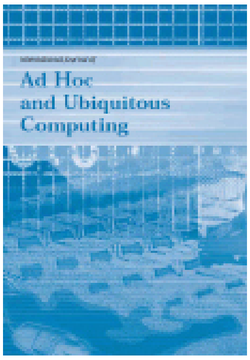

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# A survey of intelligent load monitoring in IoT-enabled distributed smart grids

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# A survey of intelligent load monitoring in IoT-enabled distributed smart grids

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**Abstract:** Power load monitoring has been a research hotspot since a few years ago. With development of artificial intelligence, construction of smart grid has become the most important part of power load monitoring. At the same time, task scheduling mechanism combined with the distributed internet of things (IoT) improves efficiency of smart grid. In this paper, applications of cloud/edge platform in the data acquisition, processing and scheduling of the IoT is introduced step by step, as well as applications and differences of artificial intelligence algorithm in each step, including data acquisition, load disaggregation, load forecasting and so on. Finally, combined with various optimisation methods, future research directions are prospected, including data and network security issues, and challenges faced by cloud/edge architecture, adaptive fine-grained load disaggregation, and load forecasting.

**Keywords:** internet of things; IoT; smart grids; artificial intelligence; load disaggregation; load forecasting.

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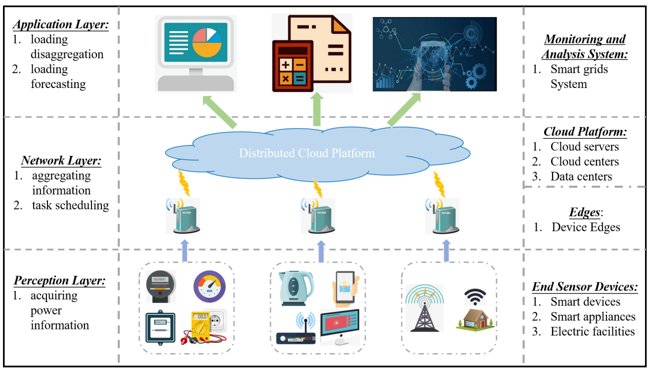
## 1 Introduction

Smart grid is an efficient power energy consumption analysis and acquisition system, which uploads and analyses data collected at the edge by combining with distributed acquisition nodes. It is an intelligent system integrating remote control and artificial intelligence real-time analysis (Liu et al., 2020a). With the development of distributed IoT, smart grid technology based on IoT has also been improved. Combined with three-tier architecture of the IoT, based on original smart grid, distributed services are used to realise various task scheduling and data analysis, which improves utilisation of various resources (Yang et al., 2021; Li et al., 2020; Li and Zhang, 2021). In recent years, development of artificial intelligence algorithm has greatly promoted the analysis efficiency of all kinds of edge nodes. Structure diagram of IoT-enabled distributed smart grids is shown in Figure 1. It shows that electrical consumption information generated by smart meters, smart appliances and some power facilities in the perception layer is uploaded to the distributed cloud platform through transmission nodes in the network layer for information aggregation and task scheduling. Distributed cloud platform is mainly composed of cloud server, cloud information centre and data centre. This main function of cloud server is to collect load and electrical consumption data collected by edge devices, and implement task scheduling management for various devices. Role of cloud information centre and data centre is to monitor the load of data using artificial intelligence algorithm. Thus, an intelligent collection and analysis system of 'cloud edge end' integration is formed. Finally, in the application layer, various load monitoring results are obtained through analysis of various artificial intelligence algorithms.

**Figure 1** Structure diagram of IoT-enabled distributed smart grids (see online version for colours)




With developments of artificial intelligence in computer field, various data acquisition and analysis methods in the IoT have also undergone great changes. First of all, all kinds of artificial intelligence data collection algorithms have been applied to all kinds of nodes in the perception layer. Artificial intelligence algorithm ensures safe transmission of data in all kinds of nodes (Liu et al., 2020b). Among them, The GFS file system framework proposed by Google is widely used in the process of file transmission from acquisition devices to cloud. Framework integrates many artificial intelligence algorithms, which provides a reliable guarantee for the transmission of data and realises high-speed storage of a large amount of data (Wang et al., 2021). Secondly, in the network layer. To ensure real-time response processing of different types of data, all kinds of artificial intelligence task scheduling algorithms has allocated varies reasonable task planning for cloud servers and information centres. Finally, after assignment of task scheduling in the network layer, various data monitoring and analysis are carried out in the application layer, and some analysed data are fed back to users to achieve effect of human-computer interaction.

For monitoring and analysis of real-time data, it is a crucial task in the application layer. At present, main function of the application layer in the distributed smart grid based on the IoT is load monitoring. On the one hand, after timely load decomposition of power information transmitted in the network layer, we can get power consumption of all kinds of electrical appliances. On the other hand, collected data is analysed and judged through load forecasting. Early warning and identification of overload data in advance. However, both load disaggregation and load forecasting. Role of artificial intelligence algorithm is indispensable.

Rest of this article is divided into following parts: the second chapter discusses applications of artificial intelligence algorithm in perception layer, network layer and application layer. In addition, it also discusses data collection, task scheduling based on cloud platform in IoT and load forecasting and disaggregation in load monitoring. What's more, it analyses challenges and progress of artificial intelligence algorithms in these four fields. The last part is the conclusion, which discusses role and significance of artificial intelligence algorithm in IoT-enabled distributed smart grids.

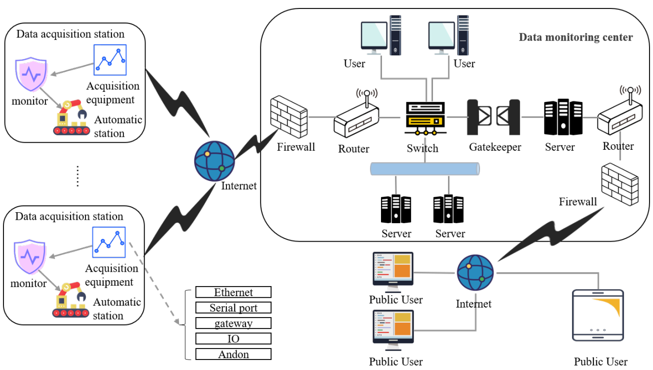
## 2 Artificial intelligence applied in load monitoring

### 2.1 *Intelligent IoT applications during load acquisition*

Load data acquisition provides strong data guarantee for developments of smart grid, and it is also the only way for developments of intelligent load monitoring. In the new era, IoT technology has permeated into power industry, offering support for load data acquisition and quality increase (Wang et al., 2022). Therefore, this section mainly analyses applications of intelligent IoT in the process of load collection. Among them, supervisory control and data acquisition (SCADA) system is the most widely used and technologically mature information system for equipment data acquisition in power system. It mainly includes networking of equipment, power data acquisition, monitoring and early warning, real-time data analysis and other links. System realises an automatic collection of power data. System architecture of SCADA is shown in Figure 2. In which data acquisition methods are mainly divided into following four types:

- *Data acquisition system and equipment networking:* Relying on communication interface protocols owned by acquisition equipment, such as serial port and Ethernet, communicating with host computer and collect data in real time. Without modifying or adding intermediate equipment, it can directly communicate with LAN and data acquisition system server in real time.
- *Industrial gateway and equipment networking acquisition:* If collected equipment does not have Ethernet communication interface module or does not support the secondary increase of Ethernet communication, this industrial gateway will be used to convert data output by equipment through other interface protocols into Ethernet communication, so as to realise networking communication between equipment and data acquisition system.
- *IO module data acquisition:* Without any communication interface and PLC, The IO module is used to network with the equipment, collect switching value, electrical and pneumatic signals of equipment, convert these signals into network data, and upload them to data acquisition system server in real time through the network.
- *Andon system data acquisition:* Light installation equipment is used for manual collection + automatic reporting to realise collection, and andon system is installed on the collected equipment. For example, data such as equipment startup and shutdown, abnormality and output can also be automatically reported by manually operating the corresponding functions on the andon system, but real-time performance of data collection is much lower than that of automatic collection.

