data generated in the electrical grid will be analyzed, processed, and stored at the edge of the network. Aided with edge computing paradigm, the IoT-based smart grids will realize the connection and management of substantial terminals, provide the real-time analysis and processing of massive data, and foster the digitalization of smart grids. In addition, we propose a privacy protection strategy via edge computing, data prediction strategy, and pre-processing strategy of hierarchical decision-making based on task grading (HDTG) for the IoT-based smart girds. The effectiveness of our proposed approaches has been demonstrated via the numerical simulations.

INDEX TERMS Edge computing, IoT-based smart grids, data prediction, artificial intelligence, data privacy protection, cloud computing.

I. INTRODUCTION

With the supports of some new technologies, such as edge computing, big data, the 5-th generation wireless technologies (5G), IoT, and artificial intelligence (AI), smart grids have been regarded as important research topics. How to apply these new technologies to conventional power systems and establish smart grids have attracted extensive research efforts from industries and academia [1]–[3]. Conventional power systems mainly include power generations, power transformations, power transmissions, and power distributions. There are various types of power terminals and sensors in smart grids, for instance, humidity sensors, temperature sensors, immersion sensors, vibration sensors, current leakage sensors, intelligent video sensors and so on, which can support IoT based intelligent power systems [4], [5]. In this typical scenario where IoT technologies are applied to power systems, key charateristics of smart grids can be significantly improved such as data visualizations, load forecasting, failure prediction, and self-healing. As a result the optimum power systems operation and management can be achieved [6], [7]. Up to now, there are a number of technical challenges still to be further studied for IoT deployment in smart grids.

1) The transformation from traditional power systems to smart grids will encounter a large number of technical challenges. Hence, it is necessary to achieve data standardization and data fusion for establishing a digital transformation of power systems.
2) According to the statistics of the China Electricity Council, mismatches between power supply and power sales always happen in power systems, and the transmission line losses are large [8]. As shown in Fig.1 and 2, from 2010 to 2017, there still exists wide gap between power supply and power sales, and the line losses are generally on the rise. On the basis of statistics on the electricity consumptions of the whole society,

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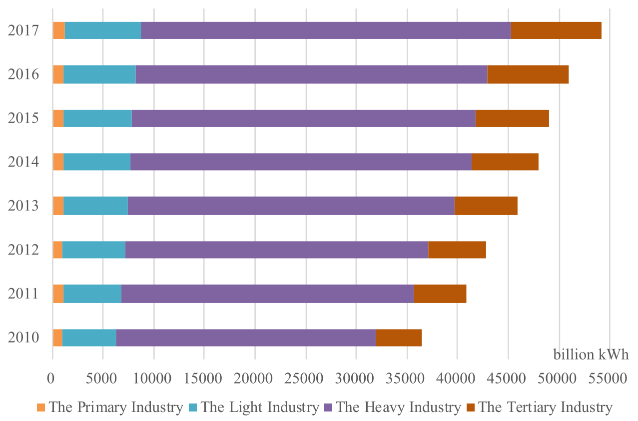

FIGURE 1. Imbalance between power supply and power sales.

the electricity consumptions vary greatly among different industries, especially between the primary industry and heavy industry. However, the present power systems cannot be deployed in real time to satisfy consumer's electricity demands [9], [10].

3) With the emergence of an increasing number of new intelligent distributed power terminals, it is necessary to achieve the plug-and-play and interoperability among devices.

Although current cloud-based power systems can partially solve these problems, they still cannot fully meet these requirements, and also bring about new challenges. The main relevant issues include:

1) The cost is high since the cloud computing should be equipped with large data center. Meanwhile the maintenance of centers is arduous and requires high transmission bandwidth.
2) Traditional cloud architecture requires high-speed processing and large-scale data storage capacities, without effective real-time services.
3) Cloud data centers of smart girds have difficulties in processing and analyzing tremendous data in an effective and real-time manner.
4) When a single node in a power systems fails in an actual metering system, several problems about how to upload data of all faulty devices to the cloud for analyses remain unresolved. First, the resolution time is long, but the cost is high. Second, many data need to be uploaded which requires high transmission bandwidths in communication networks.

Recently the general discussions discovering the relations between big data and environmental sustainability relevant green challenges have been provided in [11], [12], while the relationship between big data and cyber-physical systems (or IoT) has still been a open problem in the electricity sector. [13]. To solve these issue, the new system mainly introduces edge computing in the traditional cloud-based power systems, establishing a new software and hardware architecture. It deploys an edge computing paradigm for smart grids, which includes control, condition monitoring, information gathering, and application scenario of IoT-based smart grids. With the realization of parallel processing and analysis of data from various collection terminals, smart devices and end-users of smart grids at the edge of network, the distributed fast response services and edge intelligent services such as data prediction, privacy protection, resource allocation optimization will be provided. The advantages for the adoption of edge computing are as follows:

- **Low latency:** Edge computing process the demands of users within close proximity to the terminals, which may alleviate service latency and offer intelligent decisions.
- **Customization of personal needs:** In the metering system, the edge computing devices statistically analyse the electricity consumptions of users, thereby dynamically adjusting the power supply of each electricity consumption area and formulating a reasonable economic and energy-saving transmission and distribution scheme.
- **Decentralization:** In distributed power systems, the presence of the edge computing devices alleviate the burden on the network core nodes of the cloud computing terminals for the power systems and weaken their dependency on the cloud centers.
- **Geographical distribution:** Distributed deployment of edge computing devices can help high-speed mobility devices such as unmanned aerial vehicles for inspecting transmission lines to have better communications with each other.
- **Location awareness:** The edge computing devices can promote resource management to provide local decision-making for power transmissions.

The rest of paper is organized as follows. Section II addresses related works about IoT-based smart grids and edge computing. Section III illustrates the architecture of edge computing for IoT-based smart grids, which includes power distribution surveillance system for EC-IoT based smart grids, micro-grid system of EC-IoT smart grids, and Advanced metering system of EC-IoT smart grid. Then, applications of edge computing in IoT-based smart grids are described in section IV. We elaborate data security and privacy protection, dynamic pricing prediction and hierarchical decision-making based on task grading (HDTG) in EC-IoT based smart grids. Numerical results were presented in Section V. Finally, we conclude the paper as well as discuss the further works in Section VI.

II. RELATED WORKS

In this section, we first provide an overview of existing works in IoT-based smart grids, and then introduce the concept of edge computing.

A. IoT-BASED SMART GRIDS

IoT-Based smart grids are considered as the critical infrastructure in future [14]. With the development of 5G technologies, IoT has been of great importance to people's daily life. Integrating smart devices, information technologies, communication technologies, and artificial intelligences into traditional power systems becomes promising. At present,

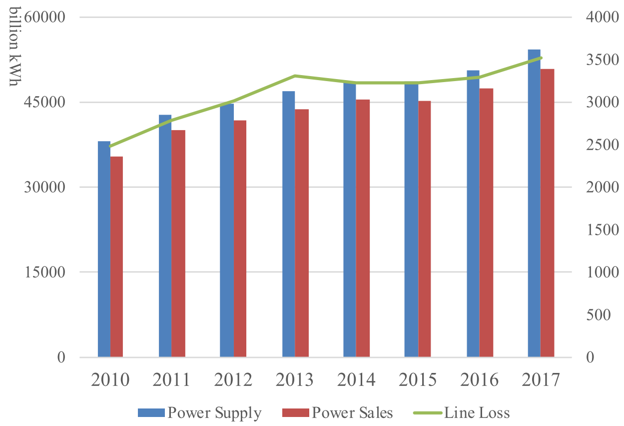

FIGURE 2. Total electricity consumptions.

the key to implement these technologies is how to build a new network structure of power systems to meet the physical layer construction of these new inventions. Obviously, the emergence of IoT-based smart grids has opens up possibilities to the realization of these technologies.

IoT-Based smart grids is a new form of network with deep integration of traditional industrial technology and IoT technologies. [4], [5]. The IoT-based smart grids may include six emblematical characteristics:

1) Plug-and-play for all kinds of terminals,
2) Wide interconnection of devices,
3) Comprehensive awareness of status of smart grids,
4) Upgraded application mode of power systems,
5) Rapid iteration of services in power systems,
6) Efficient use of electric distribution system.

The advantages of IoT-based smart grids are to realize the comprehensive sensing, data integration and intelligent application of the distribution network by utilizing the comprehensive interconnection, intercommunication and interoperability between devices in the system. It aims to meet the demand for excellence in power system management and support the rapid advancement of the energy internet, as well as achieve intelligent allocation of power resources. [15]–[17].

In order to realize the IoT-based smart grids, six fundamental technologies need to be developed, including model protocols, software-defined devices, edge computing-based application analysis, intelligent sensing technology, network information security technology, and low-cost and a wide coverage area local communication technologies. Among them, edge computing is the most important core technology to achieve real-time demand response of IoT-based smart grids and various types of edge intelligent services. The challenges for cyber-security of cyber-physical systems (or IoT) have been analyzed in [18].

B. EDGE COMPUTING IN IoT NETWORKS

Edge computing is a technology developed in the context of high bandwidth and time sensitive IoT integration. In the future, more than 50% of data need to be analyzed, processed and stored at the edge of the network [19]. As devices access the Internet of Things in large scale, the massive volumes of data generated on the terminals can provide commercial values but are very challenging in data processing. Owing to the limited network bandwidths and the real-time response requirements, edge computing has been considered as one of the new technical trends for the development of IoT [20]. Edge computing, providing an information technology (IT) service environment and extra cloud-computing capabilities, can be deployed at the edge of radio access networks (RAN) in close proximity to mobile subscribers [21]. The application of edge computing has been recognized as a significant means to achieve efficiency of network operations and latency reduction for better end user experience. It also satisfies the needs in terms of agile connectivity, real-time services, data optimization, application intelligence, and privacy protection. [22], [23].

Therefore, edge computing could be widely applied in smart cities, intelligent transportation, health care, smart manufacturing, smart home, and other application areas [24]. In particular, issues including smart grids related with edge network, demand response and energy-saving transmission have attracted heated discussions both in academics and industries [25]–[30]. As there are numerous power sensor nodes in the IoT-based smart grids, these devices need to process the data sources at the edge of networks to meet the real-time demand responses, such as real-time local electric distributions, transmissions, and accident alarms. With edge computing, there is no need to upload the edge data to a remote cloud network for analysing and processing, leading to delayed responses. In this case, an open platform for connection, computing, storage and application is needed at the edge of the network close to the object or data source, which can provide edge intelligent services for the data of the power sensor nodes. Meanwhile, considering that data are no longer necessarily transmitted over distant networks, the security and stability of the system is more controllable.

III. ARCHITECTURE OF EDGE COMPUTING FOR IoT-BASED SMART GRIDS

In this section, we present the system of IoT-based smart grids. Then we will introduce the specific services of IoT-based smart grids supported by edge computing, which are applied to the three main scenarios, including power distribution surveillance systems of EC-IoT smart grids, micro-grid systems of EC-IoT smart grids, and advanced metering systems of EC-IoT smart grids.

As shown in Fig. 3, in the three typical scenarios of smart grids, the applications of IoT and edge computing technologies make intelligence and automation of power systems enter into a new stage. parallel processing and analysis of data from various collection terminals, smart devices and end-users of smart grids can be realized at the edge of network via deploying the edge computing model for the smart grids with supporting technologies such as micro-super-computing, data fusion, multi-agent and deep learning, providing a distributed

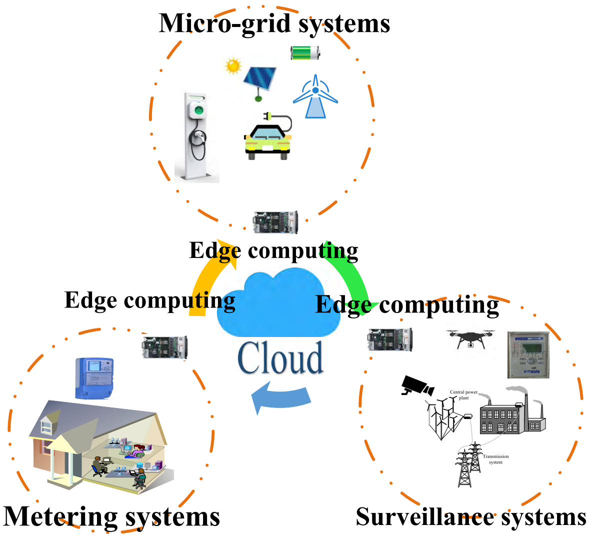

FIGURE 3. Architecture of edge computing for IoT-based smart grids.

information computing service with large volumes of data and fast responses. Under such circumstance, this mode can satisfy the demand of rapid responses required by devices and users in the smart grids and provide supports for advanced applications of smart grids such as intelligent scheduling, intelligent maintenances, intelligent user responses, and rapid market responses.

This paper proposes an edge computing hardware and software architecture for power systems, which combines with the reference architecture of industrial edge computing [31], and consists of five layers as shown in Fig. 4 and explained briefly as follows:

1) **Device layer:** Devices generally include applications, security modules, networks, security operating systems, and core control chips.
2) **Network layer:** The network layer satisfy the demand of rapid responses required by devices and users as network security, access control, and real-time terminal connection.
3) **Data layer:** The data layer mainly provides data security, data analysis, data privacy protection, and data fusion functions.
4) **Application layer:** Application layer primarily covers application security, intelligent edge services, and edge computing applications.
5) **Cloud computing layer:** Cloud computing layer typically offers services, such as SaaS (software-as-a-service), PaaS (Platform-as-a-service), IaaS (Infrastructure-as-a-service), and DaaS (Data management as a service).