**Figure 2** SCADA system architecture diagram (see online version for colours)




SCADA data acquisition system can carry out online networking of different equipment, realise centralised control of all equipment, online collect and analyse data of equipment switching, operation, alarm, operation and maintenance, production capacity and other data, and present them to managers in a visual way, so as to improve utilisation rate of equipment and efficiency of production, operation and management. In addition, Wang et al. (2019) designed a new energy-saving trusted protocol based on mobile fog computing. The confidence model is established on the fog element to assess sensor nodes and generate mobile data acquisition way with the greatest utility value, so as to avoid accessing unnecessary sensors and collecting untrusted data, and save energy cost. Liu (2018) established a software and hardware system to design collection, data processing, feature classification and intelligent tracking of power loads, so as to realise classification and monitoring of different types of power loads synchronously. Rahhman et al. (2019) proposed design, development and performance of data acquisition system for variable load solar PV modules. During data collection, wireless sensor networks are widely used. Among them, the key problem is to improve the energy saving of data acquisition. For this purpose, Gattani and Jafri (2016) proposed a scoring-based load balancing algorithm to improve the service life of the sensor. Diván and Sánchez-Reynoso (2021) proposed a load shedding technology based on metadata and Z-score, which realised distributed data collection locally. Tanjim et al. (2020) proposed a web-based portable data acquisition and control system, which is carried out under influence of the research on the existing advanced supervisory control and data acquisition system. Cost of this system is lower than that of existing SCADA technology. In addition, error rate of data acquisition is reduced, and switching time is calibrated. Based on NB-IoT communication technology, Abdul Haleem et al. (2022) realise the collection, storage, statistics, monitoring and analysis of comprehensive energy consumption information such as electricity and gas. Krishnamoorthy et al. (2020) have realised energy management system based on the IoT technology. Automatic energy meter runs in an intelligent way, and uses GPRS network to collect data and display it on the website. System can collect and control the load data in the environment of IoT. Gautam et al. (2019) proposed that data be collected in the form of voltage and current as the original input, and then further processed by node microcontroller unit, so as to obtain size of assorted power consumption applying data mining technology. Friansa et al. (2017) developed a battery monitoring system based on IoT to monitor operation and function of batteries in smart microgrid system. Data acquisition plan is implemented every minute to collect overall data of battery management system (BMS) IoT to the ECS. Ahammed et al. (2021) proposed a real-time non-invasive load classification (RT-NILC) system based on the IoT, which has developed a data acquisition system (DAS) and measures and stores RMS voltage, current, active power and power factor data at a sampling rate of 1 Hz. Balakrishna et al. (2018) proposed the IoT sensor data acquisition and analysis framework for data analysis and visualisation. Magare and Pal (2018) introduced the implementation and results of liquid or solid liquid level monitoring and data acquisition using industrial liquid level sensors, which have been displayed on the instrument panel and from remote locations using wireless networks. Kamat et al. (2021) connects various sensors to devices and uses sensors to capture their data and store it in the cloud platform for further analysis. Further data analysis of accumulated sensor data can be used for predictive maintenance of equipment. Amudhevalli and Sivakumar (2021) used smart meters to collect fine-grained power consumption information based on advanced metering infrastructure system. However, such power consumption information may reveal information about consumers' lifestyles. Based on this, Mohammed et al. (2018) proposed an effective method using symmetric key encryption and hash operation to collect power consumption information while protecting consumers' privacy. Garg and Sharma (2022) tried to focus on the IoT and machine learning in the smart grid to help smart grid makes decisions. Through this investigation and research in this section, it is concluded that power companies can mine valuable information from massive information to provide users with better power services. In addition, the IoT integrated network system is vulnerable to network attacks and network threats, which need to be fully solved in the near future.

Through various intelligent algorithms and intelligent collection systems, load data is collected to the cloud/edge platform. Then, cloud/edge platform completes the intelligent load analysis of load data with data collection and task scheduling mechanism.

### *2.2 Intelligent collection and scheduling in IoT-enabled cloud/edge platforms*

With rapid development of sensors and network devices, the IoT has also ushered in a huge leap, which interconnects numerous sensing and computing devices to form a vast network. Moreover, it makes these traditional decentralised and isolated nodes more intelligent by using technologies such as storage, computing and communication. Communication technology is an important way to realise interconnection between various nodes of the IoT, which allows data and resources to be exchanged between communication nodes and connected devices and people (Koo and Kim, 2022). Computing is process of using software and hardware or computer systems to perform and complete specific tasks, such as computers performing scientific calculations or other applications. Caching refers to temporary storage of data on the local device, and then on-demand transmission of this data to server according to the latency-tolerant scheme required by the application scenario. Data scale of the IoT is growing very rapidly, and development of sensing technology has made data structure more complex and diverse, especially unstructured data. Cloud paradigm is the basic computing infrastructure part of the IoT, which provides data storage and computing services for the IoT. The cloud/edge platform enables users to gain benefits from the massive data collected by processing big data in real time (Li and Cianfrocco, 2021).

As a technical model, cloud computing provides users with instant, on-demand computing, storage and communication services through the internet. It is a big data distributed computing paradigm, in which resources are abstracted and virtualised, and these virtualised resources can be dynamically delivered to users for on-demand use through the network. This makes cloud computing the preferred platform for integrating resources and providing services (Hu and Li, 2022). This is very different from traditional model, especially in terms of scalability. Therefore, cloud computing can be divided into three categories according to types of services it provides, and can be divided into three types, namely infrastructure as a service (IaaS), platform as a service (PaaS), software as a service (SaaS). Examples of SaaS include e-mail services, social media, etc. These are application software deployed by service providers on cloud computing servers, and users as consumers can directly access and use them through the network. Applications of PaaS include app engine, Microsoft or Amazon's cloud platform services, etc. They are cloud architectures provided by service providers, and then users develop applications on them, as well as test and deploy them. IaaS is an on-demand computing infrastructure, and these resources are mainly provided to users in the form of virtualised servers, storage, and networks. Application scenarios of IaaS include Alibaba Computing Cloud and so on. Edge computing was created in response to the limited-service capabilities provided by cloud computing to edge nodes. Affected by network transmission speed, delay, etc. it is difficult for cloud data centres to provide high-quality services for edge devices. Edge computing is a computing technology implemented at the edge of the network far from the data centre, which assists cloud computing in processing network edge data (Jiang et al., 2022). For example, smartphones can assist cloud computing in application enhancement on wearable devices, and gateways in smart manufacturing can also coordinate between manufacturing equipment and the cloud. Rationality of edge computing lies in fact that computing should take place near the data source, providing low-latency services that cannot be provided by cloud computing, and transmitting all data in the link to the cloud with the communication burden and computational burden (Bouras et al., 2020). Because almost all types of electronic devices will be part of the IoT in the future, at the end of the network, the amount of equipment and data generated by the equipment will increase dramatically. In this case, it is unrealistic for all the data brought by IoT to go to the cloud, and they must be processed and consumed at the edge of the network. Therefore, Core concept of edge computing is to integrate network services, computing services and storage services at the network edge close to end users (Xu et al., 2022b). The internet of vehicles promotes rapid development of autonomous driving. In the internet of vehicles, considering high speed of vehicles, it is necessary to meet low-latency scheduling requirements, otherwise it may lead to dangerous traffic accidents. Therefore, by introducing edge computing into the internet of vehicles, Shortage of internal computing resources in vehicles can be effectively improved, high-quality services can be provided for users, and driving safety can be ensured.