Among them, edge computing devices, on the basis of the hardware platform, mainly have a network layer, a data layer, and an application layer. In addition, the network management module, the computing management module, and the memory management module are also contained. The edge computing devices can also ensure the secure access of various terminals in the device layer and keep themselves and cloud computing layer to work collaboratively through application programming interfaces (API).

The power terminals and various types of sensing devices in the equipment layer can be connected with the edge computing devices through two approaches, a wireless (such as WiFi, buletooth, ethernet, 3G/4G wireless) network and a wired network. The reference architecture can provide edge

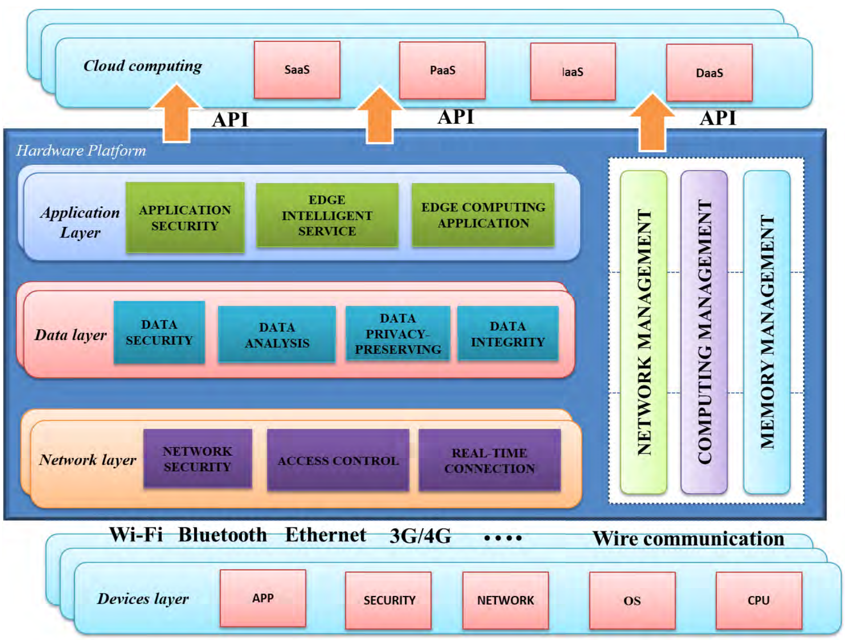

FIGURE 4. Edge computing reference architecture for IoT-based smart grids.

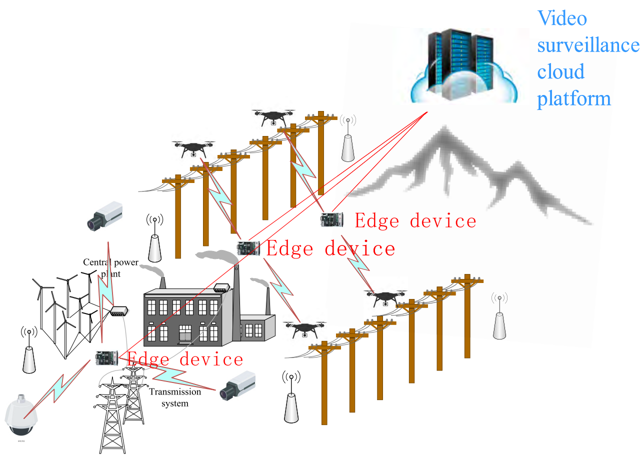

FIGURE 5. Power distribution surveillance system of EC-IoT smart grids.

intelligent services in close proximity to users so as to achieve digitization of power systems. In this regard, it will give prominence to the advantages of edge computing in agile connections, real-time services, data optimization, application intelligences, cloud collaborations, and localized computing.

The power distribution surveillance system is mainly composed of state detection and video surveillance of the transmission and distribution networks, which plays the roles of remote control, telemetry and remote signaling. Operation status of the transmissions and distribution processes can be fully mastered in time through real-time collection and display of various operating switch states and power parameters during generations, transmissions, and conversions of power. More importantly, faults can be found promptly, and corresponding decisions can be made and dealt with [32], [33]. The edge computing-based power monitoring system adds edge computing device nodes to the traditional cloud-based power monitoring system. The device nodes can implement agile control, data storage, and application of edge computing, and meanwhile process some real-time response locally without uploading data to the cloud. Moreover, other characteristics that benefit the devices own in the system include real-time analyses of power loads in local areas, reasonable scheduling of power consumptions, and fast responses to the distribution and transmission system.

The Fig. 5 mainly describes the two service applications of intelligent inspection for transmission lines utilizing unmanned aerial vehicles and video surveillance in the power monitoring system based on edge computing.

A. POWER DISTRIBUTION SURVEILLANCE SYSTEM FOR EC-IoT BASED SMART GRIDS

1) TRANSMISSION LINE MONITORING BY UNMANNED AERIAL VEHICLE

Deployed in local areas, edge computing device nodes can perform data interactions with groups of unmanned aerial vehicles when they fly into the regions under the control of edge computing networks. Then, through real-time processing information, offline information, end-users' information, parameters of electrical structure of power grids, and geographic information gathered by inspection of unmanned aerial vehicles, preliminary judgment of the accident level and real-time processing feedbacks can be provided. In the event of a natural or man-made failure, it is possible to effectively control and eliminate the adverse consequences caused by failures in a timely manner while maintaining the stable operations of the grid system. Simultaneously, the edge computing devices can also aggregate the relevant conditions and upload the situation to the cloud computing center to realize panoramic and long-term data accident analyses.

2) VIDEO SURVEILLANCE

Deployed in substations, edge computing device nodes can be integrated with system services such as anti-misoperation, transmission line monitoring, power transmission and transformation surveillance, electric brakes monitoring for abnormality, and power dispatching automation. They support accesses to multiple monitoring devices and can be set in different substations as needed. Besides, the devices at the edge of the network realize the unified terminal management of video data, environmental data, power data and alarm data, which ensures the warnings before events, the suppression during events, and the reviews after events.

Compared with the traditional cloud architecture, the edge computing-based power monitoring system has the advantages of short delays, fast local response time, data filtering and pre-processing. It is not necessary to transmit every original data to the cloud, which reduces the needed transmission bandwidth for direct uploading to cloud and reduce transmission costs. In addition, the system will work with the cloud according to the amount of data and the complexity of the architecture. For example, edge computing can be used as a collection unit of cloud data to support big data analysis of cloud applications, while cloud computing can feedback the optimized information to the terminal through big data analysis, and then makes further processing through edge computing. Edge computing can realize the quick responses in light of the situation scale to attain the efficient and stable operations of the smart grids.