With emergence of new cloud/edge platform-based applications, such as smart grid, smart transportation, etc. new requirements are also put forward for data collection and job scheduling. Therefore, more efforts need to be made to improve utilisation of IoT resources. Nowadays, due to large speed and quantity of data generated by many devices, the fast transmission and efficient processing of data has become a bottleneck restricting development of the IoT. For example, in the process of self-driving cars, about 1 GB of data is generated per second, which requires real-time processing by the vehicle to make correct decisions (Sridharan et al., 2022). This requires extremely high data transmission speed and response speed, so current network bandwidth and reliability will face the challenge of supporting numerous secondary autonomous driving capabilities in one region. In addition, people also generate data from different devices, such as computers, mobile phones and various applications on them. This also challenges scheduling and processing capabilities of these IoT-based cloud/edge platforms. Previous work usually studies collaboration elements related to cloud platforms from a single perspective, such as resource or business scheduling, and fails to examine the collaboration of the service value chain from a system perspective. In Wu et al. (2022), an online scheduling scenario is proposed, and a mixed integer linear programming model for multiple 3D printing tasks based on an additive manufacturing cloud platform is constructed to minimise the average cost per volume of material. Liu et al. (2021d) conducted a system engineering analysis from three dimensions of product cycle, core service business and stakeholders, and proposed a collaborative service model, expounding the multi-stakeholder collaboration and multi-collaboration process. Then comprehensively consider cloud platform service, business and target collaboration and coordination mechanism, and build a cloud platform-based service value chain collaboration framework. Niu et al. (2022) proposed a large-scale factory access task scheduling scheme under cloud-edge collaborative computing architecture by studying big data-driven space physics system, and realised big data-driven scheduling optimisation of the space physics system based on cloud platform algorithm. Zhu (2021) studies real estate virtual e-commerce model based on big data technology. By taking advantage of e-commerce and combining with virtual community design, it can more efficiently analyse and process mobile phone data and make friends virtual e-commerce platform. In this way, needs of customers can be more accurately obtained, and more reasonable options can be provided for them, which can also promote healthy development of real estate industry. Xu et al. (2022a) studies how to minimise user's task processing delay when edge server resources are also limited. Therefore, it proposes a task offloading scheme F-TORA based on game theory and Takagi-Sugeno fuzzy neural network (T-S FNN).

As scale of the IoT continues to expand, these cloud/edge-based platforms also need to have corresponding scalability to better adapt to and handle various applications (Solaiman et al., 2016). Because in the future, more and more devices will be connected to these platforms, at the same time, a larger amount of data will need to be pushed from perception layer to cloud for storage or processing. The realisation of smart cities is inseparable from ability to process these massive devices and data. Therefore, to meet the service requirements of these related applications in the future, it is necessary to effectively improve data transmission and storage efficiency between IoT devices and IoT applications carried by the cloud. IoT platform components deployed in the cloud can scale horizontally or vertically on the end-to-end path from devices to data storage to coordinate processing loads from requests and improve service quality (Zhalgasbekova et al., 2017). Araujo et al. (2019) conduct a comprehensive analysis of the cloud-based IoT platform FIWARE and develops a scalable testbed to simulate large-scale data updates from IoT devices. Online applications are moving to cloud, but long-distance transmission of data to cloud and then processing back brings high latency. Therefore, for latency-sensitive applications, edge computing is being used for scaling (Jiang et al., 2022). Some of these data processing tasks are moved closer to the data source, which greatly reduces network communication pressure and transmission time. Processing of these data streams can be optimised by establishing data pipelines, that is, controlling the complete lifecycle of data streams from data source collection, edge processing, to cloud storage and analysis. Poojara et al. (2022) investigate benefits of building SDPs (serverless data pipelines) for IoT data analysis and evaluates several different approaches to designing SDPs. Finally, these strategies are applied to edge applications to compare their processing time and resource utilisation. Hsu et al. (2022) extended virtual infrastructure manager with network awareness and proposed a multi-layer orchestration system, adding an orchestration between the virtual infrastructure manager and network controller to integrate different resource domains. It proposes a decentralised IoT data analysis model and designs an innovative IoT agriculture platform for cloud and fog computing. Layered and coordinated edge/cloud computing architecture brings great benefits to IoT data storage and task processing, as it enables us to allocate intelligence and computing, including artificial intelligence, machine learning, and big data analytics, to achieve an optimal solution (Gill et al., 2022). Due to the cascading, cross-layer, and distributed nature of the model, to achieve effective combination and complementary advantages of IoT, edge, fog, and cloud computing, design, deployment, or evaluation challenges need to be overcome. Firouzi et al. (2022) propose an overall reference architecture for edge/cloud IoT platforms, and discusses aspects such as infrastructure design, service migration, resource allocation, offloading, service model, provisioning, and security. Gui et al. (2022) proposed a new MEFCS (fog-edge-fog-cloud system) structure for error prediction and control, aiming at the thermal error reducing geometric accuracy of machined gear. Applicability of the finite element model of the bidirectional long short-term memory network is established and verified. Failure of the IoT gateway itself or the failure or overload of the associated network link may cause the IoT application to be temporarily or even permanently unavailable. Batista et al. (2021) propose to use software-defined networking to perform load balancing on IoT platforms through programmability. Aiming at challenges of transformer status diagnosis brought about by the distribution of power transformers far from power plants, Elsisi et al. (2022) proposed a new method to integrate IoT architecture and deep learning to combat network attacks to improve online monitoring of power transformer status.

Cloud/edge platform achieves intelligent monitoring of load data by combining artificial intelligence algorithms. Among them, intelligent monitoring is mainly divided into load disaggregation and load forecasting. Load disaggregation can effectively classify all kinds of electrical appliances, so as to help cloud/edge platform implement function scheduling. Load forecasting can forecast future data trend, which is conducive to future planning of cloud/edge platform.

### *2.3 Intelligent load disaggregation in IoT-enabled distributed smart grids*

Development of IoT-enabled distributed smart grids has led to collection and disclosure of various public datasets on electricity, which provides basis for further exploration of intelligent load disaggregation. Intelligent load disaggregation identifies energy consumption distribution of internal devices through total energy consumption data collected by devices, thus enabling effective feedback from demand side of the smart grid. Traditional steps of intelligent load disaggregation can be divided into data collection, event detection, feature extraction, load identification and load disaggregation (Ruano et al., 2022). Different functional loads in intelligent load disaggregation have different internal circuits and operational control strategies, which make them have different load characteristics. Depending on their operating processes, load characteristics can be divided into steady-state and transient characteristics. Steady-state characteristics are characteristics of the equipment in each stable operating state (Mengistu et al., 2018). The most common of these characteristics are active and reactive power. In addition, steady-state characteristics include current harmonics, voltage and current waveforms and V-I trajectories. Transient features are features collected from switching of equipment states, such as power changes during transients, start-up current waveforms, voltage noise, edge size or cliffness of current waveform spikes, etc. They can be used as load features, and most transient features are obtained indirectly through transformation techniques such as the Fourier transform (Le and Kim, 2018). Compared with steady-state characteristics, transient characteristics are more closely related to characteristics of equipment itself, so equipments can be identified better. In addition, steady-state and transient characteristics of the load can be combined for load identification and disaggregation, which can fully Take advantage of both (Mulinari et al., 2018).

With widespread use of deep learning methods on sequential data such as speech recognition and machine translation, research on intelligent load disaggregation has begun to shift towards unsupervised deep learning methods (Zhang et al., 2018). Various load decomposition methods based on deep learning are shown in Table 1. Compared to traditional intelligent load disaggregation methods, deep learning methods can perform load disaggregation directly without detecting electrical switching events. It uses a given total energy consumption to try to directly infer power consumption of an individual appliance, so that effects of other appliances can be ignored and the whole calculation process can be seen as a denoising process (Krystalakos et al., 2018). Facing energy consumption data with time-series characteristics, Kelly and Knottenbelt (2015) used three deep neural network architectures of LSTM, DAE and Convolutional Regressor to solve the load disaggregation task, and effectively explored possibility of deep learning method in load energy consumption extraction and start-up and stop state identification.

Because of its good performance in classification and extraction, convolutional neural network is applied to classification and regression tasks in the field of load decomposition. Zhang et al designed a CNN architecture with five one-dimensional convolution layers. It uses difference as the main input to obtain better decomposition effect and effectively reduce the amount of model calculation. Considering the different working modes of different electrical appliances, Zhou et al. (2020) fused the features of different receptive fields on the basis of conventional convolution network, and effectively extracted the load feature information by using multi-scale residual network structure. Its structure is shown in Figure 3. Compared with the traditional neural network architecture, this network effectively improves decomposition accuracy. At the same time, design of extended convolution and residual network effectively alleviates problems of insufficient receptive field and degradation of ordinary convolution performance.

**Figure 3** Structure of multi scale network (see online version for colours)

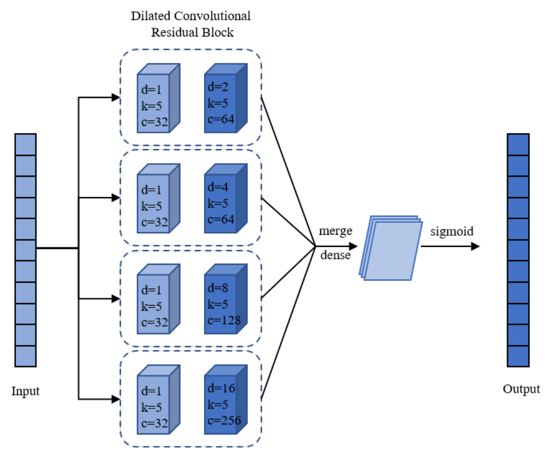
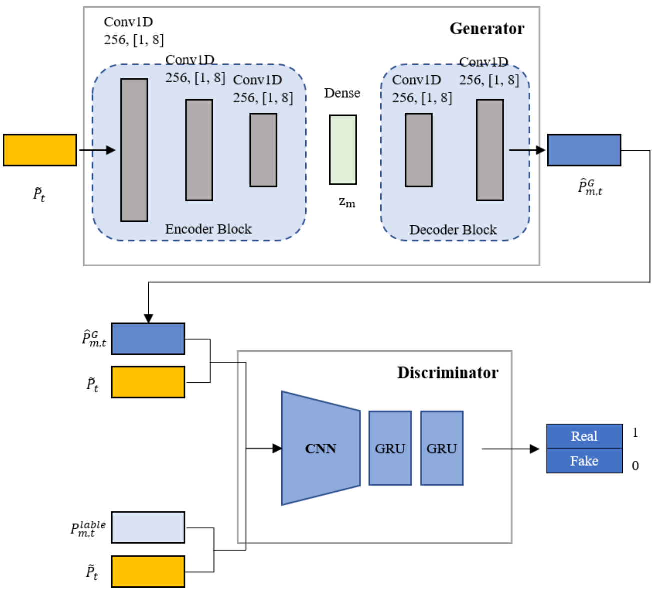


**Table 1** Comparison of load disaggregation models

| *Feature* | *Methods* | *Datasets* | *Application scenario* | *Disadvantage* |
|---|---|---|---|---|
| Steady-state | Multi-scale network (Barber et al., 2020) | UK-DALE | 87% less parameters, it can be implanted into home end measuring equipment. | The model calculation amount is large, and the model prediction accuracy is low for unstable data with large fluctuations. |
| | DLDA (Rafiq et al., 2021) | REDD, UK-DALE | Using the generated synthetic data for data enhancement, the generalisation is good. Consider complex situations such as noise interference. | Not suitable for large datasets. Poor performance when the number of features per data point exceeds the number of training data samples. |
| | CoBiLSTM (Kaselimi et al., 2020) | AMPds, REFIT, REDD | It effectively extracts the contextual information of future samples, seasons, geographical locations and electrical operation modes, and has good scalability. | There will be the shortcomings of gradient disappearance and gradient explosion, the amount of calculation is large, and it is not good at dealing with long-term time series. |
| Transient | Power signature analysis based on V-I trajectory (Mulinari et al., 2019) | COOLL | The load recognition rate is high and the number of features is effectively reduced. | The amount of calculation is high, the model response time is long, and there is still the problem of gradient explosion. |
| | Multivariate DNN (Mariño et al., 2021) | UK-DALE, LATAM | Contributing new datasets. The importance of instantaneous characteristics is verified by taking high-frequency characteristics as multivariable input and increasing the number of network layers. | The model structure is more complex and the interpretability is low. Not good at dealing with long time series. |
| | NCNN (Ciancetta et al., 2020) | BLUED | The detection and classification events can be processed in parallel to reduce the computing time. Only current information needs to be collected. | The structure of the model is complex, and the calculation of the model itself is high. For long-term time series, the prediction accuracy is low. |

**Figure 4** Structure of EnerGAN++ network (see online version for colours)




Automatic coder uses the process of compression and reconstruction between high-dimensional and low-dimensional data to effectively extract hidden features. In intelligent load disaggregation, because the total energy consumption can be regarded as mixture of target load and noise, denoising automatic encoder has received enough attention. García-Pérez et al. (2020) proposed a full convolution noise reduction auto-coding network, which has better performance and better robustness compared with the vanilla DAE network. Kaselimi et al. (2021) used the game idea of generating confrontation to take DAE network as the generator, and CNN and GRU networks form a discriminator. Its architecture is shown in Figure 4. EnerGan++ takes the minimum value of the difference between predicted value generated by decoder in generator and real data as a loss function, which effectively reduces power error. For input data mixed with Gaussian noise, this model has good robustness.