B. MICRO-GRID SYSTEM OF EC-IoT SMART GRID

The micro-grid system is a small-scale power distribution system consisting of distributed power sources, energy storage devices, energy conversion devices, and devices for electrical load, monitoring and protection. It aims to implement flexible and efficient application of distributed power supply and tackle the problem of interconnection between massive and diverse distributed power supplies. The development and extension of the micrograds can fully promote the large-scale access of distributed power and renewable energy as well as achieve highly reliable supplies of multiple forms of energy sources. This is an effective way to establish a proactive electric distribution system, making the transition from traditional grids to the smart grids [34]. The micro-grid system of EC-IoT smart grids is set on the foundation of

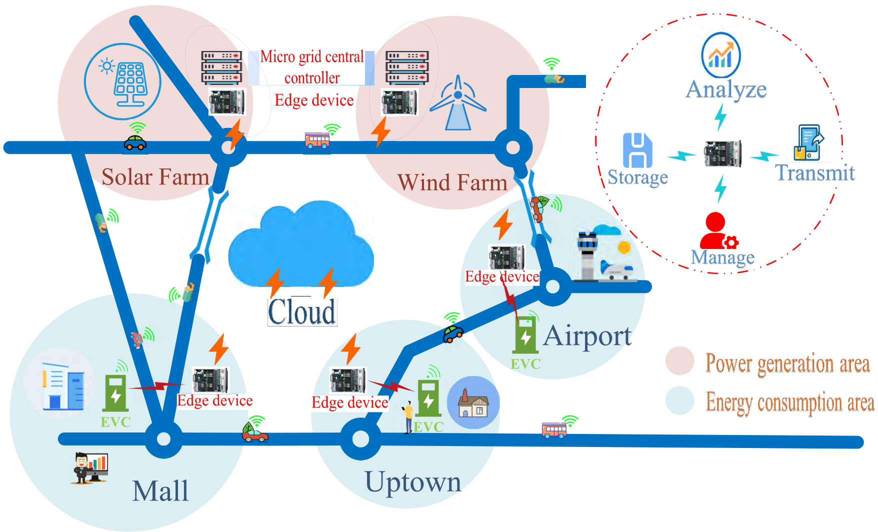

FIGURE 6. Micro-grid system of EC-IoT smart grids.

cloud-based renewable energy micro-grid system. Its control center and the edge computing devices are taken as local edge computing nodes to establish a real-time edge service scenario on the demand side for the electricity consumptions within the area.

Fig. 6 mainly depicts the two scenarios of edge computing applied in smart grids, namely, power supply management of charging points, and power balance and identification of malicious behaviors in electricity consumptions.

1) POWER SUPPLY MANAGEMENT OF CHARGING POINTS

Charging point is a boundary point for integrating power systems, information networks, and transportation networks. Large-scale attacks can lead to drastic fluctuations in power systems and traffic congestion. The local edge computing nodes can analyze the features and the consumption mode in consuming electricity of the charging points and memorize the features. Besides, it can analyse the sudden fluctuations of power consumptions, and balance the dynamic features of local power consumptions. For sudden, malicious, and aggressive power fluctuations, edge computing can identify them and report the results to the cloud management center.

2) IDENTIFICATION OF MALICIOUS BEHAVIORS IN ELECTRICITY CONSUMPTION

The edge computing devices collect the photovoltaic power generation in real time from micro-network central controller and grid-connected interface controller of distributed power supplies, and establish the electricity generation behavior mode of each device, which is characterized by quantity of electricity and time of the photovoltaic power generation equipment. Correspondingly, these devices use the power consumption behaviors of users in the micro-network as parameters to build the electricity behavior mode and identify the power balance and malicious behavior of the smart energy.

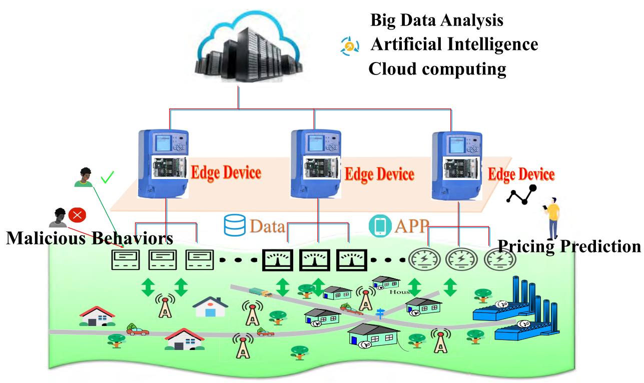

FIGURE 7. Advanced Metering system of EC-IoT smart grids.

C. ADVANCED METERING SYSTEM OF EC-IoT SMART GRID

The advanced metering system can realize automatic collection, remote transmission and storage, and pre-processing of electricity consumption data, ensuring the reliability, uniqueness, accuracy and continuity in the process of collecting, transmitting, and processing these data. The advanced metering systems for EC-IoT smart grids lay out edge computing devices in power meter concentrators within traditional cloud-based metering systems. Those edge computing devices mainly are equipped with the functions of edge computing application service analyses, data storage, and data analyses. The system can achieve real-time responses on the demand side in power meter concentrators based on edge computing. The Fig. 7 mainly represents the architectural features of the system. At the metering client side, their own power usage information is first uploaded to the centralized metering device with edge computing capability through wired and wireless communication. And then power metering service based on the edge computing service can be implemented. For instance electricity price forecasting in metering systems (dynamic pricing prediction) and identification of malicious behaviors in electricity consumptions. Through collecting the information about power usage recorded in electricity meter and then predicts the real-time electricity price under the national pricing constraints. The predicted price will be sent to the user through the APP to select the power usage time. In this way, it is expected to realize friendly interactions between power supply and consumers. The power meter concentrators with edge computing take the information of power consumption and usage time recorded by each meter as parameters to establish the power consumption behaviors. Also, they will identify the sudden or phased changes in the use of electricity and evaluate damages towards the grids due to abnormal changes. Finally, these data will be reported to the cloud management center.

Compared with the traditional cloud-based metering system, metering system of EC-IoT smart grids can realize accurate real-time electricity price forecasting, localize real-time analysis of application service in smart grids, optimize resource allocation scheme, improve reading efficiency of metering system and cut costs. In particular, in the edge computing device layer, metering system can achieve terminal compatible access, information sharing transparency, integrated standard specification, and facilitate the synergy and interoperability of information management service in power systems. Furthermore, the system has a role play in reliable data storage and optimization management for massive user electricity and power grid data. As a whole, the intelligent analyses of grid data and accessory decision supports can be improved by means of fully exploiting the potential values of information.

IV. APPLICATION OF EDGE COMPUTING IN IoT-BASED SMART GRIDS

In this section, we will present the typical applications and the related advantages brought by the architecture based on the three scenarios of the EC-IoT grid system. Depending on features of edge computing, users' data privacy can be protected, meanwhile dynamic power price forecasting in advanced metering systems can be provided. Furthermore, hierarchical task real-time processing response strategies will be achieved for electricity users' timely demand response.

A. DATA SECURITY AND PRIVACY IN EC-IoT BASED SMART GRID

Privacy is information that individuals and institutions are unwilling to be known by others. In general, it refers to sensitive data, such as illnesses, bank card numbers, and so on. The user privacy of the advanced metering system is mainly presented by their personal information, such as the ID number, contact information, and electricity-consumption habits. In IoT-based smart grids, some people with ill-intentions can obtain user privacy through data mining technologies. In order to solve this problem, on account of the features of edge computing, we propose a differential privacy data distortion technique based on Laplace mechanism and Gaussian mechanism.

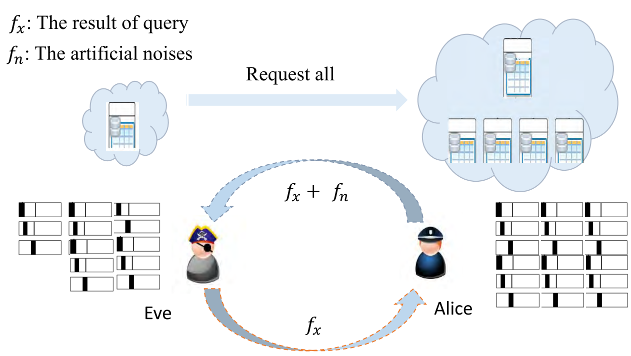

FIGURE 8. Attack model of interactive data access.

The proposed technology is implemented by edge computing devices, in which artificial noises are added to the power consumption data of each smart meter, thus hiding the electricity behavior model and avoiding leakage of privacy. We first introduce the Laplace differential privacy mechanism before elaborating on the Gaussian differential privacy mechanism, both of which can be used for data privacy protection. Differential privacy protection protects sensitive data by adding artificial noises, while ensuring that the data retains the same statistical characteristics as the original data set after adding the artificial noises, making the published data meaningful and facilitating data mining [35].

We establish an attack model of interactive data accesses as shown in Fig. 8. Eve is the attacker and Alice is the publisher of a database. First, Eve is disguised as the legal identity and initiates a request for querying the database to Alice. After Alice implements the privacy protection towards the query result, she sends it to Eve. Hypothesizing that the attacker Eve gets the original sensitive data set that are very similar to the real data set owned by Alice (in the worst case, for example, the data set of attacker Eve are only different from the real data set in one piece of information), the privacy protection method still needs to ensure that the attacker Eve cannot obtain sensitive content of this information regardless of what are the adopted methods. According to the attack model, the mathematical definition of differential privacy is: A randomized algorithm H with domain $\mathbb{N}^{|X|}$ is (ε, δ) differentially private if for all $T \subseteq Range(H)$ and for all $x, y \in \mathbb{N}^{|X|}$such that $\|\mathrm{x}-\mathrm{y}\|_1 \leqslant 1$:

$$\Pr[H(x) \in T] \leq \exp(\varepsilon)\Pr[H(y) \in T] + \delta \tag{1}$$

where ε stands for privacy budget as security indicator. The smaller the indicator ε is, the higher the security level will be.

Algorithm 1 Laplace Mechanism

Input: a private database X, an adaptively chosen stream of sensitivity l_1 queries $g_1...g_j$.
Output: an adding noise database $\hat{\text{X}}$.

LM $(x, \{g_i\}, \varepsilon, \sigma)$.
Calculate the $\Delta_1 g$, using formula (2).
Calculate the scale parameter $b = {}^{\Delta_1 g}/_{\varepsilon}$.
Calculate the noise $N = \frac{1}{2}(1 + sgn(x)(1 - \exp(\frac{|x|}{b})))$.
Calculate the adding noise database $\hat{\text{X}} = X + N$.
Output: $\hat{\text{X}}$.

1) LAPLACE MECHANISM

We firstly define sensitivity, an essential concept in this mechanism. Specifically, it refers to the degree of impact on the results of our query after the artificial noise is added to the data set that needs privacy protection.

The l_1 sensitivity of a function g: $\mathbb{N}^{|X|} \rightarrow \mathbb{R}^k$ is:

$$\Delta_1 g = \max_{\substack{x, y \in \mathbb{N}^{|X|} \\ \|x - y\|_1 = 1}} \|g(x) - g(y)\|_1 \tag{2}$$

The Laplace distribution is the distribution with probability density function:

$$Laplace(x|b) = \frac{1}{2b} \exp(-\frac{|x|}{b}) \tag{3}$$

Given any function $g(x)$:$\mathbb{N}^{|X|} \rightarrow \mathbb{R}^k$, the Laplace mechanism is defined as:

$$M_L(x, g(x), \varepsilon) = g(x) + (Y_1, \ldots, Y_k) \tag{4}$$

where Y_i are independent and identically distributed (i.i.d.) random variables drawn from $Laplace(\Delta_1 g/\varepsilon)$. This mechanism preserves $(\varepsilon, 0)$ -differential privacy. Algorithm 1 implements a privacy protection method based on the Laplace noise mechanism, which uses sensitivity l_1 and the query function, $g_j(x)$. After the queries of users, scale parameter b, the artificial random noise of Lap(b), is added to the feedback result and generated $\hat{\text{X}}$, thereby achieving differential privacy protection for in the privacy data of set X.

2) GAUSSIAN MECHANISM

Gaussian noises are very commonly used in modeling communication systems. Similarly, we can also implement privacy protection by adding artificial Gaussian mechanism noises, but, if this mechanism is adopted, we need to have some conditional restrictions, and to broaden the definition of differential privacy. Again, in the same way as Laplace, we first define the sensitivity, here the l_2 sensitivity is applied:

The l_2 sensitivity of a function g: $\mathbb{N}^{|X|} \rightarrow \mathbb{R}^k$ is:

$$\Delta_2 g = \max_{\substack{x, y \in N^{|X|} \\ \|x - y\|_1 = 1}} \|g(x) - g(y)\|_2 \tag{5}$$

The Gaussian distribution is the distribution with probability density function:

$$Gaussian(x|\mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp(-\frac{(x - \mu)^2}{2\sigma^2}) \tag{6}$$

Given any function $g(x)$: $\mathbb{N}^{|X|} \rightarrow \mathbb{R}^k$, the Gaussian mechanism is defined as:

$$M_L(x, g(x), \varepsilon) = g(x) + (Y_1, \ldots, Y_k) \tag{7}$$

where Y_i are i.i.d. random variables drawn from Gaussian distribution $\mathcal{N}(x|0, \sigma^2)$, $c^2 > 2\ln(\frac{1.25}{\delta})$, and $\sigma > \frac{c\Delta_2 g}{\varepsilon}$. This mechanism preserves (ε, δ)-differential privacy. Algorithm 2 implements a privacy protection method based on the Gaussian mechanism, which uses sensitivity l_2 and the query function, $g(x)$. After the queries of users, the normal distribution random noise of the scale parameter $N(0, \sigma)$ is added to the feedback result and generated $\hat{\text{X}}$, thus achieving differential privacy protection for $(\varepsilon, \delta = 0)$ in the privacy data of set X. The values of ε and c are strictly defined, otherwise the differential privacy cannot be satisfied.