## 2.4 *Intelligent load forecasting in IoT-enabled distributed smart grids*

Under background conditions of 'energy internet + new electricity reform', new technologies for power energy management represented by smart grids are continuously integrated with advanced information technologies such as cloud platforms and IoT (Catlett et al., 2020; Malek et al., 2021). Distributed smart grid with IoT-enabled is an information monitoring system that collects and analyses daily load data. In the face of massive load data, intelligent load forecasting has become an essential information monitoring algorithm (Huang et al., 2022). Intelligent load forecasting can be summarised as a practical application in time series forecasting analysis, and time series forecasting analysis is a part of time series monitoring (Qi et al., 2020). Time series refers to collection of massive datasets collected by major nodes in a uniform time interval, which can be divided into year, month, week, day, hour or even minute. Time series forecasting algorithm analyses and predicts time series data by analysing time series feature information in each time interval. In recent years of research, time series forecasting can be divided into two categories: short-term time series forecasting and long-term time series forecasting according to the types of time intervals analysed.

Short-term time series forecasting is for minute, hour, day, week and month, etc. time series with time interval less than five months. And long-term time series forecasting is for time series of year or even several years with time interval greater than five months (Liu et al., 2021g). Time series forecasting algorithm are widely used based on time periods and data types. According to types of time series data and development of forecasting algorithms, current popular time series forecasting artificial intelligence algorithms can be divided into three categories: machine learning and artificial intelligence algorithms, hybrid machine learning algorithm, and hybrid artificial intelligence algorithms (Mahalakshmi et al., 2016). In the remainder of this section, this paper will describe in detail the existing time series algorithms and compare the advantages and disadvantages of different time series algorithms.

### *2.4.1 Machine learning and artificial intelligence algorithms*

Under influences of non-stationary and multi factors, machine learning algorithm and artificial intelligence algorithm are often used to forecast and analyse relevant time series. Typical machine learning algorithms such as support vector machine (SVM) and artificial intelligence algorithms include recurrent neural network (RNN), long short-term memory network (LSTM).

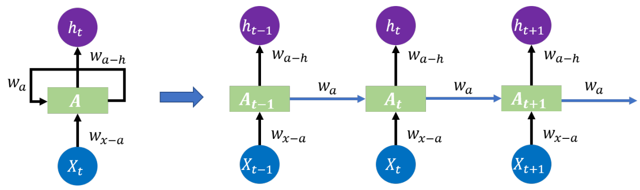
- *Support vector machine:* SVM is a machine learning model for text classification proposed by (Vapnikk et al., 1964). It is a generalised linear classifier based on VC dimension theory and risk minimisation. With the passage of time, SVM is not only used for text classification, but also gradually suitable for pattern recognition and time series prediction according to the combination of different algorithms.

  Yan and Chowdhury (2014) constructed a new machine learning model by combining SVM and ARMAX to forecast PJM power grid data. Compared with single SVM and single ARMAX, SVM-ARMAX improves forecasting accuracy by calculating linear module, and optimises shortcomings of SVM in time series forecasting. Men and Liu (2011) proposed a least squares support vector machine (LS-SVM) algorithm and made forecasting using local dataset with a history of five years. This algorithm takes into account trend component and periodic component by introducing SVM, which makes the load forecasting algorithm more in line with characteristics of power load. The accuracy of time series forecasting is greatly improved.

  Compared with other time series algorithms, advantage of support vector machine is that: on the one hand, it can deal with linear time series and nonlinear time series. On the other hand, support vector machine can effectively avoid the over fitting of data and problem of local minimum caused by too large sample data. However, using a single support vector machine to forecast the time series, the accuracy of the forecasting value is often very low. Some machine learning algorithms and classical prediction algorithms are usually used for hybrid forecasting.

- *Recurrent neural network:* With progress of times, artificial intelligence algorithms have gradually been widely used by researchers. Dealing with time series, RNN has become an efficient artificial intelligence algorithm widely used. RNN generally takes time series as the input of the whole, and presents a recursive state in the form of the whole series. At the same time, each convolution node is connected, and finally a path is formed to analyse the whole time series. Differences between RNN and other convolution algorithms are that RNN has more detailed characteristics of time series and more memory in data transmission. Structure diagram of RNN is shown in Figure 5.

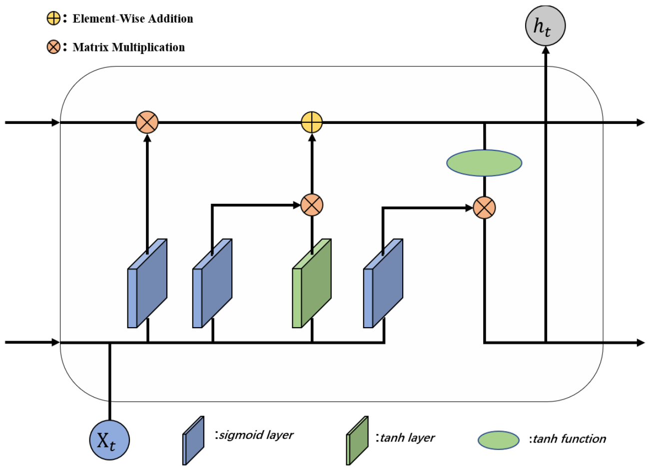
**Figure 5** The structure diagram of RNN (see online version for colours)




Among them, $X_t$ is input time series data, which is weighted into hidden layer by $w_{x-a}$ to obtain output $A$ of hidden layer. On the one hand, the $A$ of output layer is weighted by $w_{a-h}$ to obtain final output $h_t$. On the other hand, passed to next hidden layer weighted by $w_a$. Therefore, it can be seen from the RNN structure diagram that output value at time $t$ is composed of $X_t$ and $A_t$ It is also composed of current forecasting input $X_t$ and hidden layer output $A_{t-1}$ of previous moment. RNN is currently widely used in various time series forecasting. Tokgöz et al. (2018) used the RNN model to analyse the load data in Turkey, compared with traditional models such as ARIMA and analyse relative advantages and disadvantages.

- *Long short-term memory network:* Compared to the RNN algorithm, LSTM is a variant of the RNN algorithm. High accuracy forecasting can be made for long time series. At the same time, LSTM and baseline RNN are not particularly structurally different, but they use different functions to calculate 'hidden' states. LSTM can avoid long-term dependency problem, and central idea is cell state. The network consists of gates of various structures. Creation of a gate is completed through the sigmoid function and dot product operation. However, in the face of long time series data, LSTM will have problems such as gradient disappearance. The structure diagram of LSTM is shown in Figure 6.

**Figure 6** The structure of LSTM (see online version for colours)




The LSTM has to decide which part of original cell state to prune. This decision is made through a structure called a 'forget gate'. The 'forget gate' will read previous output $h_{t-1}$ and current input $x_t$, make a nonlinear mapping of sigmoid, and then output a vector $f_t$, which is finally multiplied by cell state $C_{t-1}$. At the same time, in order to determine information required by the cell state, input information needs to be filtered with the sigmoid function first, and then the tanh function is used to create a new updated state $\widetilde{C}_t$. New state $C_t$ is multiplied by old state $C_{t-1}$ and $f_t$ generated by the forget gate to determine the information that needs to be updated, and then add product of parameters generated by the input gate: $i_t * \widetilde{C}_t$. Final output is obtained by fitting the sigmoid function and the tanh function (Liu et al., 2021f).