Algorithm 2 Gaussian Mechanism

Input: a private database X, an adaptively chosen stream of sensitivity l_2 queries $g_1...g_j$. Privacy budget ε, δ, σ, constant c.
Output: an adding noise database $\hat{\text{X}}$.

$GM(X, \{g_i\}, \varepsilon, \delta, \sigma, c)$.
Let $\Delta_2 g$, using formula (5).
If $0 < \varepsilon < 1$.
    If $c^2 > 2\ln(1.25/\delta)$.
        Let $\sigma \geq c\Delta_2(g)/\varepsilon$.
        $N = \frac{1}{2}(1 + sgn(x)(1 - \exp(\frac{|x|}{b})))$.
        Let $\hat{\text{X}} = X + N$.
        Else halt.
    End if.
Else halt.
End if.
Output $\hat{\text{X}}$.

B. DYNAMIC PRICING PREDICTION IN EC-IoT BASED SMART GRIDS

Whether the power supply and power sales can achieve the optimal supply and demand relationship is an unresolved issue of the power grid company nowadays. Similarly, it is also important for power consumers to be informed that how they can exploit reasonable power consumption schemes to meet daily expenses and achieve cost savings. To satisfy these demands, edge computing-based real-time data prediction algorithms can be adopted.

Whatever a power consumer or a power grid company is, all power consumption is generated in time series. According to the prediction of the time series, the electricity consumption will vary in line with the influence of the time period. For these time series, there is some correlation in a certain sense.

It is necessary to find an algorithm suitable for the EC-IoT based smart grids framework to predict the consumption data of the user. On one hand, this enables power supplier to timely understand the needs of the consumer and reasonably adjust relationship between supply and demand. On the other hand, the forecast information of acceptable price will be given to help consumers choose the electricity consumption period efficiently. Therefore, the dynamic pricing prediction plays an important role in smart grids. Generally, for forecasting the electricity prices there are many different approaches like Auto Regressive Integrated Moving Average (ARIMA) models, simpler Auto Regressive (AR) models modern techniques such as ANN, Fuzzy logic [36]. In this paper, considering the current demands in smart grids, we propose a real-time data prediction algorithm based on long short term memory (LSTM), which could deal with long term information dependency. LSTM is a special case of Recurrent Neural Network (RNN) [37]. However, unlike traditional RNN, LSTM will selectively remember or delete a piece of information based on whether it is useful or not. The LSTM is used in this study to forecast the price because this method has high capability to learn the complicated relationship between the input and output through a supervised training process with historical data. LSTM adds 3 gates, forget gates, input gates, and output gates respectively on the ground of RNN to avoid long-term dependency problem [24].

Mathematical Model:

Dataset:

$$\{x_1, x_2, \cdot\cdot\cdot, x_t\} \rightarrow y_t$$

where x_k means the input of time k, and the length of time series is t. Correspondingly, y_t is the surveillance information at time t.

Forget gate layer:

$$f_t = \sigma(U_f \cdot h_{t-1} + W_f \cdot x_t] + b_f) \tag{8}$$

Input gate layer:

$$i_t = \sigma(U_i \cdot h_{t-1} + W_i \cdot x_t] + b_i) \tag{9}$$

$$C_t = \tanh(U_c \cdot h_{t-1} + W_c \cdot x_t + b_c) \tag{10}$$

$$\hat{C}_t = f_t * C_{t-1} + i_t * C_t \tag{11}$$

Output gate layer:

$$o_t = \sigma(U_o \cdot h_{t-1} + W_o \cdot x_t + b_o) \tag{12}$$

$$h_t = o_t * \tanh(\hat{C}_t) \tag{13}$$

$$y_t = soft\max(h_t) \tag{14}$$

Computing of cross-entropy loss:

$$\min_\theta J(\theta) = \sum_{j=1}^{m} loss(\hat{y}_t, y_t)$$

$$\theta = [U_f, W_f, U_c, W_c, U_o, W_o, b_f, b_i, b_c, b_o] \tag{15}$$

where σ sigmoid function is an activation function that converts the output value to a value of $0-1$, thus retaining parts

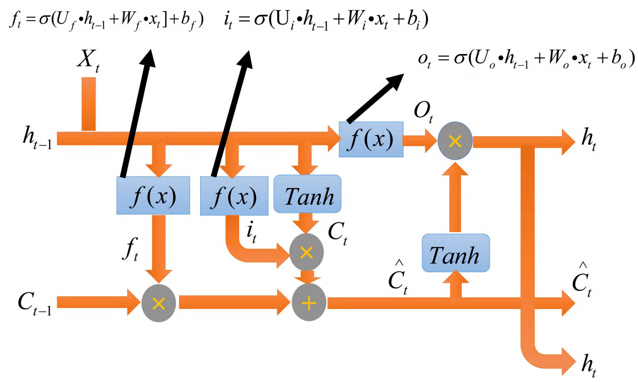

FIGURE 9. The LSTM unit.

of information. x_t inputs vector to the LSTM unit, h_t outputs vector of the LSTM unit. W, U, b weight matrices and bias vector parameters which need to be learned during training. *Tanh* is an activation function that converts the output value ranging from -1 to 1.

The LSTM has three main phases to controll three gates as shown in Fig. 9. First, for the previous node h_{t-1}, x_t, selective forgetting content is generated through function 8 calculating f_t, in which 0 stands for completely discard, and 1 complete reservation. Next, $\hat{C}_t = f_t * C_{t-1} + i_t * C_t$ is to update the cell from C_t to $\hat{C}_t$. Finally, our final output is confirmed by the function. Algorithm 3 can predict the electricity price of the next moment in the light of the power consumption information in time series, and provide users with the power consumption information for the next period, hence reducing the power supply pressure, and also encouraging off-peak power use.

C. PREPROCESSING STRATEGY OF HIERARCHICAL DECISION-MAKING BASED ON TASK GRADING (HDTG) IN EC-IoT BASED SMART GRIDS

There are a large number of intelligent terminals in the power systems, and their demand responses are different. For example, some terminals need to respond to application service in real time, and some coordinate with cloud computing to analyse massive information to achieve global situational awareness. Besides, some devices need timely interactive communications to provide real-time edge computing intelligent services. In these services, it is an open problem how to evaluate the service level and offer a reasonable service processing strategy and network structure. To solve this problem, we propose an algorithm of preprocessing strategy of hierarchical decision-making based on task grading. First, the user initiates a service request, and then edge computing devices evaluates results according to the service demands, such as assessments for real-time demand service responses, task computational complexity, security levels, storage spaces, application demands, and data volumes.

Subsequently, the edge computing devices, in accordance with the task grading made by the access device, selects the corresponding policy method, which is mainly categorized

Algorithm 3 LSTM for Dynamic Pricing Prediction in EC-IoT Based Smart Grids

Input: the data-set X and learning rate l_r.
Output: the prediction model $F(x)$.

Data processing.
Normalization of data $X = \frac{X - mean(X)}{var(X)}$.
Establish the training dataset X_{train}.
Establish the test dataset X_{test}.
Defining neural network variables and establishing the original LSTM model.
Calculate the Forget gate, using formula (8).
Calculate the Input gate, using formula (9,10,11).
Calculate the Output gate, using formula (12,13,14).
Initialize variables U, W, b.
Model creation was completed.
Using the training set to train the model.
Calculating the loss function according to cross entropy.
$\min_{\theta} J(\theta) = \sum_{j=1}^{m} loss(\hat{y}_t, y_t)$.
Using Adaptive moment estimation to optimize algorithm.
Getting the optimal solution when learning rate is l_r.
Updating parameter U, W, b.
Setting prediction model $F(x)$.
Output prediction model $F(x)$.

into four levels, (1) real-time processing in devices close to the user, (2) partial storage in the side of edge, (3) uploading for processing, and (4) deletion.

The rating is expressed as

$$level[N] = \sum_{i=1}^{4} \sum_{j=1}^{n} \frac{1}{2n} |sgn[T_i - f_j(x)] - 1| \tag{16}$$

where T_i represents every evaluation basis, $f_j(x)$ is every evaluation function. Evaluation levels and results are shown below.

Results	0 or 1	2	3	4
Operation	Delete	Processing	Partial storage	Uploading
Devices Level	1	2	3	4

Algorithm 4 establishes a pre-processing level evaluation method suitable for the EC-IoT based smart grids.

V. NUMERICAL SIMULATIONS

In order to verify the feasibility of the above theory, we performed numerical simulations on data prediction, privacy protection, and transmission consumption with edge computing and cloud computing framework.

A. DATA PREDICTION

We use hypothetical data sets to simulate electricity prices in a urban area. In order to validate the effect of numerical simulation, we make the data set have a fluctuating trend with time. We have adopted algorithm 3, and respectively set the number of hidden layers as 10, the learning rate 0.0006,

Algorithm 4 Pre-Processing Level Evaluation Mechanism

Input: a message x, an adaptively chosen testing function $f_j(x)$, and T_i is threshold for every evaluation level.
Output: the level of access devices Level[N].

$GM(X, f_j, T_1, T_2, T_3, T_4, Level[N])$.
The sensor sends task demand information to the edge computing nodes.
The setting of T_i determines the standard of the scores of each test item, and can appropriately adjust the respective scoring benchmarks considering the importance of each test item.
For i=1 to 4.
  For j=1 to n.
    If $f_j(x) > T_i$, the edge computing node gives the evaluation result according to the item of the test. Among them, T_i is evaluation criterion of the item.
    This item scores 1.
    Else.
    This item scores 0.
    End if.
  End for.
End for.
Output the sum of the individual evaluation items is counted. If the sum is 0 or 1, the level is 1. If the sum is 2, the level is 2. If the sum is 3, the level is 3. If the sum is 4, and the level is 4.

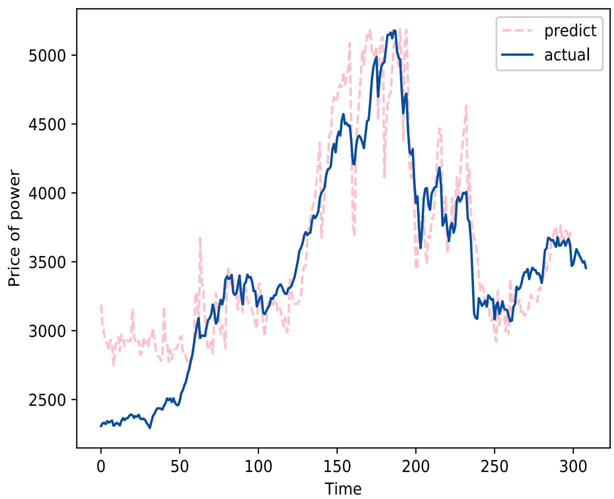

FIGURE 10. Data prediction.

the training data set 3800, the test data set 2000, and the optimal solution iteration times 30 times in the simulation. The simulation results are shown in Fig. 10. It can be seen that this algorithm can accurately make predictions. As time passes, the results of prediction curve is more and more matched with the real values. The accuracy of the algorithm has been demonstrated.

The simulation results have shown that the LSTM algorithm can be used to predict the power price at the edge computing devices. Meanwhile, the consumer can

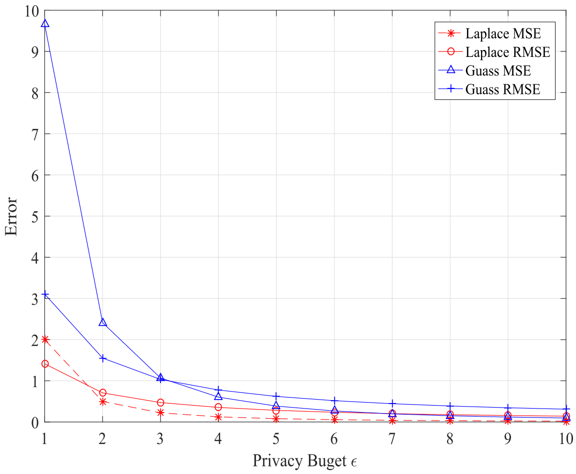

FIGURE 11. Differential privacy.

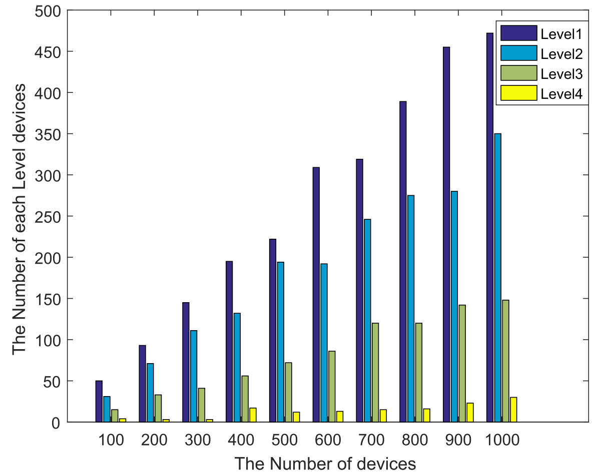

FIGURE 12. The preprocess by edge computing.

adjust the electricity consumption behavior in a reasonable way in accordance with predicted electricity price by edge computing devices. For example, when electricity price is high during the peak hours, the consumer can choose to avoid power consumption in the peak period as much as possible.