In summary, machine learning and artificial intelligence algorithms make up for various deficiencies of classical time series forecasting algorithms, and effectively solve problem of time series forecasting under influence of nonlinearity and multi-features. In particular, rise of artificial intelligence algorithms has opened up a new track for time series forecasting, and hybrid models based on artificial intelligence algorithms have gradually become mainstream. Although machine learning algorithms and artificial intelligence algorithms can solve problems of low accuracy of traditional forecasting algorithms under influence of nonlinear and multi-features. However, complex network structure and weak interpretability of artificial intelligence algorithms also make artificial intelligence algorithms much lower than traditional algorithms for simple time series analysis. Therefore, scholars often adopt hybrid models centred on artificial intelligence algorithms to make more accurate forecasts for various time series.

### *2.4.2 Hybrid machine learning algorithm*

For problems of poor prediction accuracy of small sample data load prediction. On the basis of single machine learning, many scholars use the advantages of machine learning such as SVM and XGBoost to mix other machine learning models, which solved problems of small sample size and low precision. Liao et al. (2019) combined SVM with particle swarm optimisation (PSO). Parameters of SVM are optimised by PSO optimisation algorithm. Compared with a single SVM model, PSO-SVM effectively improves the coupling ability of the model and the prediction accuracy of load data. Song et al. (2021) constructed SSA XGBoost load forecasting model by combining XGBoost model with sparrow search algorithm (SSA). This model uses SSA optimisation model to optimise the variables of xgboost model. Load data of area in Zhejiang Province from January 2019 to December 2020 are used for verification. It is proved that SSA xgboost fusion algorithm has the most significant effect on prediction accuracy.

Compared with a single machine learning algorithm, all kinds of hybrid machine learning algorithms have significant advantages in parameter optimisation, prediction accuracy and so on. Whether it is a single machine learning algorithm or a combined machine learning algorithm, in terms of short-term load forecasting, machine learning algorithm makes regression statistics on the data (Wu et al., 2021; Dowling et al., 2021), Through parameter optimisation and other analysis, prediction value with high prediction accuracy can be obtained. However, in the face of long-term load data, traditional machine learning algorithms will produce errors due to various complex and diverse feature information. Compared with machine learning algorithm, hybrid artificial intelligence algorithm can analyse various complex and diverse characteristic information by combining other artificial intelligence algorithms in dealing with long-term time series, which greatly improves the prediction accuracy (Kohler et al., 2022).

**Table 2** Comparison and analysis of three types of forecasting models in long-short time series

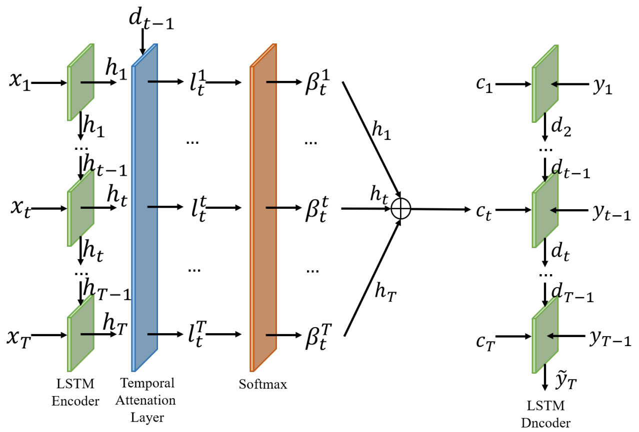
| *Time series* | *Method* | *Dataset characteristics* | *Advantage* | *Disadvantage* |
|---|---|---|---|---|
| Short-time series | SVM (Lu et al., 2009) | Data dimension is high but the data scale is small and nonlinear. | Be good at handling high-dimensional, small-sized small datasets, high interpretability, and strong generalisation ability. | Calculation amount is large, and prediction accuracy is low. |
| | SVR (Aji et al., 2018) | The data is discrete data and nonlinear, data dimension is high and data size is small. | Robust to outliers.<br>It has excellent generalisation ability and high prediction accuracy.<br>The model structure is simple. | Not suitable for large datasets. |
| | RNN (Park and Ahn, 2019) | Data is short-dependent, nonlinear.<br>Data can be affected by other external factors. | Be good at processing short-term time series data, high generalisation ability. | There will be the shortcomings of gradient disappearance and gradient explosion.<br>It is not good at dealing with long-term time series. |
| | LSTM | Data can be long-dependent, nonlinear.<br>Can be affected by other external factors. | Be good at processing long-short-term time series data, and also solve the problem of gradient disappearance in RNN. | The amount of calculation is high, and there is still the problem of gradient explosion. |
| | Hybrid-CNN LSTM (Ren et al., 2021) | Data is short-dependent, can be either linear or nonlinear.<br>High data volatility and high uncertainty. | Be good at handling short-term time series data with high volatility.<br>Higher prediction accuracy for irregular data. | The model structure is more complex.<br>Not good at dealing with long time series. |
| | DRNet | Data is short-dependent, can be either linear or nonlinear.<br>Data correlation is low and volatility is high. | The peak prediction ability is strong.<br>The requirements for data quality are low.<br>The prediction accuracy is high. | The structure of the model is complex.<br>For long-term time series, the prediction accuracy is low. |
| Long-time series | LSTM | Data can be long dependent and nonlinear.<br>At the same time, the data can be affected by other external factors. | Good at dealing with long-term and short-term time series data, with high generalisation ability.<br>Solving the problem of gradient disappearance in RNN. | The amount of calculation is high, the response time of the model is long. |
| | MTGNN (Wu et al., 2020) | The data can be multivariate long-time series, interdependent. | It can effectively make accurate prediction and analysis of multivariate time series.<br>For long time series, the prediction accuracy is high. | The amount of calculation of the model is large and the response time is long. |
| | Informer (Zhou et al., 2021) | Data can be multivariate long-time series. | The model itself has good long-range alignment ability and high prediction accuracy for long-time series. | The model has great computing power.<br>For long-time series, although the prediction accuracy is high, the response time is long. |

### *2.4.3 Hybrid artificial intelligence algorithm*

In order to make up for complex model structure of machine learning and artificial intelligence algorithms for time series, and for longer time series, both RNN and LSTM will have problems of gradient disappearance. Today, many scholars try to integrate other models to solve various problems. Guo and Lin in 2018 proposed a forecasting model for long-term and short-term dual time series, namely long-term and short-term time series network LSTNet. Network extracts feature information of long and short-term time series by reconstructing convolutional layer inside RNN and combining recurrent layer proposed by author. Among them, the main function of convolutional layer is to extract various dependencies in each time series. The main role of the recurrent layer is to capture various dependencies in long-term time series. Thereby, forecasting accuracy relationship for long time series is improved (Lai et al., 2018). LSTNet achieves high forecasting on long and short-term data by effectively using recurrent layers to optimise RNNs to effectively capture relevant forecasting in data in long and short sequences.

At the same time, Qin et al integrated the self-attention mechanism into the recurrent neural network and proposed DA-RNN for accurate forecasting of long-term sequences. Experimental analysis based on SML-2010 and NASDAQ-100 datasets. This structure of DA-RNN algorithm is shown in Figure 7. This model proposes two-stage attention to address weak dependence of native RNN models in capturing long-term time series. In the two-stage attention, one stage adaptively pays attention to the feature information of each stage through the attention mechanism at each information extraction stage. The second stage uses an attention mechanism to select various hidden states of the relevant encoders in all time periods to enhance forecasting accuracy (Qin et al., 2017).

**Figure 7** The structure of DA-RNN algorithm (see online version for colours)




In summary, hybrid model for artificial intelligence is complex and diverse with generation of various optimisation models, but model structure is also gradually complicated (Li et al., 2021; Oloulade et al., 2021). At the same time, with emergence of various extraction methods that focus on feature information such as attention, time series model is not limited to the division of long-term and short-term, but instead realises comprehensive forecasting of long-term and short-term complex time series. According to the two types of prediction algorithms, Table 2 summarises applicable scenarios of various predictions and their respective advantages and disadvantages.

## 3 Discussion

### 3.1 *Concern of data and network security*

Massive data generated in the IoT promotes vigorous development of big data, which is inevitably accompanied by threats and challenges to data and network security (Bai et al., 2022; Qi et al., 2022b). This section mainly discusses security issues and challenges of data and network.

#### 3.1.1 *Main threats to data and network security*

- *Abnormal traffic attack:* A large amount of data generated in the field of IoT is often stored in a distributed manner. However, due to relatively simple data protection method, hackers are easy to find vulnerabilities and invade, resulting in security threats (Kou et al., 2021). Mainly through long-term attack of apt, a large amount of data is obtained, resulting in great security risks.
- *Privacy protection and risk of disclosure:* When collecting and extracting information data, consider user privacy data security of storage space for information transmission and exchange of distributed computing to prevent it from being disclosed and used. In dealing with dynamic incremental attributes of data and protecting the existing sensitive data to ensure complex security of a large number of data, we should focus on the issues.
- *Hidden danger of data transmission:* Due to heterogeneity, multi-source and correlation of data, there are often risks of distortion, tampering and information leakage in the process of data transmission. Security risks may also occur due to unauthorised and damaged data. Although distributed platform provides an important carrier for data transmission and collection, which meets the basic needs, it also brings security problems of data storage, which hinders the development of data transmission.
- *Data storage management risk:* In various data storage platforms, due to different data structure types, it is very likely to cause a variety of application concurrent processes, repeated disordered operations, and disordered data storage, which will bring security risks to data storage and post-processing. Therefore, it is a great test to store massive data based on distributed platform to meet increasingly updated data storage requirements.

#### 3.1.2 *Future development trend of data and network security*

Aiming at diversified problems faced by network data security, it also provides new technologies and requirements for the attack and defence means of network security (Korn, 2021). This section mainly discusses blockchain, artificial intelligence and new ecology of network security. As shown in Figure 8.

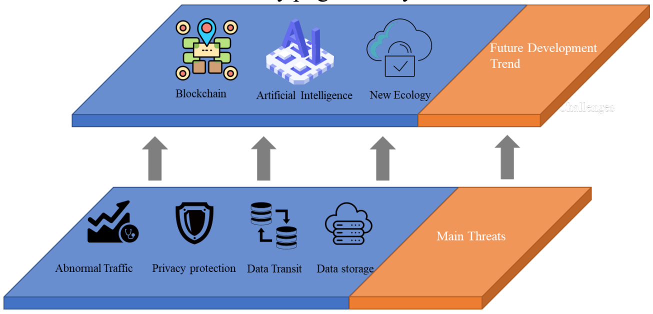
- *Blockchain is used to solve network security problems:* At present, it is almost impossible for blockchain technology to change data, and end-to-end encrypted data service has replaced traditional encryption tools because of its decentralised characteristics. It has obvious technical advantages in network security, and there is a lot of rooms for development in the future. Firstly, it is used to protect network data. It mainly uses backlinks data structure and consensus mechanism to protect the data. It is to conduct overall monitoring within the boundary, screen data within the monitoring range, eliminate false and retain true. If these data are attacked by this network, it means to take whole blockchain network as the enemy, and loss is often great and the gain outweighs loss. Secondly, online asset management and traceability. Make use of non-random change characteristics of blockchain to ensure the uniqueness and non-random tampering of data, and manage and label assets in combination with IoT technology. At the same time, reliable communication on the network is realised, because the blockchain network has no important centralised nodes to interrupt. Even if most nodes are disconnected, the normal operation of the blockchain network will not be affected.

- *Artificial intelligence for network security:* The data generated by the IoT distributed smart grid has produced a great influence in the power field and got a profound impact on our social and economic activities. At present, machine learning and deep learning are inseparable from network security. Take advantage of artificial intelligence and machine learning technology to find security vulnerabilities, process security alerts based on artificial intelligence, and improve security measures by providing real-time network threat identification and interception. It will be a trend to make full use of new technologies such as artificial intelligence, cloud computing and big data to tap the great value of information and form a strong competitive advantage.

- *New ecology of data network security:* Network operation and maintenance based on big data and artificial intelligence reduces artificial errors. Arrival of 5G has further realised the great integration of information technology and network communication. Intelligent monitoring helps to improve network security defence grade, but fictitious and software definition capabilities of 5G also bring new security risks. At the national level, developed countries such as Europe, America and Japan have strong market competitiveness and large market demand; Network security urgently needs to strengthen regional security cooperation among countries along the line to form a new ecosystem of network security.

**Figure 8** Data network security threat and future development trend (see online version for colours)

security.png security.bb




### *3.2 Challenges of AI in cloud-edge architecture*

Cloud/edge platform-based applications in IoT bring many conveniences to solving problems in real production environments (Qi et al., 2021). However, it should also be noted that there are still many problems to be solved urgently. Progress of technology often brings increase of complexity of this problem at the same time, resulting in many unexpected problems (Guezzaz et al., 2021). For example, rapid development of artificial intelligence has brought us many convenient applications, but in applications such as autonomous driving and intelligent transportation, processing of tasks requires very high latency, especially in applications involving transportation. Therefore, research on the processing and scheduling of time-sensitive tasks is very important, and it is an important part of ensuring traffic safety. With increase in the type and quantity of IoT devices and increase in various types of unstructured data, research on data flow fusion is also a promising direction. Through in-depth research on data flow, solutions can be found to reduce amount of data transmission between IoT devices and backbone network and minimise bandwidth allocation. IoT devices continuously generate data, which in turn is transmitted and processed between devices and cloud/edge platforms. How to compress or reduce data to reduce the transmission and processing burden deserves further study. Data reduction is to minimise amount of storage that needs to be stored in a data storage node, which can improve storage efficiency and reduce costs. By leveraging the cloud computing paradigm, cloud-assisted IoT can provide end-users with massive storage and high-availability computing services. When the data generated by IoT devices is continuously sent to the cloud centre, data security also becomes a new challenge. How to ensure secure transmission of data while avoiding inability to achieve data search and access control after using encryption technology is a direction worthy of further research. 5G has gradually matured, and the 6G standard will realise omniscient coverage of large-scale IoT networks. Satellite-based communication will be an important means to meet the needs of IoT services in the 6G era. Therefore, the research of access technology is crucial for the effective deployment of satellite-based IoT.