B. DATA PRIVACY PROTECTION

We have performed numerical simulations of two privacy protection mechanisms and compared the two mechanisms. We have used Matlab to randomly generate a private data set that needs to be protected. Then we have built the attack model according to Fig. 3. For the convenience of numerical simulations, it is assumed that the value of l_1 sensitivity and l_2 sensitivity of the attackers query function all are equal 1. The artificial noises are added to the query results of the attacker by algorithm 1 and 2, which is Laplace noise and Gaussian noise respectively. The mean squared error (MSE) and root mean squared error (RMSE) are taken as the availability evaluation, and ε the privacy budget. Then, the data set and the original data after the noise addition have been compared and analyzed. The smaller the privacy ε, the higher the privacy of the data, but lower the availability of the data.

The simulation results are shown in the Fig. 11. First, the two curves, with the increase of ε, the MSE and RMSE value all show a downward trend, indicating that the availability of the data is gradually improved when the privacy budget is reduced. Second, with the changes of ε from 1 to 10, we have found that the noise curve based on Laplace is under the Gaussian mechanism curve in general, showing that the overall performance of the noise of the Laplace mechanism is better than that of the Gaussian mechanism. Based on the performance results, we prefer to using the Laplace mechanism for privacy protection, while the Gaussian mechanism can be used as an alternative.

C. PREPROCESSING OF HIERARCHICAL DECISION-MAKING BASED ON TASK GRADING(HDTG)

It is assumed that 100 to 1000 power terminal devices are connected to the EC-IoT based smart grids, and task level evaluation is performed at the edge computing devices. The evaluation level is classified into four levels, and the number of devices at each level is counted. The simulation involves 2 steps. At first, we use Matlab to randomly generate the amount of 100-1000 device vectors. The vector owns 4 dimensions. The dimension value is evaluation score from 1 to 100 that are randomly generated. Then the algorithm 4 is applied to establish edge computing-based task scoring and grading strategy. Finally, setting T_1, T_2, T_3, T_4, and the value of each them is 60. As shown in Fig. 12, the simulation results have manifested that, in the case of different access devices, the edge computing devices grade the decision results for the services demand of 100-1000 devices by algorithm 4. Next, according to the task grading of access terminals made by edge computing devices with the purpose of ranking the task level, we have obtained the result from first level to the fourth level.

The demand response task of the access terminal is preprocessed by the edge computing devices. As a result, they perform corresponding processing on different task levels. For example, the edge computing devices locally process the low-level service requirements, but the tasks with higher-level response requirements which edge computing is incapable of processing should be uploaded to the cloud and processed in conjunction with cloud computing. This is how to reduce the amount of transmission data to be uploaded to the cloud. In the second simulation, it is assumed that the four bandwidths for uploading service demand responses is 5, 10, 15, 20 $* 10^4$ bits per second and their transmission distance is different. Among them, the transmission distance of service demand responses that the grid architecture with cloud center require is much longer than that of the architecture edge computing deployed. The results of the hierarchical response of a large number of accessed devices are given by the last numerical simulation.

The simulation results are shown in Fig. 13 and Fig. 14, which mainly include four points:

1) The transmission bandwidth required by the traditional cloud-based grid is rising with the increase of the

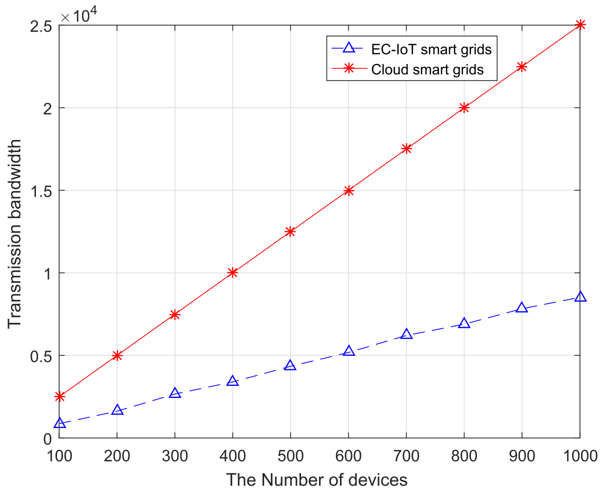

FIGURE 13. The need of bandwidth.

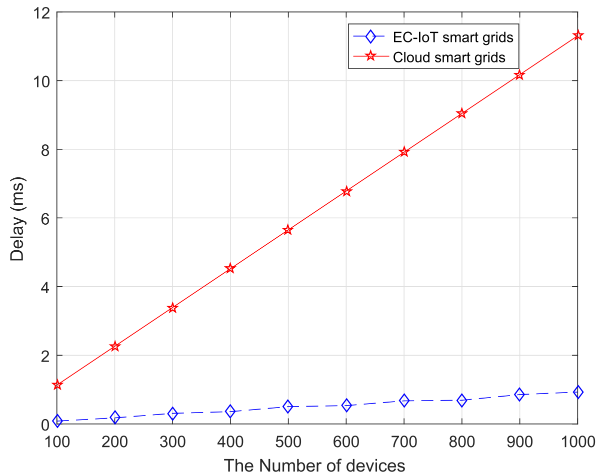

FIGURE 14. The time delay.

number of devices compared with EC-IoT based smart grids.

2) The requirement for transmission bandwidth of framework with edge computing is always smaller than that of cloud.
3) It is demonstrated that a power system with an edge computing architecture has the advantage of reducing transmission bandwidth.
4) Delay and bandwidth are two indicators of quality of service (QoS). From numerical simulation of bandwidth and delay, it can be seen that the QoS performance of the edge computing architecture is better than the cloud-centric smart grids.

VI. CONCLUSION

In this paper, we have mainly focused on solving the problems caused by the IoT-based smart grids, such as the rapid response for user's requirement, intelligent scheduling, intelligent maintenances, intelligent response for consumers, and rapid market responses. Here, we have proposed an architecture introducing edge computing into IoT-based smart grids. Moreover, in the three major scenarios of power systems that power distribution, Micro-grid, advanced metering systems, application of edge computing are well represented. Whether it is real-time response or edge computing-based service, both of them fully reflect its advantages in comparison with traditional cloud-based power systems. Subsequently, we have proposed algorithm strategies, data privacy protection, data prediction, and task grading strategies appropriate to the new architecture. From numerical results, we have concluded that our proposed strategy can effectively protect the data privacy in the system and bring new opportunities for the realization of IoT-based smart grids. In future work, we will implement edge computing into power grids to support applications in reality. In addition, the business value of edge computing applied in power systems will be manifested and practical feasibility of our algorithm will be verified as well.

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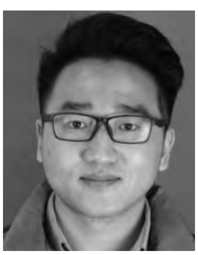

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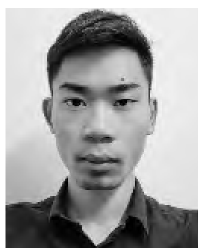

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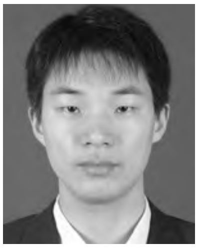

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