### *3.3 Opportunities of adaptive and fine-grained load disaggregation*

Developments of technologies such as the IoT, 5G/6G, artificial intelligence and distributed cloud computing has driven the intelligent transformation and upgrade of the power grid. Problems of insufficient metering equipment, incomplete energy consumption information, poor real-time monitoring, and lack of load management solutions in traditional load monitoring are expected to be solved (Da Silva Nolasco et al., 2021). Load disaggregation, as one of the basic technologies for building smart grids, still has much room for improvement in related research, although its recognition accuracy is improving.

#### *3.3.1 The variety of public datasets is limited*

Most research is currently focused on residential users, whose data can be obtained relatively easily through research recruitment, but there are few studies for industrial users. In addition, this published datasets can be used for load decomposition studies, such as REDD, BLUED, AMPds, UK-DALE, etc. (Liu et al., 2021b, 2019), are mainly distributed in Europe and the US, and there are no available public datasets in Asia, which restricts the development of load monitoring systems for the Asian region. It is a challenge to obtain a wider range of datasets to achieve a universal and effective load decomposition.

#### *3.3.2 Fine-grained load decomposition needs to be improved*

Existing methods are more accurate in identifying commonly used high-powered home appliances. However, as there are many different types of electrical devices in real-life scenarios, and there are certain differences between different brands of similar goods, it is still a challenge to achieve fine-grained load decomposition by effectively differentiating the power consumption of similar electrical devices through a common single network model.

#### *3.3.3 Poor adaptive load decomposition*

Different regions and countries have different electrical equipment due to cultural differences and geographical factors. Different quality and safety standards for different electrical equipment also lead to differences in power consumption. In addition, seasonal and climatic changes affect the use of some devices, for example, heaters are turned on in winter, while air conditioners are mainly used to cool down in summer, and drying functions are used more often in rainy seasons. How to optimise generalisation performance of decomposition algorithm in different regions and seasons and improve adaptive effect of load decomposition is a question that researchers should consider.

Intelligent load disaggregation model constructed using deep learning methods can bypass the problem of appliance switching event detection and effectively reduce difficulty of model training, but there is still a certain distance for practical application of adaptive and fine-grained load disaggregation. Future research can be carried out from the following aspects:

- *Enriching dataset sources:* Using the IoT and internet technologies to build a data collection platform to collect energy consumption data from different regions, especially in Asia. Enrich the composition of user data, cooperate with the industrial sector to expand the subject of research, no longer limit it to residential users, and build an energy dataset with a wider data volume, more collection areas, and a rich variety of appliances.
- *Combining more input information:* Research work related to load disaggregation is heavily influenced by factors such as equipment type, power consumption cycle, data and quality, etc. Combining low and high frequency input information, such as power, voltage and current waveforms, V-I trajectories, start-up current waveforms and edge size or cliffness of current waveform spikes, to optimise load feature extraction and thus improve the fine-grained load decomposition effect.
- *Improving scalability:* Load monitoring has high requirements for latency and uses pruning and residuals to reduce model parameters and training time. Combined with cloud computing technology, it can realise lightweight online decomposition algorithm, which can effectively improve user experience. In addition, by linking load disaggregation with the fields of speech recognition and machine learning, the adaptive load disaggregation optimisation can be explored by combining migration algorithms to improve the generalisability of the model.

### *3.4 Prospect of short-term and long-term load forecasting*

As shown in Table 2. This section mainly compares and analyses current load forecasting algorithms from machine learning algorithms, artificial intelligence algorithms and hybrid machine learning algorithms. Finally, according to advantages and disadvantages of various algorithms, development directions and application scenarios of load forecasting are discussed.

It can be found from Table 2 that classical time series algorithm and artificial intelligence algorithm have advantages and disadvantages for both short-term load data and long-term load data. For linear time series data with simple structure, classical time series algorithms are still widely used by scholars because of their simple structure and low computation. In the face of growing data, considering that most of the real data are diversified and nonlinear time series data, classical time series algorithm is no longer applicable. Artificial intelligence algorithm gradually replaces classical time series algorithm (Sun et al., 2019; Liu et al., 2021c, 2018). In particular, artificial intelligence algorithm with LSTM as core has been further improved in various time series models. However, each artificial intelligence algorithm inevitably has many limitations. Specifically, a single artificial intelligence algorithm often has negative effects such as gradient disappearance or gradient explosion. In the face of this impact, it is often mixed with many kinds of artificial intelligence algorithms to learn from each other and build a new artificial intelligence hybrid model. This kind of artificial intelligence hybrid model is often much higher than single artificial intelligence model in the effect of data analysis, but complexity and calculation of this model are greatly improved. Memory loss is huge. Therefore, how to ensure forecasting accuracy of short-term and long-term load forecasting and reduce complexity and calculation of the model is a problem to be solved.

In view of gradient vanishing problem of current deep learning algorithm for long-term time series, scholars at home and abroad generally adopt combination model for optimisation (McNealy, 2021; Liu et al., 2021a; Shao et al., 2022). In particular, combination with image field, using graph convolution (Qi et al., 2022a) or residual network, can effectively alleviate problems of gradient disappearance, and more effectively take into account all kinds of feature information in long-term time series. For short-term load forecasting, although a single neural network can quickly predict value of next time series, prediction accuracy is low (Liu et al., 2021e). In view of this phenomenon, connection method of jump residual is adopted. Under condition of not affecting response time, prediction accuracy is effectively improved. Compared with the multi-channel connection of the combined neural network, jump residual is connected linearly, which effectively reduces the response time and ensures the accuracy.

## 4 Conclusions

This paper takes the collection, processing and storage of smart grid data as research background, and systematically investigates the intelligent load monitoring in IoT-enabled distributed smart grids. With developments of artificial intelligence and cloud computing, data processing efficiency of edge devices has been greatly promoted. Distributed cloud platform effectively realises collection and storage of data, thus forming a cloud-side-end integrated intelligent collection and analysis system. To this end, this paper first introduces collection method of IoT device data. Then, the application of cloud/edge platform in IoT data collection, processing and scheduling is introduced. With the powerful computing and storage capabilities of cloud computing centres and the high response speed of edge devices, it can greatly improve the real-time data processing in smart grid demand. This paper also summarises and analyses the load decomposition and load forecasting methods. In the face of energy consumption data with time series characteristics, we explore effectiveness of intelligent load decomposition of neural network models such as LSTM, CNN, and GRU in the distributed smart grid of the IoT. Time series forecasting algorithms and load decomposition methods based on machine learning and artificial intelligence algorithms are introduced, and application of artificial intelligence hybrid models in time series forecasting is introduced, and these methods are compared.

In the last part of this paper, future research directions are prospected, including data and network security issues, challenges faced by cloud/edge architecture, adaptive fine-grained load decomposition and load prediction. In general, for data and network security issues, the IoT system is vulnerable to network attacks and threats. For this problem, integrating communication protocol security has become a future improvement method. For cloud/edge platforms, efficient data transmission and how to reduce latency are also persistent potential problems. However, with upgrading of various hardware and development of communication technology, research of 6G technology has become a direction worthy of exploration in the future. For load monitoring, how to ensure accuracy of long-term and short-term forecasting, while reducing complexity of load decomposition model and calculation complexity is also a highly expected research direction.

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